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Full Papers

Adaptive Driving Situation Characterization for Predicting the Driving Load of Electric Vehicles in Uncertain Environments

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ABSTRACT

Battery powered electric vehicles (EVs) have emerged as a promising solution for reducing the consumption of fossil fuels in modern transportation systems. Unfortunately the battery pack has a low energy storage capacity, which causes the driving range of the EV to become very limited. It is therefore essential to properly characterize the different driving situations of the vehicle in order to better predict the driving load along the road ahead and to better estimate the remaining driving range (RDR). However, this prediction cannot be achieved straightforward due to sources of uncertainty introduced by the randomness of the driving environment. In this paper a novel approach for characterizing driving situations and for predicting the driving load of an EV is presented. The prediction of the driving load occurs in a model-based fashion, where the model input variables are modeled as discretetime Markov processes. An approach for estimating the transition probabilities between Markov states in the presence of sparse driving data is introduced. Furthermore, to capture the changes in the driving environment a Bayes-based methodology for recursively updating the established transition probabilities is presented. The validity of the proposed approach is illustrated through simulation and by a series of experimental case studies.

1. INTRODUCTION

In modern times, the use of battery powered electric vehicles (EVs) has grown due to they offer a promising solution for reducing the consumption of fossil fuels. However, the limited energy storage capacity of the battery pack causes the driving range of the EV to become very limited. A proper characterization of driving situations is therefore essential in order to better predict the driving load, i.e., the electrical power demanded to propel the EV along the road ahead. Such a prediction can be used, for example, by an advanced driver assistance system (ADAS) to estimate the RDR of the EV in a more accurate manner. However, this prediction cannot be achieved straightforward due to many sources of uncertainty introduced by the randomness of the driving environment. Key affecting factors such as the road profile, the driving style or the traffic conditions are highly uncertain and are usually difficult to predict.

To the best of our knowledge, few studies have addressed the problem of predicting the driving load in EVs. (Wang, Xu, Li, & Xu, 2007) combine cascade neural networks with a nodedecoupled extended Kalman filter to forecast the driving load. In this work the authors define five load levels by fuzzy logic and, instead of predicting an entire sequence of loads, the load level is forecast. In (Yang, Huang, Tan, & He, 2008) the driving load of a hybrid electric vehicle (HEV) is predicted by using the discrete cosine transform (DCT) together with support vector machines (SVM). Similar to the approach previously mentioned, the authors classifie the driving load into five predefined levels. The forecasting task deals with the decision about the next load level. An approach that predicts the battery power requirements for EVs in real time by combining road information from a static map with historical driving data is introduced by (Kim, Lee, & Shin, 2013).

The drawback with the aforementioned approaches is that none of them treat the driving load in a stochastic manner. As it has been shown in (Oliva, Weihrauch, & Bertram, 2013), estimating the RDR of an EV requires characterizing the uncertainty introduced by driving environment. Because of this, this contribution deals with a novel approach for characterizing driving situations and with an algorithm for predicting the driving load of an EV. The prediction of the driving load takes place under a model-based approach. A model of the powertrain of an EV is used to compute the electrical power demand of the electric motor as response to the road properties, the vehicle speed and the acceleration, which in this paper constitute the input variables of the model. The evolution of the input variables in time is first modeled as a homogeneous discrete-time Markov process. An offline approach for

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estimating the transition probabilities between states in the presence of sparse data is introduced. This allows completely characterizing the uncertainty in the transition probabilities of the Markov state space even if information about some transitions between states is unavailable. However, relying solely on the Markov transition models identified offline for predicting the driving load usually does not adequately describe the most recent driving situation. For this reason we also present a Bayes-based methodology for updating the transition probabilities as new information about the driving situation becomes available.

The remainder of this paper is organized as follows: Section 2 deals with the physical model of an EV used to compute the driving load. In section 3 the characterization of driving situations is discussed and two offline methods for estimating the transition probabilities between Markov states are introduced. Section 4 explains the steps needed for updating the transition probabilities on receipt of new information about the driving situation. In section 5 the algorithm used for predicting the driving load is described. Section 6 presents the simulation and experimental results used for validating the proposed approach. Finally, section 7 concludes the findings of this work and provides an outlook on our future work.

2. DRIVING LOAD MODELING IN EVS

As it was already mentioned, the prediction of the driving load is carried out in a model-based fashion. From a physical point of view, the driving load can be either modeled by a forward-facing or by a backward-facing approach (Guzzella & Sciarretta, 2005). In the forward-facing approach the EV is controlled to follow a desired speed. This approach considers the physical properties of each component of the powertrain and the dynamic interaction between them. The drawback with this modeling approach is the high computational burden required to solve the set of differential equations presented in the model. This paper employs the backward-facing approach, for modeling the driving load of the EV. The backwardfacing approach is computationally efficient since it assumes that the EV moves exactly with an imposed speed. The model calculates the forces acting on the wheels and processes them backwards through the powertrain. The computation of the power demand depends only on algebraic equations, decreasing in this manner the computational effort of the model. Fig. 1 depicts the structure of the model used to compute the driving load. As it is explained in the following two sections, the input \mathbf{u} is given by the speed v and acceleration a of the vehicle and by the inclination (slope) θ of the road. The output y of the model is the electrical power demanded by the electric motor, denoted here as P_{ele} .

The following section explains the model in detail. We omit expressing the variables of the model as time dependent, since this model is described by a set of algebraic equations.



Figure 1. Structure of the backward-facing approach for modeling the driving load of an EV.

2.1. Backward-facing Approach

An electric vehicle is composed by many components which, for simplification purposes, can be considered to move uniformly. As shown in Fig. 2, the force F_x required to propel the vehicle forward can be computed by

$$F_x = F_{air} + F_g + F_r + F_i, \tag{1}$$

where:

- $F_{air} = \frac{1}{2}\rho_{air}c_w Av^2$ is the aerodynamic drag force,
- $F_q = mg\sin(\theta)$ is the hill climbing force,
- $F_r = mgK_r$ is the rolling resistance and
- $F_i = ma$ is the force needed to accelerate/decelerate the vehicle.

The parameter ρ_{air} is the density of air, c_w is the aerodynamic drag coefficient, A and m are the frontal area and the mass of the vehicle, g is the gravitational acceleration and K_r is the rolling resistance coefficient.



Figure 2. Forces acting during the motion of an EV.

The mechanical power P_{mec} demanded by the electric motor is easily calculated by means of a polynomial power requirement model as follows:

$$P_{mec} = F_x v = \frac{1}{2} \rho_{air} c_w A v^3 + mg \sin(\theta) v + mg K_r v + mav.$$
(2)

As suggested by (Guzzella & Sciarretta, 2005), the relationship between the mechanical and the electrical power demand of an electric motor can be computed, with a certain degree of accuracy, by employing a stationary map of the electric motor's efficiency as a function of the rotor's rotational speed and the torque demand

$$P_{ele} = \frac{P_{mec}}{\eta_m \left(\omega_m, T_m\right)}, P_{mec} > 0.$$
(3)

In Eq. (3) the electric motor's efficiency is represented by η_m , $\omega_m = \frac{vi_d}{r_{tire}}$ is the rotational speed of the rotor and $T_m = \frac{F_x r_{tire}}{i_d}$ is the torque demand of the motor. Here r_{tire} and i_d are the tire's radius and the gear ratio of the driveline respectively.

One important feature of modern EVs is that certain amount of the kinetic and the potential energy can be recovered by means of the regenerative braking system. During braking maneuvers the electric motor is operated as a generator, providing in this manner an extra braking torque to the wheels. The recovered energy can then be used to supply power either to the powertrain or to the auxiliary accessories. The amount of braking torque depends on the operation strategy of the braking system. The operation strategy optimizes the distribution of braking torque between the mechanical and the regenerative brakes in such a way, that the maximum electrical power is generated. The electrical power generated is computed by

$$P_{ele} = P_{mec}\eta_m \left(\omega_m, -T_m\right) k_{v_x}, P_{mec} < 0.$$
(4)

Since the generated power depends on ω_m , it would be a difficult task to supply power to the power bus at low speeds. Because of this the parameter k_{v_x} is used to limit the usage of the electric motor in generator mode according to Eq. (5), so that the mechanical brakes are applied at very low speeds and at high speeds the vehicle is braked mostly by the electric motor.

$$k_{v_x} = \begin{cases} 0 & v_x \le 3.5 \text{ m/s} \\ \frac{v_x - 3.5}{5} & 3.5 < v_x < 8 \text{ m/s} \\ 0.9 & v_x \ge 8 \text{ m/s} \end{cases}$$
(5)

The efficiency map η_m is usually well defined just for the motor mode (upper quadrant of Fig. 3). In order to extend the map to the generator mode, the power losses are mirrored as follows

$$\eta_m(\omega_m, -T_m) = 2 - \frac{1}{\eta_m(\omega_m, T_m)}.$$
(6)

Even though the computed efficiency map obtained by applying Eq. (6) slightly differs from the data that can be obtained by measuring the efficiency of the electric motor working as generator, it offers a practical and accurate solution for modeling the electric motor also in generator mode.



Figure 3. Efficiency map of an electric motor.

2.2. Factors Affecting the Prediction of the Driving Load

To properly predict the driving load under a model-based approach it is necessary to analyze the dynamics of each of the parameters of Eq. (2) and to determine the source of information needed to acquire them, in order to differentiate between time invariant and time variant model parameters, from now on referred as *constants* and *input variables*, respectively. On the one hand, input variables are characterized by their high dynamic and are usually easily measurable. On the other hand, the constants, as the term suggests, rarely change or change very slowly. Table 1 summarizes the dynamics and presents the sources of information required to acquire each of the parameters involved in the computation of P_{mec} .

Parameter	Dynamics	Source of information
$a (m/s^2)$	Very high	Driver, road, traffic
v (m/s)	High	Driver, road, traffic
m (kg)	Nearly constant	Vehicle design
$g (m/s^2)$	Nearly constant	Altitude
K_r	High	Road
θ (°)	High	Road
$\rho_{air} (\text{kg/m}^3)$	Low	Altitude
c_w	Nearly constant	Vehicle design
$A (m^2)$	Nearly constant	Vehicle design

Table 1. Dynamics and sources of information required for the acquisition of the parameters affecting the prediction of the driving load.

The parameters g and ρ_{air} , even though they can be easily determined, depend on the altitude and rarely change during a trip. Also m, c_w and A can be easily acquired. They don't change since they depend on the vehicle design. The friction coefficient K_r , despite its high dynamics, cannot be measured, and therefore it has to be either assumed or estimated. For this reason we consider it as a constant parameter under the assumption that the road conditions do not change drastically during a trip.

The slope θ changes rapidly according to the road type and can be easily acquired either by integrating a GPS into the EV or by using a navigation system with a preloaded static GIS (Geographic Information System). The speed v and the acceleration a depend on many factors that are difficult to predict and that exhibit some degree of randomness. To these factors belong the road type, the traffic conditions or the driver aggressiveness, just to name a few. Hence v and a change very dynamically and have to be treated as time variant.

The parameters v, a and θ are considered in this work as the model input variables, since they meet the requirements previously mentioned. Accordingly, the input vector, used here to denote a driving situation, is given by

$$\mathbf{u} = \begin{bmatrix} v & a & \theta \end{bmatrix}^T. \tag{7}$$

The characterization of the input variables is explained in detail in the following section.

3. DRIVING SITUATION CHARACTERIZATION

By assuming that the input vector $\mathbf{u} = \begin{bmatrix} v & a & \theta \end{bmatrix}^T$ evolve in time following a discrete-time stochastic process $\{\mathbf{u}_k\}$ and that it can take on values in a countable set \mathcal{U} , called the state space, then its behavior can be successfully modeled as a first order Markov chain, under the assumption that it satisfies the so called Markov property. This property states that, the future state \mathbf{u}_{k+1} depends only on the current state \mathbf{u}_k and not on all previous states $\mathbf{u}_0, \mathbf{u}_2, \dots, \mathbf{u}_{k-1}$. In other words, for all $\{\mathbf{u}_k, k \ge 0\}$

$$\pi_{i,j} = p\left(\mathbf{u}_{k+1} = j | \mathbf{u}_k = i, \mathbf{u}_{k-1}, \dots, \mathbf{u}_0\right)$$
$$= p\left(\mathbf{u}_{k+1} = j | \mathbf{u}_k = i\right), \tag{8}$$

where $\pi_{i,j}$ is known as conditional transition probability and k denotes the discrete time step. All transition probabilities between states are grouped in a transition probability matrix Φ of the form

$$\mathbf{\Phi} = \begin{bmatrix} \pi_{1,1} & \pi_{1,2} & \cdots & \pi_{1,m} \\ \pi_{2,1} & \pi_{2,2} & \cdots & \pi_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{m,1} & \pi_{m,2} & \cdots & \pi_{m,m} \end{bmatrix}.$$
 (9)

Then, Eq. (8) can be expressed as

$$\pi_{i,j} = \mathbf{\Phi} \left(\mathbf{u}_{k+1} = j | \mathbf{u}_k = i \right), \tag{10}$$

where $\pi_{i,j}$ is the ij^{th} element of Φ . Since the elements jof Φ represent the transition probabilities to all other states from i, each row satisfies the condition $\sum_{j=1}^{m} \pi_{i,j} = 1$ for all $j \in \mathcal{U}$. Eq. (10) is said to be *time homogeneous* since $\pi_{i,j}$ is independent of k. To better estimate the transition probabilities of Eq. (10) the input state space is splitted up into $\mathbf{u}_k = \begin{bmatrix} \mathbf{u}_k^{va} & u_k^{\theta} \end{bmatrix}^T$, where $\mathbf{u}_k^{va} = \begin{bmatrix} v_k & a_k \end{bmatrix}$ and $u_k^{\theta} = \theta_k$ represent parts of the input state space given by the tuple (v, a) and by the slope θ , respectively. As shown in (Oliva et al., 2013), two transition probability matrices, namely Φ^{va} and Φ^{θ} can be used to store all the information regarding the transition probabilities of the input variables. The following section introduces the methodology used in the estimation of the transition probabilities of both transition probability matrices (TPMs).

3.1. Characterization of Φ^{va}

In the presented approach, the structure of Φ^{va} differs slightly from that of Φ as it was introduced by Eq. (9). The states of the Markov chain are composed by $v_s \in \mathcal{V}$ and by $a_i \in \mathcal{A}$, where \mathcal{V} and \mathcal{A} represent the state space of the speed and acceleration of the EV. The definition of the conditional transition probability given by Eq. (10) is reformulated for this matrix as

$$\pi_{i,j}^{v_s a} = \Phi^{v_s a} \left(a_{k+1} = j | a_k = i, v_k = s \right), \qquad (11)$$

where $\pi_{i,j}^{v_s a}$ describes the probability of accelerating at rate a_j over the next time step given that the EV accelerates with a_i at given speed v_s in the current time step. The structure of Φ^{va} , with $\Phi^{v_s a} \in \mathbb{R}^{M \times M}$ and $v_s \in \mathbb{R}^N$, is shown in Fig. (4).



Figure 4. Structure of Φ^{va} .

The purpose of modeling \mathbf{u}_k^{va} as a homogeneous Markov process is to describe the stationary distribution of speed and acceleration. In this work the transition probabilities of Φ^{va} are estimated from historical driving data. Both a and v have to first be discretized. Accordingly, the state space is discretized as $\mathcal{A} = \{a_{\min}, \ldots, -2a_{\mathrm{res}}, -a_{\mathrm{res}}, 0, a_{\mathrm{res}}, 2a_{\mathrm{res}}, \ldots, a_{\mathrm{max}}\}$ and by $\mathcal{V} = \{0, v_{\mathrm{res}}, 2v_{\mathrm{res}}, \ldots, v_{\mathrm{max}}\}$, where $v_{\mathrm{res}} = 1 \text{ km/h}$, $v_{\mathrm{max}} = 140 \text{ km/h}$, $a_{\mathrm{res}} = 0.2 \text{ m/s}^2$, $a_{\mathrm{min}} = -3 \text{ m/s}^2$ and $a_{\mathrm{max}} = 3 \text{ m/s}^2$. The resolutions v_{res} and a_{res} offer a good trade-off between computational effort and accuracy.

3.1.1. Estimating the Stationary Distribution of Φ^{va}

In this work we use the maximum likelihood estimation (MLE) scheme (T. C. Lee, Judge, & Zellner, 1970) for estimating the time-invariant transition probabilities of Φ^{va} . A transition

probability $\pi_{i,j}^{v_s a}$ is computed by

$$\pi_{i,j}^{v_s a} = \frac{n_{i,j}}{n_i},$$
(12)

where $n_{i,j}$ represents the number of times the EV changes its acceleration from a_i to a_j and n_i is the total number of times the EV accelerates with a_i at given speed v_s . This approach is very practical since the estimation can by achieved by simply *counting* the number of times a change in the acceleration occurs.

3.1.2. Approximating Φ^{va} for unavailable data

As it will be shown in section 5, the construction of the Markov chain for a_k may lead to speed states v_s , computed by Eq. (29), where $\Phi^{v_s a} \rightarrow \{0\}$, i.e., where no information about the distribution of the acceleration in the next time step is available. This is caused due to the sparsity of the historical driving data used for estimating the transition probabilities.

This issue can be sorted out by finding a suitable probability distribution function of the form $f(a_{k+1}|a_k = i, v_k = s)$ that can be employed for all $\Phi^{v_s a} \to \{0\}$. The shape of such a function can be better understood by analyzing the distribution of a_{k+1} at different (v_k, a_k) . One strong candidate for choosing f is the *Beta* distribution (Johannesson, Asbogard, & Egardt, 2007). Fig. 5 shows the Beta function fitted over different distributions of a_{k+1} .



Figure 5. Fitted Beta function over the distribution of a_{k+1} at different (v_k, a_k) .

The Beta density function is a versatile function which is usually employed for modeling different shapes of probability distributions, as shown in Fig. 6. The probability density function (PDF) of the generalized Beta distribution is given by

$$f(x|\alpha,\beta,b_L,b_U) = \frac{(x-b_L)^{\alpha-1} (b_U - x)^{\beta-1}}{(b_U - b_L)^{\alpha+\beta-1}},$$
 (13)

where α and β are the shape parameters of the Beta distribution and $[b_L, b_U]$ define the interval for which Eq. (13) is defined. The fact that the Beta PDF is defined just over a given interval can be exploited in that no accelerations beyond the admissible values, dictated by the performance of the EV, can be reached. Furthermore, b_L and b_U can be conveniently chosen to force any a_{k+1} , drawn from a Beta distribution given by Eq. (13), to lie within the bounds of the state space of $\Phi^{v_s a}$, i.e., $a_{k+1} \in \mathcal{A}$.



Figure 6. Different shapes of the Beta distribution on the interval with $b_L = 0$ and $b_U = 1$.

The first two moments of a_{k+1} , namely the expected value and the variance, are given by

$$E[a_{k+1}|\alpha,\beta,b_L,b_U] = b_L + (b_U - b_L)\frac{\alpha}{\alpha + \beta}$$
(14)

and

$$Var\left[a_{k+1}|\alpha,\beta,b_L,b_U\right] = \frac{\left(b_U - b_L\right)^2 \alpha\beta}{\left(\alpha + \beta\right)^2 \left(\alpha + \beta + 1\right)},$$
 (15)

respectively. The function f can be reformulated in such a way that the parameters of the Beta distribution depend on the Markov states and that the PDF is defined only over the state space of a, i.e., $f(a_{k+1}|\alpha(a_k, v_k), \beta(a_k, v_k), a_{\min}, a_{\max})$. The task is then to estimate both α and β for the entire state space. To this aim we combine the Markov states of v and a and define a two-dimensional state space denoted by

$$\boldsymbol{\mathcal{S}} = \left\{ a \in \mathbb{R}, v \in \mathbb{R} : \boldsymbol{\mathcal{A}}, \boldsymbol{\mathcal{V}} \right\}.$$
 (16)

From the historical driving data we acquired all samples of a_{k+1} and store them in the correspondent state of \boldsymbol{S} according to the values of v_k and a_k . The purpose of the aforementioned step is to sort the historical data in such manner that both $E[a_{k+1}]$ and $Var[a_{k+1}]$ can be calculated with basic statistical operations from the available samples of a_{k+1} . Since the sparsity of the driving data causes $E[a_{k+1}]$ and $Var[a_{k+1}]$ to be defined pointwise over $\boldsymbol{\mathcal{S}}$, it is necessary to identify a function g(a, v) and a function h(a, v) that describe how $E[a_{k+1}]$ and $Var[a_{k+1}]$ vary throughout \boldsymbol{S} , in order to completely parametrize the state space. This is accomplished by means of an approximation by bivariate tensor product B-Splines with a predefined sequence of knots (Johannesson, 2005). The sequence of knots is set denser where more information is available in order to better capture the behavior of the most important regions of $\boldsymbol{\mathcal{S}}$. The splines describing the variation of $E[a_{k+1}]$ and $Var[a_{k+1}]$, namely the functions g(a, v) and h(a, v), over **S** are presented in Fig. 7 and in Fig. 8, respectively.



Figure 7. Function g(a, v) representing the variation of $E[a_{k+1}]$ over S.



Figure 8. Function h(a, v) representing the variation of $Var[a_{k+1}]$ over S.

Having identified $E[a_{k+1}]$ and $Var[a_{k+1}]$ for the entire state space, the parameters $\alpha(a, v)$, $\beta(a, v)$ are estimated by moment matching, i.e., by evaluating g(a, v) and h(a, v) for each state on S and by equating the result to the theoretical moments given by Eq. (14) and Eq. (15) (Abourizk, Halpin, & Wilson, 1994). Solving the obtained equation system for $\alpha(a, v)$ and $\beta(a, v)$ leads to

$$\alpha(a,v) = \frac{-(b_L - \mu)}{b_L - b_U} - \frac{(b_L - \mu)^2 (b_U - \mu)}{\sigma^2 (b_L - b_U)},$$
 (17)

$$\beta(a,v) = \frac{(b_U - \mu)}{b_L - b_U} + \frac{(b_L - \mu)(b_U - \mu)^2}{\sigma^2(b_L - b_U)}$$
(18)

where $\mu = E[a_{k+1}], \sigma^2 = Var[a_{k+1}], b_L = a_{\min}$ and $b_U = a_{\max}$.

3.2. Characterization of Φ^{θ}

The transition probability matrix for the slope is given by

$$\boldsymbol{\Phi}^{\theta} = \begin{bmatrix} \pi_{1,1}^{\theta} & \pi_{1,2}^{\theta} & \dots & \pi_{1,h}^{\theta} \\ \pi_{2,1}^{\theta} & \pi_{2,2}^{\theta} & \dots & \pi_{2,h}^{\theta} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{h,1}^{\theta} & \pi_{h,2}^{\theta} & \dots & \pi_{h,h}^{\theta} \end{bmatrix}.$$
 (19)

The estimation of the transition probabilities of Φ^{θ} occurs similarly as shown in section 3.1.1 by applying the MLE to real road height profiles.

The state space of the Markov chain for the slope is given by $\Theta = \{\theta_{\min}, \dots, -2\theta_{res}, -\theta_{res}, 0, \theta_{res}, 2\theta_{res}, \dots, \theta_{max}\},\$ where $\theta_{\min} = -10^{\circ}, \theta_{\max} = 10^{\circ}$ and the resolution of the discretezation is $\theta_{res} = 0.5^{\circ}$.

4. ADAPTATION OF THE TRANSITION PROBABILITIES

Characterizing the driving situation relying solely on historical data provides a good estimation of how the EV moves in the long term. However, the way a driver behaves might change depending on the traffic situation, the time of the day, the mood or the road condition. Because of this, a more proper prediction scheme requires predicting the driving load under an adaptive framework. This is achieved by updating the transition probabilities of Φ^{va} and Φ^{θ} as new information about the driving situation becomes available. This allows to capture the *non-homogeneity* of the Markov process, which might be introduced by changes in the driver behavior, the traffic situation or the driving scenario. To this aim we employ a Bayesian posterior probability approach to update the established transition probabilities between Markov states.

4.1. Bayes Inference for Markov Chains

The Bayes' theorem estimates the *posterior* probability distribution of a parameter ψ by relating a *likelihood* function obtained from a set of observations **x** and an assumed *prior* probability distribution of the parameter. The update is computed by

$$p(\psi|\mathbf{x}) = \frac{\mathcal{L}(\psi|\mathbf{x})p(\psi)}{\int_{\Psi} \mathcal{L}(\psi|\mathbf{x})p(\psi) \,\mathrm{d}\psi},$$
(20)

where $\mathcal{L}(\psi|\mathbf{x})$ is the likelihood of the observed data, $p(\psi)$ is the prior probability distribution of ψ , $p(\psi|\mathbf{x})$ is the posterior probability distribution and Ψ represents the parameter space. The factor $\int_{\Psi} \mathcal{L}(\psi|\mathbf{x}) p(\psi) d\psi$ is a normalization factor of $p(\psi|\mathbf{x})$. Eq. (20) can be expressed in terms of a normalized likelihood as follows

$$p(\psi|\mathbf{x}) \propto \mathcal{L}(\psi|\mathbf{x}) p(\psi)$$
. (21)

As formulated in Eq. (21), applying the Bayes' theorem for updating a transition probability $\pi_{i,j}$, either of Φ^{va} or of Φ^{θ} , requires a likelihood function for the new observed information and an assumption about prior distribution of $\pi_{i,j}$ on each row of the correspondent TPM. The forthcoming explanation deals with the theoretical foundations for updating any transition probability $\pi_{i,j}$ belonging to the mixture $\pi_i = [\pi_{i,1}, \pi_{i,2}, \dots, \pi_{i,j}, \dots, \pi_{i,m}]$, i.e., to the *i*th row of Φ in Eq. (9). The application of this method for updating Φ^{va} or Φ^{θ} succeeds in a similar fashion.

4.1.1. Likelihood Function

Let the random variable q, representing a transition between two Markov states, to follow a multinomial distribution. The probability distribution of q can be parametrized by a vector π_i , where $\pi_{i,j} = p(q_i \rightarrow q_j) = p(q_{i,j})$ is the probability of a transition from state i to state j, as it was already stated by Eq. (10). Then, the likelihood of a sequence of new transitions $\mathcal{Q} = \{q_1, q_2, ..., q_n\}$ is given by

$$\mathcal{L}(\boldsymbol{\pi}_i|\boldsymbol{\mathcal{Q}}) = \prod_{j=1}^n \pi_{i,j}^{\beta_{i,j}},$$
(22)

where $\beta_{i,j}$ is the number of times a transition $q_i \rightarrow q_j$ occurs in Q. For the sake of convenience we express $\beta_{i,j} = \sum \delta_{i,j}$, where $\delta_{i,j} = 1$ if $q_i \rightarrow q_j$ occurs and $\delta_{i,j} = 0$, otherwise.

4.1.2. Prior Distribution

In the context of Markov chains, the task of the prior is to specify an assumption about the probability distribution of the i^{th} row π_i of Φ . Accordingly, it is necessary to find as many prior distributions as the number of Markov states. Updating the transition probabilities under a Bayesian approach works with any kind of prior. However, since we consider the arbitrary set of new transitions Q to be multinomial distributed, it is mathematically convenient to use a *conjugate prior*. The use conjugate priors offers the advantage that the posterior distribution has the same functional form of the prior. The conjugate prior of the multinomial distribution is the Dirichlet distribution (Strelioff, Crutchfield, & Hübler, 2007). Thus, assuming the transition probabilities of a row from Φ to be Dirichlet distributed leads to

$$p(\boldsymbol{\pi}_{i}|\alpha_{i,1},\alpha_{i,2},...,\alpha_{i,m}) = \frac{\Gamma\left(\sum_{j=1}^{m} \alpha_{i,j}\right)}{\prod_{j=1}^{m} \Gamma\left(\alpha_{i,j}\right)} \prod_{j=1}^{m} \pi_{i,j}^{\alpha_{i,j}-1},$$
(23)

where the hyperparameter $\alpha_{i,j}$ can be understood as a virtual count of occurrences of $q_i \rightarrow q_j$ before considering new observations. Large values of $\alpha_{i,j}$ reflect strong prior knowledge about the distributions of the transition probabilities and small values of correspond to ignorance. The parameter m stands for the number of hyperparameters that parametrize Eq. (23).

The choice of the Dirichlet distribution as the prior is a fairly

intuitive way to explain the meaning of the transition probabilities in Φ . A transition probability $\pi_{i,j}$ as defined by Eq. (10), can be understood as the first moment of the Dirichlet distribution evaluated for $\pi_{i,j}$. That is,

$$E\left[\pi_{i,j}\right] = \pi_{i,j} = \frac{\alpha_{i,j}}{\alpha_0},\tag{24}$$

where $\alpha_0 = \sum_i \alpha_i$ is the total number of occurrences of a transition starting from state *i*. The Dirichlet distribution satisfies the unit simplex requirement $\sum E[\pi_{i,j}] = 1$ and $0 \le E[\pi_{i,j}] \le 1$ complying in this way with the properties of a row π_i in Φ . Furthermore, the uncertainty of a transition probability can be computed by the second moment

$$Var[\pi_{i,j}] = \frac{\alpha_{i,j} (\alpha_0 - \alpha_{i,j})}{\alpha_0^2 (\alpha_0 + 1)}.$$
 (25)

In our approach the parameters of the Dirichlet prior distribution are obtained from the offline estimation through MLE of section 3.1.1. In the absence of prior knowledge about the hyperparameters of Eq. (23), i.e., if $\Phi \rightarrow \{0\}$ a common approach is to assume all probabilities to be equal. This can be achieved by setting all $\alpha_{i,j} = 1$, which results in a uniform prior distribution with an expectation value given by $E[\pi_{i,j}] = \frac{1}{M}$, where M represents the size of the state space.

4.1.3. Posterior Distribution

Having a multinomial likelihood and a Dirichlet prior, the posterior distribution of π_i after observing a new sequence of transitions Q can be found in a closed form by exploiting the conjugate property of the Dirichlet distribution and the multinomial distribution. Accordingly, the posterior is computed by

$$p(\boldsymbol{\pi}_{i}|\boldsymbol{\mathcal{Q}},\alpha) \propto \boldsymbol{\mathcal{L}}(\boldsymbol{\pi}_{i}|\boldsymbol{\mathcal{Q}}) p(\boldsymbol{\pi}_{i}|\alpha) = \prod_{j=1}^{m} \pi_{i,j}^{\alpha_{i,j}+\beta_{i,j}-1}.$$
(26)

The posterior is computed on receipt of new observations. Considering the fact that in our system just one transition can occur per time step, we can set $\beta_{i,j} = \delta_{i,j}$. Accordingly, the set of hyperparameter α_i can be recursively updated by setting $\alpha_{i,k+1} = \alpha_{i,k} + 1$ if $q_i \rightarrow q_j$ or $\alpha_{i,k+1} = \alpha_{i,k}$, otherwise. By employing this Bayesian scheme the updated mean $E[\pi_{i,j}]_{k+1}$ and variance $Var[\pi_{i,j}]_{k+1}$ of each element in π_i can be computed with the help of Eq. (24) and Eq. (25). As it can be seen, the posterior computed by Eq. (26) keeps the information regarding all transitions occurred up to time step k.

Thus, depending on the values of the hyperparameters, many new observations might be needed in order to converge with the new Markov process. This is inconvenient in our application, since a slow adaptation of transition probabilities would cause the characterization of the most up to date driving situation to fail. Because of this, it would be desirable to find a recursion for both $E[\pi_{i,j}]_k$ and $Var[\pi_{i,j}]_k$ without needing to deal with any prior knowledge about the hyperparameters and that can be carried such that the influence of older transitions in the computation of the posterior is progressively faded while keeping the underlying idea of an a Bayesian update.

The aforementioned recursion is achieved by means of the discounted mean-variance estimator shown in (Bertuccelli & How, 2008) such that

$$E[\pi_{i,j}]_{k+1} = E[\pi_{i,j}]_{k} + \frac{Var[\pi_{i,j}]_{k} \left(\delta_{i,j} - E[\pi_{i,j}]_{k}\right)}{\lambda_{k} E[\pi_{i,j}]_{k} \left(1 - E[\pi_{i,j}]_{k}\right)},$$
(27)

and

$$\operatorname{Var}[\pi_{i,j}]_{k+1} = \frac{\operatorname{Var}[\pi_{i,j}]_{k} E[\pi_{i,j}]_{k+1} \left(1 - E[\pi_{i,j}]_{k+1}\right)}{\lambda_{k} E[\pi_{i,j}]_{k} \left(1 - E[\pi_{i,j}]_{k}\right) + \operatorname{Var}[\pi_{i,j}]_{k}},$$
(28)

where $\lambda_k < 1$ is a factor used to scale the variance at each iteration, which makes the estimation to be more responsive to new observations. (Bertuccelli & How, 2008) shows that convergence to the true moments is achieved if $\lim_{k\to\infty} \lambda_k = 1$. We thus consider using in this work a decaying factor $\lambda_k = 1 - \frac{\lambda}{k}$, where $0 < \lambda < 1$ and k denotes the time step.

5. DRIVING LOAD PREDICTION

The prediction of the driving load proceeds as presented in Algorithm 1. At every time step measurements of the input space, i.e., $\mathbf{u_k} = \begin{bmatrix} v_k & a_k & \theta_k \end{bmatrix}^T$ are acquired and processed in order to determine the indices s, i and h, which are used to allocate the measurements in the correspondent position of the Markov state space.

First, the information about the speed and the acceleration is updated. To this aim the index *s* determines the transition probability matrix $\Phi^{v_s a}$ to be updated. The index *i* is used to find the row within the matrix, which contains the information about the last observed transition. Having located the row containing the transition of interest, all transition probabilities $\pi_{i,j}^{v_s a} \in \pi_i^{v_s a}$ are simultaneously updated by means of Eqs. (27) and (28), ensuring in this way that the entire row sums up to one. Analogous, the index *h* is used to determine the row of Φ^{θ} to be updated. The update of the slope information succeeds similarly to the procedure previously presented.

At every prediction time k_p the driving load is predicted for a given horizon length h_l . A prediction consists of synthetically generating one profile for the speed/acceleration and one for the slope via Markov chains. The generated profiles are then processed by the EV model in order to compute the driving load.

The generation of the speed/acceleration profile starts by randomly drawing from $\pi_i^{v_s a}$ a sample a_j for the next state a_{k+1} according to the current values of speed v_k and acceleration a_k . To this aim the *inverse transformation method* is employed, since $\pi_i^{v_s a}$ represents a discrete probability distribution. If no information about the distribution of a_{k+1} is available, i.e., if $\pi_i^{v_s a} \rightarrow \{0\}$, then a_j is randomly sampled from $Beta(\alpha(v_s, a_i), \beta(v_s, a_i), a_{\min}, a_{\max})$, where $\alpha(v_s, a_i)$ and $\beta(v_s, a_i)$ are given by Eq. (17) and Eq. (18), respectively. This step ensures a complete generation of the profile regardless of the lack of information about the distribution of a_{k+1} .

Algorithm 1 Driving Load Prediction

Require: $\Phi^{va}, \Phi^{\alpha}, \mathbf{u}_k, \mathbf{\Omega}, \Delta t, h_l$ **Ensure:** $\left\{P_{ele,k_p}, P_{ele,k_p+1}, ..., P_{ele,k_p+h_l}\right\}$ Initialize: Determine the indices s, i and h for the current speed, acceleration and slope. $v_s \leftarrow v_k, a_i \leftarrow a_k, \theta_h \leftarrow \theta_k$ Update $\Phi^{v_s a}$ and $\Phi^{\theta} \triangleright$ Use Eqs. (27) and (28) to: Compute $E\left[\pi_{i,j}^{v_s a}\right]$ and $Var\left[\pi_{i,j}^{v_s a}\right]$ for all $\pi_{i,j}^{v_s a} \in \pi_i^{v_s a}$ Compute $E\left[\pi_{i,j}^{\theta}\right]$ and $Var\left[\pi_{i,j}^{\theta}\right]$ for all $\pi_{i,j}^{\theta} \in \pi_i^{\theta}$ if $k = k_p$ then for l = 1 to h_l do Randomly draw a_j for the next state according to: if $\pi_i^{v_s a} \to \{0\}$ then $Beta(\alpha(v_s, a_i), \beta(v_s, a_i), a_{\min}, a_{\max})$ else $\Phi^{v_s a} \left(a_{k+1} = a_j | a_k = a_i, v_k = v_s \right)$ end if $a_{k+1} \leftarrow a_j$ Compute $v_{k+1} \triangleright$ Use Eq. (29) $\mathbf{u}_{k+1}^{va} \leftarrow \begin{bmatrix} v_{k+1} & a_{k+1} \end{bmatrix}$ Randomly draw θ_i for the next state according to: $\Phi^{\theta}\left(\theta_{k+1} = \theta_j | \theta_k = \theta_h\right)$ $u_{k+1}^{\theta} \leftarrow \theta_j$ Set the input for the next time step $\mathbf{u}_{k+1} \leftarrow \begin{bmatrix} \mathbf{u}_{k+1}^{va} & u_{k+1}^{\theta} \end{bmatrix}^T$ Compute the power demand for the current time step $P_{ele,k} = f(\mathbf{u}_k, \mathbf{\Omega}) \triangleright \text{Use Eqs. (2), (3) and (4)}$ $k \leftarrow k+1$ end for end if

Contrary to other methods for generating synthetic driving profiles (T. Lee & Filipi, 2011), our approach compute the value of the speed in the next speed instead of randomly sample it. Here v_{k+1} is given by

$$v_{k+1} = v_k + a_k \Delta t, \tag{29}$$

where Δt denotes the time step size used in the generation of the profile. Our approach is efficient, since computing Eq. (29) for obtaining the speed is more efficient than sampling it from any discrete distribution. After obtaining the values of a_{k+1} and v_{k+1} , the next step is to draw a sample θ_j for the next time step according to the value of θ_k . Having predicted $\mathbf{u}_{k+1} = \begin{bmatrix} v_{k+1} & a_{k+1} & \theta_{k+1} \end{bmatrix}^T$ the electrical power demand is computed by means of Eqs. (2), (3) and (4). To this aim the set $\boldsymbol{\Omega}$ containing the parameters of the EV model is needed. This procedure is repeated iteratively until the desired horizon length h_l of the prediction is reached.

6. RESULTS AND DISCUSSIONS

This section first introduces the experimental system used for validating the prediction of the driving load. Afterwards, the assumption regarding the Markovianity of the input variables is validated through simulation. Finally, a series of experimental case studies used to illustrate the applicability of our approach in different driving situations is presented.

6.1. Experimental Setup

The EV used as experimental platform for gathering the data and for testing the proposed approach is propelled by a 80 kW and 280 Nm synchronous electric motor mounted in the front axle and is powered by a 24 KWh Li-ion battery pack rated to deliver up to 90 kW. The vehicle is equipped with a GPS used to gather information about the speed and the acceleration of the vehicle and the height profile of the road. A system for measuring the voltage and the current of the motor is also integrated. A data acquisition system is used to synchronize the information delivered by these two systems.

EV Model Parameters		
Parameter	Value	
A	2.29 m^2	
c_w	0.28	
m	1520 kg	
K_r	0.7	
$T_{m,\max}$	$280 \mathrm{Nm}$	
$P_{ele,\max}$	80 kW	
r_{tire}	0.3 m	
$ ho_{air}$	$1.226 \mathrm{kg/m^3}$	
g	9.81 m/s ²	

Table 2. Parameters used for computing the driving load.

Table 2 shows the constant parameters used to compute the driving load. It is worth noting that both m and K_r have to be identified from real data, since they depend on the cargo weight (given by the driver) and on the road condition, respectively. In this work both parameters are identified offline by fitting, in the least-square sense, the measured power consumption for a given trip with to power demand computed by the model for the same trip.

6.2. Validating the Markov Assumption

In this work a set historical drive cycles together with a set of height profiles is employed. This information is used for estimating the transition probabilities of Φ^{va} and Φ^{θ} by MLE. Then, Φ^{va} is approximated with the methodology presented in section 3.1.2 for those regions with unavailable data. Due to the wide spectrum of driving situations covered by the chosen driving data, the estimated TPMs offer a proper starting point for predicting the driving load under different driving scenarios.

To validate the assumption about the Markovianity of the input variables a set of synthetic profiles is generated as shown in Algorithm 1, with the only difference being that the update step is skipped. This allows us to model the input variables as a *homogeneous* Markov process, which suffices at this stage of the validation. The simulated profiles are then compared with the data used for training the TMPs in order to see if the distribution of the synthetic input variables correspond to that of the original data. In this work we compute the probability distribution of the data by means of kernel density estimation. As it can be seen in Fig. 9, the distribution of the generated profiles accurately describes the original data. It is important to notice that the probability distribution of the speed is left truncated, due to only non-negative speeds are considered.



Figure 9. Probability distribution of the measured and simulated speed (top), the acceleration (bottom-left) and the slope (bottom-right). The solid and the dashed lines correspond to the measurements and to the model, respectively.

Furthermore, it is of interest to investigate the impact computing the speed with Eq. (29) instead of considering it part of the Markov chain. To this aim we employ the joint speedacceleration frequency distribution (SAFD) depicted in Fig. 10. The SAFD offers a good overview of the driving situations exhibited by the driving data. As it can be appreciated, the simulated driving profiles successfully models the real driving data in low-speed regions. However, the simulated data lies very tight in regions above 80 km/h. This is due to the drive cycles chosen to estimate Φ^{va} mainly describe driving situations in the city and rural areas. The usability of the methodology presented in section 3.1.2 can be proved by simulating driving data and by finding out the percentage of data generated by using a Beta distribution. From 500 000 s of simulated data a total of 4.7% was identified to be generated using this methodology.



Figure 10. Joint frequency distribution of the measured (top) and simulated (bottom) speed and acceleration profiles.

The power demand is computed by simulation using both the training and the simulated input variables together with the parameters shown in Table 2. Fig. 11 depicts the distribution of the power demand. As it can be seen, the proposed approach accurately models the power demand of the EV, specially important being the region with negative values, i.e., the distribution of power recovered through the regenerative braking system.

The auto-covariance function (ACF) confirms that the power demand of the EV can be predicted using a model-approach with input variables modeled as Markov processes.



Figure 11. Probability distribution (top) and ACF (bottom) of the measured and simulated power demand. The solid and the dashed lines correspond to the measurements and to the model, respectively.

6.3. Experimental Case Studies

The proposed approach for adaptively predicting the driving load is validated through a series of trips. Each trip takes place along a different road and under a different driving situation. Three driving situations are tested, namely driving in the city, in rural areas and driving in a combination of highway and city. All trips start with the Φ^{va} and Φ^{θ} estimated in section 6.2, so that no previous information about the driver behavior or the driving scenario is available. This allows investigating the adaptability of the TPMs for the different driving situations.

6.3.1. Scenario 1: City

The speed and the slope profile of the first trip are shown in Fig. 12. Here the EV travels 9.17 km in approximately 20 minutes. The speed profile exhibits the common behavior of a vehicle traveling in a city with many stops and a maximum speed of approximately 50 km/h.

Fig. 13 shows the probability distribution of the predicted input variables together with the computed power demand. The prediction takes place at $k_p = 600$ s, that is 10 minutes after beginning the trip and the horizon length of the prediction is $h_l = 600$ s. As it can be seen, the shape of PDF of the speed resembles the real distribution. In the same manner the PDF of the distribution fits the measured data. The difference in the distribution of the predicted slope profile with the real measurements is due to the discretization resolution used in the Markov chain.

This causes the predicted slope to be more focused in some regions, e.g. 0° , in comparison to the real measurements where the data is more widespread. Despite the difference in the slope distribution, the PDF of the electrical power succeeds to describe the distribution for both demanded and recovered power.



Figure 12. Driving situation representing a trip in the city.



Figure 13. Snapshot at $k_p = 600$ s of the probability distribution of the predicted input variables and the power demand for $h_l = 600$ s in the city scenario. The solid and the dashed lines correspond to the measurements and to the model, respectively.

6.3.2. Scenario 2: Rural Areas

The second trip is depicted in Fig. 14. In this trip the EV travels 17.03 Km along a rural road. The approximate duration of the entire trip is 30 minutes. This driving scenario is characterized by transition between zones with maximum speed of 50 km/h and 70 km/h. The height profile remains almost constant during the trip, with exception of the last 5 minutes where the slope of the road slightly increases. The probability distribution of the predicted input variables and the computed power demand is presented in Fig. 15. The distributions shown are the result of a prediction carried out 5 minutes after the beginning of the trip. i.e., $k_p = 300$ s. In this case the $h_l = 1500$ s. As it can be noticed, the distribution of the predicted speed presents a region of high probability near to the zero speed. This is the result of the large stop of approximately 100 s occurred at time step k = 400 s. Similarly to results shown in the previous case, the distribution of the power demand successfully captures the uncertainty of the prediction.



Figure 14. Driving situation representing a trip in rural areas.



Figure 15. Snapshot at $k_p = 300$ s of the probability distribution of the predicted input variables and the power demand for $h_l = 1500$ s in the rural scenario. The solid and the dashed lines correspond to the measurements and to the model, respectively.

6.3.3. Scenario 3: Highway-City

The last experimental case study illustrates the flexibility of our approach. Both the speed and the high profile are shown in Fig. 16.

The purpose of this experiment is to test the ability to adapt the driving load prediction to the change in the driving situation. To this aim the EV travels 75.28 Km on the highway followed by 20.3 Km in the city. The driving behavior on the highway is characterized by a mean speed above 100 km/h and by very few stops. A very important feature of this driving scenario is the large increment on the height profile in one segment of the road. In this case two prediction were carried out, each of them with a horizon length $h_l = 1500$ s.

Fig. 17 shows the probability distribution of the predicted input variables and the power demand for the first prediction at $k_p = 1\ 800\$ s. As it can be seen the PDF of the predicted speed differs from the real distribution, in that the region with low speed is almost neglected. This is due to the segment of city contained withing the horizon length of the prediction is not taken into consideration. This causes the power demand to be slightly overestimated.

At $k_p = 3\ 600$ s a new prediction is carried out. In this case the EV travels in a city driving scenario. As it can be seen in Fig. 18 the PDF of the predicted speed profile seems to converge to the real distribution. Accordingly, the distribution of the predicted driving load resembles very accurately the shape of the real distribution. This shows that the proposed approach succeeds in predicting the driving load even if remarkable changes in the driving situation occur.

7. CONCLUSIONS AND FUTURE WORK

In this work a methodology for predicting the driving load of an EV in uncertain environments is presented. The pre-



Figure 16. Driving situation representing a trip combining highway and city segments.



Figure 17. Snapshot at $k_p = 1\,800$ s of the probability distribution of the predicted input variables and the power demand for $h_l = 1\,500$ s in the combined highway-city scenario. The solid and the dashed lines correspond to the measurements and to the model, respectively.



Figure 18. Snapshot at $k_p = 3\ 600$ s of the probability distribution of the predicted input variables and the power demand for $h_l = 1\ 500$ s in the combined highway-city scenario. The solid and the dashed lines correspond to the measurements and to the model, respectively.

diction takes place under a model-based approach, in which the input variables of an EV model, used to describe the driving situation, are modeled as first order discrete-time Markov processes. The transition probabilities between Markov states are first estimated offline from historical driving data via maximum likelihood estimation. Furthermore, an approach for estimating transition probabilities in the presence of sparse data is introduced. In order to account for most up to date driving situations, road conditions and driving behaviors in the driving load prediction, the transition probabilities are recursively updated via Bayesian inference.

The validity of the proposed methodology is illustrated through simulation and by means of a series of experimental cases of study. The obtained results suggest, that the driving load can be successfully predicted with our approach regardless of the driving environment. Nevertheless, it has been realized that by abrupt changes in the driving situation within a trip, the time the transition probabilities take to converge to the new driving situation can become large.

An aspect we aim to investigate in the future is therefore to model the transition between driving situations as a Markov jump process. In this way, it would be possible to choose different TPMs according to some stochastic process describing the change between driving situations.

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REFERENCES

- Abourizk, S. M., Halpin, D. W., & Wilson, J. R. (1994). Fitting Beta Distributions Based on Sample Data. *Journal* of Construction Engineering and Management, 120(2), 288-305.
- Bertuccelli, L., & How, J. (2008). Estimation of nonstationary markov chain transition models. In *Decision and Control (CDC), IEEE conference on* (p. 55-60).
- Guzzella, L., & Sciarretta, A. (Eds.). (2005). Vehicle propulsion systems: Introduction to modeling and optimization. Springer Verlag, Heildelberg.
- Johannesson, L. (2005). Development of a time invariant stochastic model of a transport mission (Tech. Rep.).
- Johannesson, L., Asbogard, M., & Egardt, B. (2007). Assessing the Potential of Predictive Control for Hybrid Vehicle Powertrains Using Stochastic Dynamic Programming. In *Intelligent transportation systems, IEEE transactions on* (Vol. 8, p. 71-83).
- Kim, E., Lee, J. L., & Shin, K. G. (2013). Real-time pre-

diction of battery power requirements for electric vehicles. In ACM/IEEE 4th international conference on cyber-physical systems (ICCPS 13).

- Lee, T., & Filipi, Z. (2011). Representative real-world driving cycles in Midwestern US. In *Les rencontres scientifiques d'IFP energies nouvelles - RHEVE 2011*.
- Lee, T. C., Judge, G. G., & Zellner, A. (Eds.). (1970). *Estimating the parameters of the markov probability model from aggregate time series data*. North-Holland, 2nd edition.
- Oliva, J. A., Weihrauch, C., & Bertram, T. (2013). A modelbased approach for predicting the remaining driving range in electric vehicles. In *Annual conference of the prognostics and health management society 2013.* (p. 438-448).
- Strelioff, C. C., Crutchfield, J. P., & Hübler, A. W. (2007). Inferring Markov Chains: Bayesian estimation, model comparison, entropy rate, and out-of-class modeling. *Physical Review E (Statistical, Nonlinear, and Soft Matter Physics)*, 76(1).
- Wang, Z., Xu, G., Li, W., & Xu, Y. (2007). Driving load forecasting using cascade neural networks. In Advances in neural networks ISNN 2007 (Vol. 4493, p. 988-997). Springer Berlin Heidelberg.

Yang, J., Huang, X., Tan, Y., & He, X. (2008). Forecast of driving load of hybrid electric vehicles by using discrete cosine transform and Support Vector Machine. In *Neural networks, IEEE International Joint Conference* on (p. 2227-2234).

BIOGRAPHIES

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A Real-time Data-driven Method for Battery Health Prognostics in Electric Vehicle Use

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ABSTRACT

Online prognostics of the battery capacity is a major challenge as ageing process is a complex phenomenon, hardly directly measurable. This paper offers a new methodology for real-time estimating of the global battery performances for Electric Vehicle (EV) use. The presented data-driven framework build a model based on the modifications in battery signals behavior, according to the performance level. A first pattern extraction step consists in the selection of battery signals corresponding to specific acceleration profiles in real uses, allowing to highlight the battery behavior. These extracted voltage and current patterns are then considered to determine the battery behavior for each State of Health (SOH) feature. Studied patterns are compared using signal processing techniques, allowing the estimation of the battery performance, through statistical learning methods. The application of signal processing and Relevance Vector Machines (RVM) model with multiple kernels, provides a powerful tool to diagnose battery health online, only based on real signals. Furthermore, this methodology also allows the prediction of battery Remaining Useful Life (RUL) during real use. The proposed algorithm is validated using datasets from real EV uses. Presented diagnostics results on real data demonstrate the good accuracy of this new framework for battery SOH prognostics in real-time constraints, with uncontrolled conditions.

1. INTRODUCTION

Lithium-ion (Li-ion) batteries are becoming the battery of choice in Electric Vehicles (EV) utilization. However, battery health and lifetime remain a major drawback to the use of Liion batteries in stringent life requirements. In EV context, accurate battery health assessment is primordial to improve the users confidence in the battery range. Indeed, it is one of the biggest obstacles to widespread acceptance of EVs. Market experts evaluated the effects of low range resources of EVs, as a significant feature for users' purchases intentions (Peters & Dütschke, 2014).

The field of prognostics and health management offers different approaches for estimating battery age level and remaining lifetime (Saha & Goebel, 2008). There are many datadriven methodologies that focus on the battery State of Health (SOH) estimation (Barré et al., 2013). However, most of these data-driven approaches perform well on their training data only, under specific operational experiments, inducing robustness and generalization mistakes. In real life, external conditions cannot be controlled and these learned models are subject to misestimations. Thus, an accurate way of estimating battery capacity in real-time based on real EV uses datadriven algorithm still requires investigations (Barré, Suard, Gérard, Montaru, & Riu, 2014).

In this work, we propose an alternative approach by only using data-driven methodology developed from a set of real EV uses. Such a methodology requires large amounts of training data in the development phase. In the EV context this training data requirement is very restrictive and costly. To face this problem, we investigate whether it is possible to extract relevant features from current and voltage signals collected during real EV uses, under non controlled conditions. A key

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Figure 1. Battery signal analysis framework consisting of the data aquisition, the extraction of specific patterns, the formation of new feature space and the estimation of the battery health level along with its remaining useful life

issue explored by this paper is how battery capacity can be estimated during real EV uses, without specific requirement, based only on real use data.

Section 2 presents the global theoretical framework and details the methods used for the SOH estimation and RUL prognostic in real time. Then, Section 3 details the obtained results for SOH estimation and RUL prognosis in real EV uses context. Finally, Section 4 presents the main conclusions and discussions of this research.

2. METHODOLOGY

In this section, we present our approach to predict the battery State of Health (SOH) and its corresponding Remaining Useful Life (RUL). As a first step, signal patterns were estimated from the acquired data, in order to observe the battery behavior modification. To quantify these modifications Dynamic Time Warping (DTW) is introduced. Then, a multiple kernel Relevance Vector Machines (RVM) model is learned to estimate the battery SOH in real time. Based on the SOH estimations, the RUL is predicted with a bootstrap approach. The global framework is illustrated in Figure 1.

2.1. Patterns extraction

The proposed methodology is based on the assumption of battery behavior modification along the battery life. Time series signal can be used to diagnose health by analyzing battery behavior. Thus, for a similar battery request, it is possible to detect battery ageing effects based on signal shapes such as current and voltage.

To observe a signal behavior modification, it is necessary to compare battery signals under comparable uses. For example, during an identical speed profile criterion, the battery voltage does not react the same way depending on its health level. Thus, the common reference here is the speed signal. In the following study we consider maximal accelerations from 10 to 60 km/h in less than 12.5 seconds as a reference criterion. This choice allows to extract patterns with a relatively large length permitting to detect battery behavior. These extracted training data are consequently issued from real EV uses, providing a large amount of data under uncontrolled conditions.



Figure 2. Average signals profile corresponding to a maximal acceleration under four different health levels, based on 10-60 km/h accelerations - Level 1 (SOH = 100 - 98%, T $\simeq 24^{\circ}$ C) - Level 2 (SOH = 98 - 96%, T $\simeq 22^{\circ}$ C) - Level 3 (SOH = 96 - 92%, T $\simeq 12^{\circ}$ C) - Level 4 (SOH = 92 - 87%, T $\simeq 30^{\circ}$ C)

To compare the pattern behaviors under different health levels we proceed to an average shape of the patterns for different battery health classes. Thus, the average shapes of the extracted signals, under four different health classes are presented in Figure 2. These classes represent four battery health levels, sorted from the least period "Level 1" to the most aged battery level "Level 4". The SOH level used to build these groups, is here extrapolated from several complete characterizations permitting to obtain SOH reference values. The average temperature values of each class are various, going from 12°C for Level 3 to 30°C for Level 4. It is important to note that these temperature conditions can induce potential pattern behavior modification.

Figure 2 illustrates the variations of signals behavior for different battery health levels. The extracted speed profiles are really close to each other, forming good comparative samples. However, in real-life context it is impossible to obtain exactly twice the same speed profile, implying a slight diversity among the extracted speed signals.

On the contrary, the corresponding extracted current and voltage patterns have various shapes. For example, the current pattern of Level 4 (SOH between 92 and 87 %) is clearly below the other ones, and its corresponding voltage pattern increases faster than for the other health classes. This can be explained by a difference of battery reaction for a same power demand at different health levels. These behavior modifications demonstrate the alteration of the battery reaction in correlation with health degradation.

The objective of the following study is to use these battery behavior modifications to estimate its health level, only based on the extracted patterns.

2.2. Dynamic Time Warping

In order to compare the signals pattern and quantify their similarities, we have to consider a metric adapted to this problem. Thus, beyond usual measures, the current state-of-theart of shape similarity quantification is the Dynamic Time Warping (DTW). It permits to compare asynchronous signals of different lengths. The primary goal of DTW is to compare sequences respecting their shapes by finding an optimal alignment function stretching them. Since its introduction in the 70s, DTW has commonly been used in signals similarity problems in many fields : speech processing, signals recognition, data mining and imaging (Aach & Church, 2001; Bar-Joseph, Gerber, Gifford, Jaakkola, & Simon, 2002; Petitjean, Kurtz, Passat, & Ganarski, 2012).

This method is based on the Levenshtein distance (Sakoe & Chiba, 1971) and finds the optimal path between two sequences, considering temporal distortion. This optimal path produces an alignment function, along with a shape-based similarity measure. Formally, we have two sequences $X := (x_1, ..., x_N)$ of length $N \in \mathbb{N}$ and $Y := (y_1, ..., y_M)$ of length $M \in \mathbb{N}$. In the following we fix a feature space denoted by \mathcal{F} . To compare two different features $x, y \in \mathcal{F}$, one needs a local cost measure, defined by a function c:

$$c: \mathcal{F} \times \mathcal{F} \to \mathbb{R}_{>0} \tag{1}$$

Typically, the cost c(x, y) is low if x and y are similar to each other, otherwise c(x, y) is high. Evaluating the local cost measure c(x, y) for each pair of elements of the sequences X and Y, one obtains the cost matrix $C \in \mathbb{R}^{N \times M}$ defines by $C(i, j) = c(x_i, y_j)$. The goal is to find the alignment between X and Y minimizing the overall cost. A warping path is a sequence $p = (p_1, ..., p_L)$ with $p_l = (n_l, m_l) \in [1 :$ $N] \times [1 : M], \forall l \in [1 : L]$, satisfying the conditions :

$$\begin{cases} p_1 = (1,1) \text{ and } p_L = (N,M) \\ n_1 \le \dots \le n_L \text{ and } m_1 \le \dots \le m_L \\ p_{l+1} - p_l \in \{(1,0), (0,1), (1,1)\}, \ \forall l \in [1:L-1] \end{cases}$$

$$(2)$$

A warping path $p = (p_1, ..., p_L)$ defines an alignment between two sequences X and Y by assigning the element x_{n_l} of X to the element y_{m_l} of Y. The alignment conditions imply that the first elements of X and Y as well as their last elements are aligned to each other. The total cost $c_p(X, Y)$ of a warping path p between X and Y with respect to the local cost measure c is defined as :

$$c_p(X,Y) = \sum_{l=1}^{L} c(x_{n_l}, y_{m_l})$$
(3)

Furthermore, an optimal warping path between X and Y is a warping path p^* minimizing total cost among all possible warping paths. The DTW distance $d_{DTW}(X, Y)$ between X and Y is then defined as the total cost of the optimal warping path p^* :

$$d_{DTW}(X,Y) = c_{p^*}(X,Y) = \min\{c_p(X,Y) | \forall p\}$$
(4)

The local cost measure c is defined as the distance between elements of sequences, e.g., the Euclidean distance. An example of DTW warping paths is given in Figure 3.



Figure 3. Illustration of paths of index pairs for a sequence X of length N = 6 and a sequence Y of length M = 8 (a) Admissible warping path (b) Example of a non admissible warping path due to boundary conditions and step size conditions

This DTW distance permits the comparison and the quantification of different signals shape. It is particularly adapted to battery signals evolution. Therefore, this distance measures the difference between each extracted pattern.

2.3. Relevance Vector Machines

The Relevance Vector Machines (RVM), initially introduced by (Tipping, 2001), is based on a Bayesian formulation of a linear model with an appropriate prior that results in a sparse representation. Given the set of training patterns $\{t_i | i = 1, ..., N\}$ along with their corresponding health level $\{h_i | i = 1, ..., N\}$, assume that $h_i = f(t_i) + \epsilon_i$, where ϵ_i are assumed to be independent samples from a Gaussian noise process with zero mean and σ^2 variance, i.e. $\sigma_i \sim \mathcal{N}(0, \sigma^2), \forall i$. The aim is to learn a dependency model of the targets on the inputs to make accurate predictions of h for unseen values of t. Typically, predictions are based on some function f(t) defined over the input space, and learning is the process of inferring the parameters of this function. This function takes the form :

$$f(t) = \sum_{i=1}^{M} w_i K(t, t_i) + w_0$$
(5)

where f(t) is the function output, $K(t, t_i)$ is a kernel function and $w = [w_1, ..., w_N]^T$ are the weights.

Therefore, the likelihood of dataset can be written as :

$$p(h|w,\sigma^2) = (2\pi\sigma^2)^{-\frac{N}{2}} \exp\{-\frac{1}{2\sigma^2}||h-\phi w||^2\}$$
(6)

where $\phi = [\phi(t_1), ..., \phi(t_N)]^T$, and $\phi(t_N) = [1, K(t_i, t_1), K(t_i, t_2), ..., K(t_i, t_N)]^T$

When attempting to learn the relationship between t and h, we wish to constrain complexity and hence the growth of the weights w by defining an explicit prior probability distribution on w. Our preference for smoother and therefore less complex functions is encoded by using a zero-mean Gaussian prior over w. This gives us :

$$p(w|\alpha) = \sum_{i=1}^{N} N(0, \alpha_i^{-1})$$
(7)

where we have used α_i to describe the inverse variance of each w_i . This means that there is a hyperparameter α_i associated with each weight, modifying the strength of the prior thereon. To complete the specification of this hierarchical prior, we must define hyperpriors over α ; as well as over the noise variance σ^2 .

Having defined the prior, Bayesian inference proceeds by computing the posterior over all unknows given the data from Bayes' rule, i.e. :

$$p(w,\alpha,\sigma^2|h) = \frac{p(h|w,\alpha,\sigma^2)p(w,\alpha,\sigma^2)}{p(h)}$$
(8)

Assuming that the new test target is h_* , and the new test input t_* are used to make predictions. The predictions are made according to :

$$p(h_*|h) = \int p(h_*|w, \alpha, \sigma^2) p(w, \alpha, \sigma^2|h) dw d\alpha d\sigma^2 \quad (9)$$

We can decompose the posterior $p(w, \alpha, \sigma^2 | h)$ as :

$$p(w, \alpha, \sigma^2 | h) = p(w | h, \alpha, \sigma^2) p(\alpha, \sigma^2 | h)$$
(10)

And so, the posterior distribution over the weights is :

$$p(w|h,\alpha,\sigma^2) = \frac{p(h|w,\alpha,\sigma^2)p(w|\alpha)}{p(h|\alpha,\sigma^2)} \sim \mathcal{N}(w|\mu,\Sigma) \quad (11)$$

where the posterior covariance and mean are respectively :

$$\Sigma = (\sigma^{-2}\phi^T\phi + A)^{-1} \tag{12}$$

$$\mu = \sigma^{-2} \Sigma \phi^T h \tag{13}$$

with $A = diag(\alpha_0, ..., \alpha_N)$. Note that σ^2 is also treated as hyperparameter, which can be estimated from the data.

Therefore, machine learning becomes a search for the most probable hyperparameters posterior α_{MP} and σ_{MP}^2 . Predictions for a new input data t_* are made according to the integration of weights to obtain the marginal likelihood for the hyperparameters :

$$p(h|\alpha_{MP}, \sigma_{MP}^2) = \int p(h_*|w, \sigma_{MP}^2) p(w|\alpha_{MP}, \sigma_{MP}^2) dw$$
$$p(h|\alpha_{MP}, \sigma_{MP}^2) = \mathcal{N}(h_*|t_*, \sigma_*^2) \quad (14)$$

with :

$$h_* = \mu^T \phi(t_*) \tag{15}$$

$$\sigma_*^2 = \sigma_{MP}^2 + \phi(t_*)^T \Sigma \phi(t_*) \tag{16}$$

In order to employ the DTW measure in the RVM process, we have to use a kernel function K considering the DTW measure. Several attempts were made to derive kernels based on the DTW distance (Lei & Sun, 2007). We consider in this paper the Gaussian Dynamic Time Warping (GDTW) kernel (Bahlmann, Haasdonk, & Burkhardt, 2002), with a parameter γ , defined as :

$$K_{GDTW}(t, t_i) = exp(-\gamma d_{DTW}(t, t_i))$$
(17)

2.4. Extension of RVM to Multiple Kernel

The use of different kernels in a same process allows the combination of different characteristics. In the case of complex phenomena, a multiple kernel approach can be useful as each used kernel is subject to extract a different characteristic, obtained with different kernel formations or parameters (Suard & Mercier, 2009). In order to assign specific kernel for each patterns, the prediction function is written :

$$f(t) = \sum_{i=1}^{N} \sum_{j=1}^{k} w_{i,j} \cdot K_j(t,t_i) + w_0$$
(18)

One possible way to write this function is to define a kernel basis. This definition decomposes the kernel K into different

blocks. The multiple kernel, for k kernels, is then composed like a kernel basis :

$$K = [1 K_1 K_2 \dots K_k]$$
(19)

If we consider that all columns are independent, we can finally write the prediction function with :

$$f(t) = \sum_{i=1}^{N*k} w_i \cdot K_i(t) + w_0$$
(20)

Thus, this formulation shows that we can extend RVM to multiple kernel with a kernel basis approach.

2.5. RUL prediction

The fitted model is used to estimate battery health at different times. Based on these SOH estimations $\{h_{i*}|i = 1, ..., N\}$, the aim is to predict the battery Remaining Useful Life (RUL). The RUL is defined as the remaining time until the battery reaches an End of Life (EOL) criterion, commonly chosen as 80% SOH level.

Remaining Useful Life (RUL) is derived by projecting out the capacity estimates into the future until expected capacity hits the certain predetermined End of Life (EOL) threshold. As opposed to the SOH estimations, this process does not require to be done in real time as the SOH dynamic is too slow to modify the RUL at every EV use. Thus, at a given time T, the proposed methodology considers a polynomial regression to fit all the past SOH estimations $\{h_{i*}|i = 1, ..., N\}$, with $N \leq T$. The polynomial regression finds the coefficients of a polynomial p of degree d that fits p(T) to the estimated battery health level h_{i*} at a time i, in a least square sense. The polynomial p of degree d is defined as :

$$p(T) = p_0 + p_1 T + \dots + p_d T^d = \sum_{j=0}^d p_j T^j$$
 (21)

Considering this polynomial construction, the aim is to build a RUL probability density function. For this, we use a bootstrap technique to predict the value of the RUL with a statistical sampling.

Thus, we sample past SOH estimations $\{h_{i*}|i = 1, ..., N\}$, with replacement, obtaining bootstrap data $\{h_{i*}^B|i = 1, ..., N\}$. For this bootstrap data we calculate the corresponding polynomial p and then use this polynomial to predict its associated RUL.

Repeating these steps L times, we obtain a family of bootstrap RUL predictions $\{\widehat{RUL}_g^B | g = 1, ..., L\}$. The distribution of the \widehat{RUL}_g^B allows the construction of a predicted RUL probability density function (pdf) at a time T.

Even with few SOH estimations, this bootstrap permits the

obtention of RUL pdf. Note that, in battery RUL prediction context, we will consider in the following study a polynomial degree d = 2 to fit the SOH dynamics. This choice is a consequence of the slow variations of SOH evolution observed in the literature.

3. RESULTS

3.1. Model learning

The described framework is applied on battery real dataset. The considered methodology is here tested with patterns extracted with a 10-60 km/h in less than 12.5 seconds as an acceleration criterion. Note that a long acceleration pattern contains more information and less variability than the short ones. However, the longest acceleration profiles require larger datasets to obtain enough patterns for the methodology process.

The data used in this study wascollected from a real and noncontrolled EV use, during 460 days, generating 50 000 km. Thereby processing data are representative of a large variety of conditions an EV battery can be faced with. Moreover, using real data ensures compatibility of the developed methodology for embedded uses. The presented results here come from a unique EV battery to illustrate the methodology performances. This experiment also contains several battery characterizations permitting to measure the real SOH of the battery, through a complex specific process done a test bench. Thus, these measured SOH values compose the targeted health levels h, and the aim is to produce SOH estimations \hat{h} , with the explained methodology.

To illustrate the frequency of pattern extraction, on the studied real data, an acceleration profile corresponding to the defined criterion happens in average every 150 km of EV use. This value is given here as an indication as it is of course highly dependent on the driving style and to driving conditions. This property induces that during a real EV use, the model provides a new SOH estimation on average every 150 km, which represents a good frequency compared to the total battery lifetime estimated to be approximately of 160 000 km. Thus, for a utilization of 15 000 km per year, the algorithm produces two SOH estimations every week.

The extracted voltage and current patterns, as presented in Figure 1, along with capacity references obtained from specific tests are then used. The training data sets are composed of patterns issued from real EV uses and of frequent battery measurements. Thus, each extracted pattern is associated to a battery health level, permitting the training of the RVM algorithm. In this study we use 75% of the data to train the RVM algorithm and the other 25% compose the test data permitting to evaluate the methodology accuracy.

The first step of the presented methodology is to create a RVM model to estimate online the battery health during its

real uses. As explained in Section 2.3, the use of several kernels can add information into the model. Thus, in this study we consider a multiple kernel RVM approach, with the association of three different kernels. Two GDTW kernels are respectively built with the extracted current patterns and with the extracted voltage patterns. The other kernel is a Gaussian kernel calculated from the values of the battery temperature measured at each pattern extraction. Battery temperature measures are here introduced into the model construction to avoid adding information about the variable external conditions. Indeed, it is well known that the battery temperature highly influences its reaction and its signals behavior. The SOH targets h are here the extrapolations of the measures obtained with the battery characterizations. Note that this model learning step is computationally constraining, as it requires a lot of DTW calculations. But this model construction is done just once, before real time application context. The complexity of this step is consequently not a drawback to the application in a real EV use.

Therefore, the inputs of the learning RVM model are the kernels corresponding to the current and voltage patterns along with a kernel based on their associated battery temperature measures, the output is an estimation \hat{h} of the battery SOH level.

3.2. Results

Based on the learned RVM model, the methodology allows the SOH diagnosis whenever a specific 10-60 km/h acceleration in less than 12.5 seconds, is detected during EV use. Thus, the embedded trained algorithm produces a new SOH estimation at each acceleration corresponding to our criteria defined in Section 2.1. The pattern extraction step is done in real time, as it only requires a criteria comparison step. Once a speed pattern is detected as satisfying, the extraction criteria, the corresponding voltage and current patterns are then extracted, along with the temperature value. These informations are then directly used as input in the SOH estimation model, producing a SOH estimation. This estimation step is done in real time, and the calculus time is highly dependent to the variety of training datasets. Indeed, the estimation process require the quantification of DTW distance between new extracted patterns and all of the corresponding training patterns. However, this implementation is done in a few seconds and permits the application in real time. Figure 4 illustrates the obtained performances by this methodology with a battery under real EV use.

The global error between the estimations $\{\hat{h}_i | i = 1, ..., N\}$ and their respective targets $\{h_i | i = 1, ..., N\}$ is calculated with the relative error as follows :

$$\eta = \frac{1}{N} \sum_{i}^{N} \left| 1 - \frac{\hat{h}_i}{h_i} \right| \tag{22}$$



Figure 4. Estimation of the battery SOH in real-time, with a mean corresponding relative estimation error of $\eta=0.81\%$

The SOH estimations demonstrate the good accuracy of the proposed methodology as the average relative error η of the results illustrated in the Figure 4 is 0.81%. Note that the standard deviation of the obtained errors is 1.1%, inducing an interesting stability of the estimations. Moreover, the estimations trend fits with the SOH measurements, validating the reliability of this new innovative framework. Thus, Figure 4 shows that the use of machine learning process with battery patterns allows the estimation of the battery SOH. This result level is highly interesting as it performs to estimate the battery SOH with a good accuracy in real time during EV uses.

Based on these SOH estimations, the methodology detailed in Section 2.4 permits the prediction of the battery RUL at different times. Figure 5 presents the predicted battery RUL probability density functions at three different times, based on the SOH estimations illustrated in Figure 4.



Figure 5. Prediction of the battery RUL probability density function (pdf) at three different times

The three RUL's probability density functions (pdf) presented in Figure 5 demonstrate the robustness of the proposed methodology. The chosen times for RUL estimation are made artificially to illustrate the evolution of the RUL pdfs over time. Thus, the predicted RUL pdfs differ depending on the predicted time. The RUL pdf is indeed sensitive to the SOH estimation variations. For example we can see the RUL pdf predicted at 210 days considers a rapid battery capacity decrease, due to the last SOH estimations made before the prediction time.

It is also noticeable that RUL prediction improving in both accuracy and precision with the inclusion of more measurements before prediction. This is clearly visible in Figure 5, as the RUL pdf predicted at 460 days produces the best confidence level compared to the two others predictions. Thus, at 460 days the EOL criteria is predicted to be reached between 580 and 610 days, which represents a narrow range considering the total battery life.

4. CONCLUSION

This paper presents the implementation of a machine learning framework that allows the estimation of the battery State of Health (SOH) and predicting the Remaining Useful Life (RUL), and more specifically for Lithium-ion batteries. The proposed approach is based on the alteration of the battery signals behavior throughout its life to estimate the battery SOH, adapting the value of unknown model parameters during a preliminary training process. The estimated value of the battery capacity is then used to predict the battery RUL. Implementation results show the robust performance of the algorithm in real-time SOH estimation under uncontrolled conditions. The presented method performs well in a real life context, which is not the case of other existing approaches.

This study developed an innovative approach devoted to estimate the battery SOH during real EV uses, without specific requirements. Such a methodology is a particular advantage for a commercial aspect as it does not require to control the battery life conditions to make an estimation. The learned algorithm can indeed be used for estimating the SOH of all batteries with the same design. Meaning that once the estimation model is built, it can be used as an embedded estimation model in all EVs.

Furthermore, the average estimation error of less than 1% obtained in the example presented in Figure 4 can be reduced using more training data coming from different EVs. In a fleet context, an estimation model can be trained from several EVs and then be embedded into all EVs using the same battery. This would allow accurate SOH estimation in all of these EVs.

Data driven approaches require large dataset to perform, however the results presented were obtained from a model built on a single EV. This study demonstrates a new baseline for SOH estimation only based on battery signals. It would be interesting to use this algorithm with a large set of data coming from an EV fleet. Thus, the next step is to test this methodology with several batteries to demonstrate the robustness and accuracy of the developed process with a large EVs fleet. In this case, the learned model by machine learning process would deliver even more accurate SOH estimations, as it would be based on more training datasets. To extend this methodology, it can also be considered in future studies to explore new kernels associations in order to input more information to the machine learning step.

The presented methodology can also be transposed to every battery use, to estimate its SOH during real utilizations. Indeed, this study does not consider any restricting use hypothesis. This methodology is, for example, adjustable in electric aircraft context.

REFERENCES

- Aach, J., & Church, G. M. (2001). Aligning gene expression time series with time warping algorithms. *Bioinformatics*, 17(6), 495-508.
- Bahlmann, C., Haasdonk, B., & Burkhardt, H. (2002). Online handwriting recognition with support vector machines
 - a kernel approach. In *Frontiers in handwriting recognition, 2002. proceedings. eighth international workshop on* (p. 49-54).
- Bar-Joseph, Z., Gerber, G., Gifford, D. K., Jaakkola, T. S., & Simon, I. (2002). A new approach to analyzing gene expression time series data. In *Proceedings of the sixth annual international conference on computational biology* (pp. 39–48). New York, NY, USA: ACM.
- Barré, A., Deguilhem, B., Grolleau, S., Gérard, M., Suard, F., & Riu, D. (2013). A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. *Journal of Power Sources*, 241(0), 680 -689.
- Barré, A., Suard, F., Gérard, M., Montaru, M., & Riu, D. (2014). Statistical analysis for understanding and predicting battery degradations in real-life electric vehicle use. *Journal of Power Sources*, 245(0), 846 - 856.
- Lei, H., & Sun, B. (2007). A study on the dynamic time warping in kernel machines. In Signal-image technologies and internet-based system, 2007. third international ieee conference on (p. 839-845).
- Peters, A., & Dütschke, E. (2014). How do consumers perceive electric vehicles? a comparison of german consumer groups. *Journal of Environmental Policy & Planning*, 0(0), 1-19.

Petitjean, F., Kurtz, C., Passat, N., & Ganarski, P. (2012).

Spatio-temporal reasoning for the classification of satellite image time series. *Pattern Recognition Letters*, *33*(13), 1805 - 1815.

- Saha, B., & Goebel, K. (2008). Uncertainty management for diagnostics and prognostics of batteries using bayesian techniques. *Aerospace Conference, IEEE*, 1-8.
- Sakoe, H., & Chiba, S. (1971). A dynamic programming approach to continuous speech recognition. In Proceedings of the seventh international congress on acoustics, budapest.
- Suard, F., & Mercier, D. (2009). Using kernel basis with relevance vector machine for feature selection. In *Artificial neural networks icann 2009* (Vol. 5769, p. 255-264). Springer Berlin Heidelberg.
- Tipping, M. E. (2001). Sparse bayesian learning and the relevance vector machine. *J. Mach. Learn. Res.*, *1*, 211– 244.

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Online Prediction of Battery Discharge and Estimation of Parasitic Loads for an Electric Aircraft

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ABSTRACT

Predicting whether or not vehicle batteries contain sufficient charge to support operations over the remainder of a given flight plan is critical for electric aircraft. This paper describes an approach for identifying upper and lower uncertainty bounds on predictions that aircraft batteries will continue to meet output power and voltage requirements over the remainder of a flight plan. Battery discharge prediction is considered here in terms of the following components; (i) online battery state of charge estimation; (ii) prediction of future battery power demand as a function of an aircraft flight plan; (iii) online estimation of additional parasitic battery loads; and finally, (iv) estimation of flight plan safety. Substantial uncertainty is considered to be an irremovable part of the battery discharge prediction problem. However, highconfidence estimates of flight plan safety or lack of safety are shown to be generated from even highly uncertain prognostic predictions.

1. INTRODUCTION

Electric propulsion can provide a number of advantages over combustion powered vehicles, such as reduced noise, zero emissions, more responsive control of output power, reduced part count, and reduced weight. In such vehicles, it is critical to monitor battery charge and to estimate the ability of the battery to support flight activities as it is discharged.

As is the case with many applications of prognostics, unavoidable uncertainties or inaccuracies in system state estimates, system dynamics modeling, and future input estimation will complicate the prediction problem (Sankararaman & Goebel, 2013). The presence of substantial uncertainty in prognostic estimates however does not necessarily rule out its usefulness to a decision maker. If prognostic uncertainty can be represented by a probability distribution or bounded by a confidence interval, than it may still be extremely useful for evaluating the potential risk and reward of various control options (Edwards et al., 2010).

The battery discharge prognostic algorithm described in this paper uses three primary tools to manage prognostic uncertainty. First, unscented Kalman filtering (UKF) is used to update probabilistic estimates of internal battery states, based on a series of battery current and voltage observations. Second, a predefined flight plan is used to identify upper and lower uncertainty bounds around future system loading demands. Finally, uncertainty is propagated over a prognostic horizon to identify uncertainty bounds on prognostic estimates.

This paper extends our previous work on battery discharge prediction for electric vehicles. The battery modeling and UKF state estimation approaches explained here were recently published in (Quach et al., 2013). The aerodynamic and aircraft powertrain models used here to estimate future battery power demand as a function of a flight plan were recently published in (Bole et al., 2013). Our previous work considered the prediction of remaining flying time given a flight plan with no fixed termination time. That approach is supplemented here by introducing new prognostic metrics that will be used to evaluate the feasibility of completing a fixed duration mission. This paper also describes the incorporation of parasitic resistance faults into prognostic predictions.

This paper is organized as follows. The prototype electric aircraft used to demonstrate battery charge estimation and discharge prediction techniques is described in Section 2. Estimation of battery SOC using unscented Kalman filtering and an equivalent circuit model is presented in Section 3. Battery demand modeling as a function of airspeed, acceleration, and angle of climb is described in Section 4. The online detection of parasitic battery loads is described in Section 5. Mission

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Figure 1. Edge-540T during landing

feasibility prediction and battery SOC estimation at the end of a flight plan is presented in Section 6. Experimental results are described in Section 7. Finally, concluding remarks are given in Section 8.

2. PROTOTYPE ELECTRIC VEHICLE BACKGROUND

Battery discharge prognosis is analyzed here in the context of a prototype battery powered aircraft. The prototype aircraft is a 33% scaled Edge-540T, with electric propulsion, shown in Fig. 1. It is 98 inches long, with a 100 inch wing span, 1881 in² of wing area, and weighs 47.4 lbs. This aircraft is operated by researchers at the NASA Langley Research center, and has been the subject of several publications on battery discharge prediction and prognostics-based decision making (Saha et al., 2011, 2012; Balaban & Alonso, 2013).

The aircraft powertrain is illustrated in Fig. 2. The propeller of the UAV is driven by two tandem mounted outrunner brushless DC motors that are each powered by a series connection of two lithium polymer battery packs. Each of the battery packs consist of five series connections of two 3900mAh lithium polymer pouch cells wired in parallel. The total rated capacity of each pack is 7800 mAh with a 50 C max burst discharge. When fully charged, each 5-cell pack has an open circuit voltage of 21 V (4.2 V per cell).

Power flow from the battery packs to the driving motors is controlled by a Jeti 90 Pro Opto electric speed controller (ESC). The ESC sends synchronized voltages to the propeller motors at a duty cycle determined by a throttle input, which is either sent by remote control from a pilot or by an onboard autopilot.

Inductive loop current sensors are mounted on the positive lead feeding each ESC. Additional current sensors are also mounted on the positive feed from each of the four batteries. The positive lead of each battery is also tapped to provide the data system with battery voltage measurements. These are the signals that online battery discharge prognostic algo-



Figure 2. Motor System Diagram

rithms will use to estimate battery SOC and to predict SOC at end of mission.

3. BATTERY MODELING

The equivalent circuit model shown in Fig. 3 is used to replicate battery current and voltage dynamics as a function of estimated battery state of charge (SOC). This battery model containes six electrical components that are tuned to recreate the observed current-voltage dynamics of the Edge-540T battery packs. Battery charge is stored in the equivalent circuit model capacitor, C_b . The R_s , C_s and R_{cp} , C_{cp} circuit element pairs are used to capture standard battery phenomenon, such as internal resistance drops and hysteresis effects.

Because the equivalent circuit model is used to model the input-output response of a battery rather than its internal electrochemical states, the number of electrical components used, and there arrangement within an equivalent circuit can vary widely in application (Chen & Rincon-Mora, 2006). Additionally, because battery input-output dynamics are known to change as a function of internal battery charge, is often the case that some of the parameters in an equivalent circuit model are parameterized as functions of battery state of charge (SOC) (Zhang & Chow, 2010). There is no universal guidance on how equivalent circuit parameters should be varied as functions of SOC, and many differing approaches are seen in literature. It was decided based on qualitative observation that defining C_b , C_{cp} , and R_{cp} as parameterized functions of battery SOC gave an acceptable trade-off between the number of parameters to be identified and model error.

The following SOC parameterizations were used for the C_b , C_{cp} , and R_{cp} parameters in Fig. 3:

$$C_b = C_{Cb0} + C_{Cb1} \cdot \operatorname{SOC} + C_{Cb2} \cdot \operatorname{SOC}^2 + C_{Cb3} \cdot \operatorname{SOC}^3 (1)$$

$$C_{cp} = C_{cp0} + C_{cp1} \cdot \exp\left(C_{cp2}\left(\text{SOC}\right)\right) \tag{2}$$

1



Figure 3. Equivalent circuit battery model.

$$R_{cp} = R_{cp0} + R_{cp1} \cdot \exp\left(R_{cp2}\left(\text{SOC}\right)\right) \tag{3}$$

where the coefficients in the parameterized models for C_b , C_{cp} , and R_{cp} must be tuned based on observed current-voltage battery data over a range of battery SOC values.

Battery SOC is defined here as:

$$SOC = 1 - \frac{q_{max} - q_b}{C_{max}} \tag{4}$$

where q_b represents the charge stored in C_b , q_{max} is the maximum charge that the battery can hold, and C_{max} is the maximum charge that can be drawn from the battery. Note that, the maximum charge that can be drawn from the battery will be lower than the amount of charge stored in the battery due to electrochemical side-reactions that lock some portion of charge carriers in the battery. The term coulombic efficiency is used to refer to the portion of stored charge that is recoverable during the discharge of the battery. There are some mechanisms including resting the battery that can unlock some of its lost capacity, however, the overall trend is inevitably downward.

Two laboratory experiments were used to fit all of the parameters in the equivalent circuit model to the lithium polymer packs used on the Edge-540T. Adapting the equivalent circuit model to account for manufacturing variation and differences in battery state-of-health is performed by varying only the battery charge storage capacity term, q_{max} , and the series resistance term, R_s , in equivalent circuit model. All other fitted parameters in the equivalent circuit model are unvaried across all Edge-540T packs. The q_{max} and R_s terms are identified by running separate characterization cycles for each battery pack prior to flight testing. A sample implementation for the online adaptation of these parameters to track age-dependent changes in battery dynamics is found in (Bole et al., 2014).

Examples of measured and modeled battery voltage curves for two laboratory characterization cycles are shown in Figs. 4 and 5. The results shown in Fig. 4 demonstrate a characterization experiment in which a battery is discharged at a low current from a fully charged state. During this low cur-



Figure 4. Comparison between measured and predicted battery voltage over a low current discharge.



Figure 5. Comparison between measured and predicted battery voltage over a pulsed current discharge.

rent discharge test, the voltage across the C_b capacitor plays a dominate role. Thus, this experiment allows the C_b parameters in the equivalent circuit model to be fit in isolation.

Fig. 5 shows sample results from a second characterization experiment in which a battery is discharged using a series of current pulses. This experiment exposes voltage dynamics that must be fit by the R_s , C_s , C_{cp} and R_{cp} parameters in the equivalent circuit model.

3.1. Battery State Estimation

The identified battery model can then be used to implement an observer for the internal battery states based on sampled voltage and current data. The observer will attempt to estimate the internal states of each of the capacitors (C_b , C_s , and C_{cp}) in the equivalent circuit model.

The unscented Kalman filter (UKF) (Julier & Uhlmann, 1997, 2004) is a flexible tool for computing probabilistic belief in system state estimates based on stochastic (and possibly nonlinear) models of system dynamics. The UKF assumes a general nonlinear form of the state and output equations, and efficiently propagates model and state uncertainties without the need to calculate Jacobians (unlike the extended Kalman filter). The UKF is restricted to additive Gaussian noise random processes; however use of the unscented transform, a deterministic sampling method, allows random variables with non-Gaussian distributions to be incorporated using a minimal set of weighted samples, called *sigma points* (Julier & Uhlmann, 1997).

The UKF takes as inputs the system inputs, $\mathbf{u}(k)$, and the measured system outputs, $\mathbf{y}(k)$. The UKF gives as output, performing estimation using the battery model, a probability distribution for the state, $p(\mathbf{x}(k)|\mathbf{y}(0:k))$, described in the form of weighted sigma points (\mathcal{X} , \mathbf{w}). From the sigma points, estimates of SOC, and voltage can be directly derived to obtain probability distributions of these quantities.

The number of sigma points needed is linear in the dimension of the random variable, and so the statistics of the transformed random variable, i.e., mean and covariance, can be computed much more efficiently than by random sampling (Daigle et al., 2012). Readers interested in the application of UKF and UT to the estimation of battery SOC are referred to our previous papers (Bole et al., 2013; Daigle et al., 2012) and the references therein. Here, it is sufficient to say that model based filtering approaches such as UKF will be much less susceptible to initialization and measurement errors than the Coulomb counting method currently used in many battery monitoring systems (Dai et al., 2006).

4. FUTURE MOTOR POWER DEMAND MODELING

The characterization of net battery power required by aircraft motors over a given set of maneuvers was recently described in (Bole et al., 2013). The powertrain load estimation modeling introduced in (Bole et al., 2013) made use of a set of relatively simple aerodynamics and powertrain dynamics equations that will be recreated here.

The equations presented here make use of the following assumptions: (*i*) the propeller is mounted on the aircraft nose; (*ii*) the angle between the thrust vector generated by the propeller and the velocity vector of the aircraft is small; and (*iii*) aircraft turning forces are small in comparison to the thrust and drag forces on the aircraft in its direction of travel.

Given these assumptions, the sum of the forces acting in the aircraft direction of travel can be expressed as:

$$T_{x_w} = D(v) + m \cdot g \cdot \sin(\alpha) + m \cdot \dot{v} \tag{5}$$

where T_{x_w} represents the thrust produced by the aircraft in the direction of travel, D represents the drag force acting in the opposite direction of aircraft motion, v represents the aircraft airspeed in units of meters/second, \dot{v} represents acceleration, α represents angle of climb in units of radians, m represents the vehicle mass, and g represents the earth's gravity.

The drag force on the airframe was fitted to the following polynomial function of airspeed and angle of climb,

$$D(v,\gamma) = c_1 + c_2 \cdot v + c_3 \cdot v^2 + c_4 \cdot \alpha$$

for $v \ge 15$ m/s (6)

During take-off and landing maneuvers when the aircraft speed is less than 15m/s the drag force is approximated as $D = 3 \cdot v$. The fitted parameter values used here are: $c_1 = 53.9$, $c_2 = -2.4$, $c_3 = 0.07$, $c_4 = 0.56$

The product of thrust and airspeed gives the motive power exerted by the aircraft on its environment,

$$P_p = \frac{1}{\eta_p} \cdot T_{x_w} \cdot v \tag{7}$$

where P_p represents propeller output power and η_p represents the approximate propeller output power conversion efficiency. The fitted value $\eta_p = 0.7652$ was found using a commercial aerodynamics simulator.

A fixed power conversion efficiency is assumed here for the aircraft motors and other power electronics,

$$P_{ESC} = \eta_e \cdot P_p \tag{8}$$

where η_e represents a power conversion efficiency factor and P_{ESC} represents net power at the input to the aircraft's two ESCs. The average efficiency of aircraft motors and power electronics was estimated here to be about 85%, $\eta_p = 0.85$.

The net ESC input power is equal to the sum of the power outputs from the two series connected battery strings,

$$P_{ESC} = P_{B1,2} + P_{B3,4} \tag{9}$$

where $P_{B1,2}$ and $P_{B3,4}$ represent the battery power output for batteries B1,B2 and B3,B4 as denoted in Fig. 2.

Although both ESCs receive the same throttle input command, their individual power draw is known to have a proportional relationship.

$$P_{B1,2} = \lambda \cdot P_{B3,4} \tag{10}$$

where λ is constant of proportionality. This constant λ was estimated to be about 1.37 over typical use cases for the Edge-540T powertrain.

Substitution of Eqs. (5) - (8) yields an expression for the approximate ESC input power required to fly at a particular airspeed and angle of climb,

$$P_{ESC} = \frac{1}{\eta_e \eta_p} \cdot T_{x_w} \cdot v$$

= $\frac{v}{\eta_e \eta_p} \cdot (D(v, \alpha) + mg \cdot \sin(\alpha) + m\dot{v})$ (11)

The power demands on battery strings $B_{1,2}$ and $B_{3,4}$ are then estimated as,

$$P_{B_{1,2}} = \frac{\lambda}{1+\lambda} \cdot P_{ESC}$$

$$P_{B_{3,4}} = \frac{1}{1+\lambda} \cdot P_{ESC}$$
(12)

4.1. Uncertainty Representation

Uncertainty in future powertrain loading demands are considered here to be unavoidable in environmental and system dynamics modeling. Uncertainty in future load prediction is represented here by defining a median future demand prediction with an upper and lower uncertainty bound.

Fig. 6 shows predicted and measured battery output power and battery output energy respectively for the battery string B1,B2 over a sample flight of the Edge-540T. The upper and lower uncertainty bounds shown in Fig. 6 represent $\pm 30\%$ deviation from the future battery power estimated using Eqns. (11) and (12) with the following sample flight plan.

- 1. Takeoff and climb to ~200 meters (duration = 60 s) ($\alpha = 2.8^{\circ}, v_0 = 0\frac{m}{s}, \dot{v} = 0.4\frac{m}{s^2}$)
- 2. Maintain altitude and approximate airspeed of $v = 23\frac{m}{s}$ (duration = 265 s) ($\alpha = 0^{\circ}$, $v = 23\frac{m}{s}$, $\dot{v} = 0\frac{m}{s^2}$)
- 3. Maintain altitude and approximate airspeed of $v = 29\frac{m}{s}$ (duration = 225 s) ($\alpha = 0^{\circ}$, $v = 29\frac{m}{s}$, $\dot{v} = 0\frac{m}{s^2}$)
- 4. Maintain altitude and approximate airspeed of $v = 22\frac{m}{s}$ (duration = 140 s) ($\alpha = 0^{\circ}$, $v = 22\frac{m}{s}$, $\dot{v} = 0\frac{m}{s^2}$)
- 5. Land aircraft (duration = 120 s) ($\alpha = -3^{\circ}$, $v_0 = 22\frac{m}{s}$, $\dot{v} = -0.18\frac{m}{s^2}$)

It can be seen from Fig. 6 that the actual battery power does not always fall within the plotted upper and lower uncertainty bounds. Notably the battery loads during the takeoff and climb portion of the flight plan (from 0-60 seconds) are seen to exceed the maximum predicted power at some points. Also, the battery loads during landing maneuver (from 690-810 seconds) are seen to exceed the minimum and maximum predicted power. The exceedances seen in takeoff and landing maneuvers are due to unmodeled transient dynamics in the system. These transients are short lived however, and the



Figure 6. Plots of measured and predicted $B_{1,2}$ output power and energy over a sample flight.

measured battery energy consumed over the sample flight is seen to fall well within the estimated uncertainty bounds.

5. PARASITIC LOAD ESTIMATION

A potential fault mode for the Edge aircraft is some fault in the electrical power system that manifests as a parasitic load on the batteries. Because this fault mode presents an increased load on the batteries, it will have effect of increasing the battery charge required to complete a flight plan. Future battery load estimates and battery discharge prediction would thus be biased if the parasitic load faults were not incorporated. In such a situation, an integrated diagnostics and prognostics approach is required (Bregon, Daigle, & Roychoudhury, 2012).

In our case, we consider a parasitic resistance that is located in parallel with the batteries. The parasitic current, i_p , is the difference between the total battery current, *i*, and the current going to the motors, i_m . In the aircraft, both *i* and i_m are measured as well as the total battery voltage V.

A residual, defined as the difference between an observed signal and its model-predicted value, can be defined for the parasitic fault detection based on the measured values of i and i_m . In the nominal case, our model for i is $i = i_m$. We can then define a residual, r_i , as $r = i^* - i_m^*$, where the * superscript indicates a measured value. Nominally, $r_i = 0$, and we can define a simple threshold-based fault detector that

triggers when $r_i > T$ for some threshold T. More complex fault detection methods can also be used, e.g., (Daigle et al., 2010). Once a fault is detected, we can estimate the parasitic current at time k using

$$\hat{i}_p(k) = i^*(k) - i^*_m(k),$$
 (13)

The parasitic resistance can then be estimated using

$$\hat{R}_{p}(k) = \frac{V_{b}^{*}(k)}{\hat{i}_{p}(k)}.$$
(14)

The estimate $\hat{R}_p(k)$ will be noisy, since it is computed based on measured values. Assuming that R_p is constant, we take the median of all computed values to provide a robust estimate of R_p , i.e.,

$$R_p(k) = \operatorname{median}(\{\hat{R}_p(k_j) : k_d \ge k_j \ge k\}), \quad (15)$$

where k_d is the time of fault detection (and the time that fault identification begins).

Since we are only interested in diagnosing the parasitic load fault, the diagnosis approach can be very simple. In general, one may also be concerned with sensor faults, in which case a more complex diagnosis approach is required, e.g., (Balaban et al., 2013; Daigle, Bregon, & Roychoudhury, 2011). In such an approach, additional information must be used to improve the analytical redundancy required for diagnosis.

Experimental results are shown in Figs. 7(a) and 7(b). In the nominal case, parasitic current is estimated to be approximately zero, which is correct for the no fault case. For the fault cases, parasitic current is clearly observed, and parasitic resistances can be estimated. In this data, sensor noise is very low and so the results are very accurate. Additional sensor noise will have a significant impact on the computation of parasitic resistance. Fig. 8 shows the difference in results for additional noise. With higher noise, accuracy reduces and the estimate takes longer to converge. Because we are using a median, the results are still pretty smooth.

6. PREDICTION

We now consider the problem of predicting whether or not the aircraft batteries contain sufficient charge to complete the remainder of a given flight plan. The aircraft batteries are considered to be no longer able to safely support flight activities when any of the battery pack voltages drop below 17V. A 17V pack output voltage corresponds individual lithium-ion cell voltages of approximately 3.4V. Discharging the lithium-ion cells beyond this voltage risks damage or catastrophic failure.

Predictions of the future evolution of battery voltage over a flight plan are generated using estimates of the present battery state, as well as estimates of the future loads to be placed on the battery. As explained in Section 3.1, uncertainty in



Figure 7. Parasitic current and resistance estimates.



Figure 8. Parasitic resistance estimation with additional sensor noise.

battery state estimates is represented using a weighted set of sigma points. As explained in Section 4.1, uncertainty in predictions of the future battery power to be demanded over the remainder of a flight plan are represented here by upper and lower uncertainty bounds.

The experimental results presented in the next section demonstrate that high confidence assessments on the safety of completing the remainder of a flight plan can be generated by simulating all of the current sigma point state estimates against the extreme upper and lower bounds of anticipated future battery load. If the maximum and minimum sigma points resulting from the application of these future loading extremes are safe, then we must have very high confidence that the mission will be completed. If some of the simulated sigma points reach a failure state, then we can attempt to further qualify the risk of failure by applying additional analysis techniques.

7. EXPERIMENTAL TESTING OF BATTERY PREDIC-TION

Fig. 9 shows an electrical schematic for a test stand that is used to simultaneously subject batteries to both a static resistive loads and a dynamic current loads. The B_1 and B_2 batteries shown in Fig. 9 represent two batteries under test. Our test articles are batteries with the same chemistry, capacity, voltage, and manufacturer as the Edge-540T batteries. The i_f component in Fig. 9 represents a dynamic current sink that is programmed to sink the same current as was measured for the $B_{1,2}$ battery chain over a given flight of the Edge-540T. The R_p component in Fig. 9 represents a resistive load that can be switched in parallel with the batteries on command.

A Maccor Series 4000 automated battery cycler is used for the tests described in this section, and for the battery characterization cycling experiments described in Section 3. This programmable test system can be configured to draw or apply static loads or time dependent loads. The testing equipment is capable of sourcing or sinking up to 5kW of power, with current limited to 100A, and voltage limited to 50V. The cycler can be programmed to terminate a loading profile based on current, voltage, or temperature safety thresholds. In the case of the experiments conducted here, a low-voltage safety threshold of 17V per pack was used prevent over discharging the batteries. If this threshold is crossed, the battery loading experiment is terminated immediately and the batteries will be considered failed for the purposes of that simulation run.

Four battery discharge experiments are described here. In all of these experiments the i_f component in Fig. 9 is set equal to a 10 Hz sampling of the $i_{B_{1,2}}$ current as measured over a sample flight of the Edge-540T. One experiment is performed with the R_p branch of Fig. 9 open. The resultant battery voltage response should closely follow the trends seen on batteries B_1 and B_2 in the flight test, because they are being subjected to the same current loads. The addition of a parasitic resistance to the battery circuit is tested in the remaining three discharge experiments. Parasitic resistances are added into the battery circuit at approximately 200 seconds into a replayed flight. The lower the value of parasitic resistance injected, the higher the parasitic current draw on the batteries. The additional current drawn by this parasitic load effectively increases the demand on the battery over a simulated flight, and correspondingly increases the risk that the battery lacks sufficient charge to complete a given flight plan. The parasitic resistance values tested were: $\{R_p = 10 \ \Omega, R_p = 5 \ \Omega, \text{ and } \}$ $R_p = 1 \Omega \}.$

Fig. 10 shows B_1 and B_2 voltage measurements and SOC estimates collected during a sample flight, and during four



Figure 9. Schematic of battery tester, showing current sources and voltage measurement points.

battery discharge tests conducted in the laboratory. The flight data was collected over an Edge-540T flight that followed the sample flight plan described in Section 4.1. The battery voltage and SOC measurements for the nominal experiment (with no parasitic load injected) are in fact seen to follow the flight measurements. The injection of 10 Ω and 5 Ω parasitic resistances is seen to result in lowered battery voltage and SOC over a sample flight profile. Finally, the injection of a 1 Ω resistance is seen to result in the early termination of the discharge test due to an exceedence of the low-voltage safety threshold at approximately 500 seconds.

Next we consider the generation of prognostic estimates for the aircraft at regular time-indexes over a UAV mission. At each time-index the inputs to the prognostic estimator are (i)a set of sigma points representing battery state estimates; (ii)estimated $\pm 30\%$ uncertainty bounds on motor system power demands over a planned set of aircraft maneuvers; and (iii)online estimates of parasitic load faults. Prognostic estimates will be reported in terms of two metrics; (i) the predicted battery SOC at the end of a flight plan, and (ii) the predicted time to reach either the battery low-voltage cut-off threshold or the end of a flight plan.

Fig. 11 shows the evolution of prediction uncertainty bounds for the two prognostic metrics over five battery discharge data sets. The starting uncertainty bounds for the prediction of battery SOC at the end of the flight plan is seen to span from approximately 55% SOC to 10% SOC. The battery EOD estimate is seen to span from approximately 700 seconds to 810 seconds, where 810 seconds marks the expected end of the aircraft flight plan. These uncertainty bounds indicate a predicted worst-case outcome where the batteries reach the lowvoltage cut-off threshold at approximately 700 seconds, and a best-case predicted outcome in which the mission will be safely completed.

During the time interval [0,180], all of the worst-case EOD estimates are seen to converge on a belief that the mission will not cause the batteries to fail prior to flight plan completion. This convergence occurs because the battery state evolution observed over the time interval [0,180] turns out to be better that was predicted for the worst-case.




Figure 10. Comparison of voltage measurements (top) and SOC estimates (bottom) for batteries B_1 and B_2 over a sample flight and four test cases that include injected parasitic resistances of various magnitudes.

Around 200 seconds into the mission a parasitic resistance is injected in parallel with the batteries. The effect that this new parasitic resistance has on predicted future battery loads is clearly seen the predictions of SOC at end of flight plan. For the case of the 1 Ω injected parasitic resistance, predictions of SOC at end of flight plan are seen to rapidly converge to a prediction that the battery charge will be fully depleted prior to the end of the flight plan. The EOD prediction plots show an initial drop in the confidence that batteries will survive the remainder of the flight plan with 5 Ω and 10 Ω of parasitic load. The confidence in flight plan safety for the 5 Ω and 10 Ω cases is then seen to converge to predicting the safe completion of the mission.

This example demonstrates the combination of system state estimation uncertainty and future system load uncertainty into an estimate of prognostic uncertainty. Upper and lower un-

Figure 11. Prediction uncertainty bounds for two prognostic metrics plotted at 30 second time intervals over five battery discharge data sets. Predicted battery SOC at EOM is shown in the top plot, and predicted time to reach a battery EOD threshold is shown in the bottom plot

certainty bounds on the space of future outcomes are derived, and the utility of these bounds for making high confidence estimates of flight plan safety is demonstrated. Consideration of situations in which uncertainty bounds indicate that a range of both safe and unsafe evolutions of the system state are possible is identified as a topic for future work. In such situations, knowledge of a probability distribution for the prognostic uncertainty between upper and lower uncertainty bounds, may be needed to quantify the risk and reward of potential supervisory control actions. Extending the prognostic results presented here in this way is possible, but is left as a topic for future work. Flight demonstrations of autonomous and pilot-inthe-loop decision making based on online battery discharge predictions is also planned for future work.

8. CONCLUSIONS

This paper describes an approach for identifying upper and lower uncertainty bounds on predictions that aircraft batteries will continue to meet output power and voltage requirements over the remainder of a flight plan. Uncertainty bounds were generated using uncertain estimates of a battery's state and uncertain predictions of future battery demands. The establishment of upper and lower bounds on prognostic estimates was shown to enable high confidence assessments of amount of safe flying time remaining before there is appreciable risk of the battery output voltage dropping below specified lower limits.

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REFERENCES

- Balaban, E., & Alonso, J. (2013). A modeling framework for prognostic decision making and its application to uav mission planning. In Annual conference of the prognostics and health management society.
- Balaban, E., Narasimhan, S., Daigle, M., Roychoudhury, I., Sweet, A., Bond, C., & Gorospe, G. (2013). Development of a mobile robot test platform and methods for validation of prognostics-enabled decision making algorithms. *International Journal of Prognostics and Health Management*, 4(1).
- Bole, B., Kulkarni, C. S., & Daigle, M. (2014). Adaptation of an electrochemistry-based li-ion battery model to account for deterioration observed under randomized use. In *Annual conference of the prognostics and health management society.*
- Bole, B., Teubert, C., Chi, Q. C., Edward, H., Vazquez, S., Goebel, K., & Vachtsevanos, G. (2013). SIL/HIL replication of electric aircraft powertrain dynamics and inner-loop control for V&V of system health management routines. In *Annual conference of the prognostics* and health management society.
- Bregon, A., Daigle, M., & Roychoudhury, I. (2012, September). An integrated framework for model-based distributed diagnosis and prognosis. In *Annual conference of the prognostics and health management society 2012* (p. 416-426).
- Chen, M., & Rincon-Mora, G. (2006). Accurate electrical battery model capable of predicting runtime and i-v performance. *IEEE Transactions on Energy Conversion*, 21(2), 504-511.
- Dai, H., Wei, X., & Sun, Z. (2006). Online soc estimation of high-power Lithium-Ion batteries used on HEVs. In *IEEE international conference on vehicular electronics and safety.*

- Daigle, M., Bregon, A., & Roychoudhury, I. (2011, Oct). Qualitative Event-based Diagnosis with Possible Conflicts: Case Study on the Third International Diagnostic Competition. In *Proceedings of the 22nd international workshop on principles of diagnosis* (p. 285-292). Murnau, Germany.
- Daigle, M., Roychoudhury, I., Biswas, G., Koutsoukos, X., Patterson-Hine, A., & Poll, S. (2010, September). A comprehensive diagnosis methodology for complex hybrid systems: A case study on spacecraft power distribution systems. *IEEE Transactions of Systems, Man,* and Cybernetics, Part A, 4(5), 917–931.
- Daigle, M., Saxena, A., & Goebel, K. (2012). An efficient deterministic approach to model-based prediction uncertainty. In Annual conference of the prognostics and health management society.
- Edwards, D., Orchard, M., Tang, L., Goebel, K., & Vachtsevanos, G. (2010). Impact of input uncertainty on failure prognostic algorithms: Extending the remaining useful life of nonlinear systems. In *Annual conference of the prognostics and health management society*.
- Julier, S. J., & Uhlmann, J. K. (1997). A new extension of the Kalman filter to nonlinear systems. In Proceedings of the 11th international symposium on aerospace/defense sensing, simulation, and controls (pp. 182–193).
- Julier, S. J., & Uhlmann, J. K. (2004, March). Unscented filtering and nonlinear estimation. *Proceedings of the IEEE*, 92(3), 401–422.
- Quach, C. C., Bole, B., Hogge, E., Vazquez, S., Daigle, M., Celaya, J., & Goebel, K. (2013). Battery charge depletion prediction on an electric aircraft. In *Annual conference of the prognostics and health management society.*
- Saha, B., Koshimoto, E., Quach, C. C., Hogge, E. F., Strom, T. H., Hill, B. L., ... Goebel, K. (2011). Battery health management system for electric UAVs. In *IEEE aerospace conference*.
- Saha, B., Quach, C. C., & Goebel, K. (2012, March). Optimizing battery life for electric UAVs using a Bayesian framework. In *Proceedings of the 2012 ieee aerospace conference.*
- Sankararaman, S., & Goebel, K. (2013). Why is the remaining useful life prediction uncertain? In Annual conference of the prognostics and health management society.
- Zhang, H., & Chow, M.-Y. (2010). Comprehensive dynamic battery modeling for PHEV applications. In *IEEE power and energy society general meeting.*

BIOGRAPHIES



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Diagnosability-Based Sensor Placement through Structural Model Decomposition

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ABSTRACT

Systems health management, and in particular fault diagnosis, is important for ensuring safe, correct, and efficient operation of complex engineering systems. The performance of an online health monitoring system depends critically on the available sensors of the system. However, the set of selected sensors is subject to many constraints, such as cost and weight, and hence, these sensors must be selected judiciously. This paper presents an offline design-time sensor placement approach for complex systems. Our diagnosis method is built upon the analysis of model-based residuals, which are computed using structural model decomposition. Sensor placement in this framework manifests as a residual selection problem, and we aim to find the set of residuals that achieves single-fault diagnosability of the system, uses the minimum number of sensors, and corresponds to the best model decomposition for the best distribution of the diagnosis system. We present a set of algorithms for solving this problem and compare their performance in terms of computational complexity and optimality of solutions. We demonstrate the approach using a benchmark multi-tank system.

1. INTRODUCTION

Fault diagnosis, an important aspect of systems health management, is essential for ensuring safe, correct, and efficient operation of complex engineering systems. Fault diagnosis involves fault detection (whether system behavior is off-nominal), fault isolation (what is the root cause of the off-nominal behavior), and fault identification (what is the fault magnitude). The performance of the fault diagnosis system depends on the available sensors from which diagnostic information can be extracted. However, the set of selected sensors are subject to many constraints, such as cost and weight, and hence, these sensors must be selected judiciously.

For fault isolation, a valid placement of sensors should be one in which the system is diagnosable, i.e., all single faults can be uniquely isolated from each other, which is a design metric for diagnostic performance (Narasimhan, Mosterman, & Biswas, 1998). We utilize a fault isolation framework that is based on the analysis of model-based residuals, where each residual is computed as the difference between a measured sensor output and the predicted value of that sensor output. Local models of the system, that are used to make predictions of measured outputs, are generated by decomposing the global model of the system using structural model decomposition (Roychoudhury, Daigle, Bregon, & Pulido, 2013). Therefore, the problem of sensor placement is directly related to one of residual selection.

In this paper, we formulate the sensor placement problem and establish its search space through the novel concept of a complete residual set, based on structural model decomposition. We present three algorithms for solving this sensor placement problem and compare their performance in terms of computational complexity and optimality of solutions. The different algorithms are: (*i*) exhaustive search, (*ii*) stochastic search, and (*iii*) structured search. The exhaustive search is a brute force search over the residual space, and so guarantees optimality but is not scalable. The stochastic search selects random residual sets and modifies them randomly to try to improve the current set of candidate solutions. The structured search algorithm uses knowledge of what solutions are preferred in order to search a reduced space in a structured fashion. We demonstrate the approach using a benchmark multi-

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tank system (Daigle, Bregon, Biswas, Koutsoukos, & Pulido, 2012). In this work, we focus on continuous systems and adopt the single fault assumption.

This paper is organized as follows. Section 2 presents related work to set the context for our contributions. Section 3 provides the necessary background information on structural model decomposition and our qualitative fault isolation framework. The problem formulation, which defines the problem and establishes its search space, is presented in Section 4. The diagnosability-based measurement selection approach and the three algorithms are described in Section 5. Experimental results are provided in Section 6. Section 7 concludes the paper and discusses future work.

2. RELATED WORK

Efficient solutions to the sensor placement problem have been explored before. Our work is in contrast to other approaches present in literature (Basseville, Benveniste, Moustakides, & Rougee, 1987; Debouk, Lafortune, & Teneketzis, 2002; Roychoudhury, Biswas, & Koutsoukos, 2009) in that we look for solutions that obtain maximum diagnosability by minimizing the size of the submodels, which yields smaller-sized diagnosers and allows its implementation as a distributed approach. For example, in (Basseville et al., 1987), the authors propose an approach for optimal sensor location to increase the fault detection performance in dynamic systems using statistical tests. In (Debouk et al., 2002) the authors assume that the system is diagnosable given a set of sensors and look for the least expensive combination of those sensors under which the system is still diagnosable. Our decision in favor of distributed approaches is influenced by the fact that the design of fault diagnosers can have consequences in terms of computational efficiency, scalability, single points of failure, and the quickness of fault diagnosis, among others (Roychoudhury et al., 2009). For example, centralized diagnosis approaches suffer from single points of failure, large computational complexity, and scalability issues. Decomposing the diagnosis problem can address some or all of these issues.

Unlike the related approach of (Roychoudhury et al., 2009), another focus of our work is in the use of structural information to determine the best sensor locations. Several previous papers make use of structural information for solving the sensor placement problem (Krysander & Frisk, 2008; Rosich, 2012; Travé-Massuyès et al., 2006; Said & Djamel, 2013). The use of structural information allows to efficiently solve this problem for large and nonlinear differential-algebraic models. In (Krysander & Frisk, 2008) the authors propose new a method, using Dulmage-Mendelson decomposition, for computing which sensors to add to obtain maximum fault detectability and isolability. A related approach is proposed in (Travé-Massuyès et al., 2006), but following a different strategy. Instead of computing which sensors to add to obtain a certain isolability performance, in (Travé-Massuyès et al., 2006) the problem is solved by hypothesizing sensors, then computing Analytical Redundancy Relations (ARR) with all possible causalities, and then obtaining the isolability properties. In this sense, our approach is more similar to the approach of (Krysander & Frisk, 2008), since we add sensors looking for maximum diagnosability and then decompose the system to look for the smaller submodels to obtain that maximum diagnosability. However, our approach is different to both, since we include qualitative and temporal information within our models, which improves diagnosability; and second, the approach in (Travé-Massuyès et al., 2006) only allows solutions where residuals are computed by using minimal submodels.

Other approaches in the literature consider causal information within the system model (Raghuraj, Bhushan, & Rengaswamy, 1999; Rosich, Frisk, Aslund, Sarrate, & Nejjari, 2012). In (Raghuraj et al., 1999), the authors use a directed graph and algorithms based on the graph to look for the optimal sensor location to ensure observability and fault resolution. Also, the authors discuss the possibility of including signs in the graph. However, unlike the approach presented in this paper, signs are not included in the algorithms. Another difference against our approach is that they only consider residuals computed using the global system model. In (Rosich et al., 2012), the authors only allow residuals computed from minimal submodels and temporal information is not included.

One of the main problems of the structural approach to sensor placement, especially when a large number of feasible sensor locations is available, is that the computational effort to look for the optimal solution could be huge. In (Eriksson, Krysander, & Frisk, 2012) the authors use a quantitative diagnosability analysis to optimize sensor placement for fault diagnosis. In (Casillas, Puig, Garza-Castañon, & Rosich, 2013) genetic algorithms are used for the same task. Unlike the previous approaches, in (Frisk, Krysander, & Åslund, 2009) the authors use analytical equations as a solution which can handle models where structural approaches fail, however, it is limited only to linear differential-algebraic systems, which restricts severely its applicability to practical systems.

3. BACKGROUND

In this section, we first describe our approach to structural model decomposition, which, given a global system model, creates local models of system behavior. We then describe our model-based diagnostic framework that is based on analysis of residuals computed using these local models.

3.1. System Modeling

We adopt here the structural model decomposition framework described in (Roychoudhury et al., 2013). In the following,



Figure 1. Tank system schematic.

we review the main details and and refer the interested reader to (Roychoudhury et al., 2013) for additional explanation. We define a model as follows:

Definition 1 (Model). A model \mathcal{M}^* is a tuple $\mathcal{M}^* = (V, C)$, where V is a set of variables, and C is a set of constraints among variables in V. V consists of five disjoint sets, namely, the set of state variables, X; the set of parameters, Θ ; the set of inputs, U; the set of outputs, Y; and the set of auxiliary variables, A. Each constraint $c = (\varepsilon_c, V_c)$, such that $c \in C$, consists of an equation ε_c involving variables $V_c \subseteq V$.

Input variables, U, are known, and the set of output variables, Y, correspond to the (measured) sensor signals. Parameters, Θ , include explicit model parameters that are used in the model constraints. Auxiliary variables, A, are additional variables that are algebraically related to the state and parameter variables, and are used to reduce the structural complexity of the equations.

Throughout the paper, we use a benchmark multi-tank system as a running example. The system consists of n tanks connected serially, as shown in Fig. 1. For each tank i, where $i \in [1, n]$, u_i denotes the input flow, m_i denotes the liquid mass, p_i denotes the tank pressure, q_i denotes the mass flow out of the drain pipe, K_i denotes the tank capacitance, and Re_i denotes the drain pipe resistance. For adjacent tanks i and i + 1, $q_{i,i+1}$ denotes the mass flow from tank i to tank i+1 through the connecting pipe, and $Re_{i,i+1}$ is the connecting pipe resistance. The constraints for tank i are as follows:

$$\begin{split} \dot{m}_{i} &= u_{i} + q_{i-1,i} - q_{i} - q_{i,i+1} \\ m_{i} &= \int_{t_{0}}^{t} \dot{m}_{i} dt, \\ p_{i} &= \frac{1}{K_{i}} m_{i}, \\ q_{i} &= \frac{1}{Re_{i}} p_{i}, \\ q_{i,i+1} &= \frac{1}{Re_{i,i+1}} (p_{i} - p_{i+1}). \end{split}$$

For tank 1, $q_{0,1} = 0$, and for tank $n, q_{n,n+1} = 0$.

The measurements corresponding to p_i , q_i , and $q_{i,i+1}$ are p_i^* ,

$$q_i^*$$
, and $q_{i,i+1}^*$ and are described by the following constraints:

$$p_i^* = p_i,$$

 $q_i^* = q_i,$
 $q_{i,i+1}^* = q_{i,i+1}.$

Example 1. For a three-tank system measuring the output flows, the model \mathcal{M}^* is represented by the variable sets $X = \{m_1, m_2, m_3\}, \Theta = \{K_1, K_2, K_3, Re_1, Re_2, Re_3, Re_{1,2}, Re_{2,3}\}, U = \{u_1, u_2, u_3\}, Y = \{p_1^*, p_2^*, p_3^*, q_1^*, q_2^*, q_3^*, q_{1,2}^*, q_{2,3}^*\}$, and $A = \{\dot{m}_1, \dot{m}_2, \dot{m}_2, p_1, p_2, p_3, q_1, q_2, q_3\}$; and the set of constraints $C = \{c_1, c_2, ..., c_{22}\}$, where the constraints are given as follows:

$$\dot{m}_1 = u_1 - q_1 - q_{1,2}, \tag{c_1}$$

$$\dot{m}_2 = u_2 + q_{1,2} - q_2 - q_{2,3}, \qquad (c_2)$$

$$\dot{m}_3 = u_3 + q_{2,3} - q_3, \tag{c_3}$$

$$m_1 = \int_{t_0}^t \dot{m}_1 dt, \qquad (c_4)$$

$$m_2 = \int_{t_0}^t \dot{m}_2 dt, \qquad (c_5)$$

$$m_3 = \int_{t_0}^t \dot{m}_3 dt, \qquad (c_6)$$

$$p_1 = \frac{1}{K_1} m_1, \tag{(c_7)}$$

$$p_2 = \frac{1}{K_2} m_2, (c_8)$$

$$p_3 = \frac{1}{K_3} m_3, \tag{c_9}$$

$$q_1 = \frac{1}{Re_1} p_1, (c_{10})$$

$$q_2 = \frac{1}{Re_2} p_2, (c_{11})$$

$$q_3 = \frac{1}{Re_3} p_3, (c_{12})$$

$$q_{1,2} = \frac{1}{Re_{1,2}}(p_1 - p_2), \qquad (c_{13})$$

$$q_{2,3} = \frac{1}{Re_{2,3}}(p_2 - p_3), \qquad (c_{14})$$

$$p_1^* = p_1, \tag{c_{15}}$$

$$p_2^* = p_2, (c_{16})$$

$$p_3^* = p_3, \qquad (c_{17})$$

$$q_1^* = q_1,$$
 (c₁₈)
 $q_1^* = q_2$ (c₁₆)

$$q_2 = q_2,$$
 (C19)
 $q_2^* = q_3,$ (C20)

$$q_{1,2}^* = q_{1,2},$$
 (c₂₁)

$$q_{2,3}^* = q_{2,3}.$$
 (c₂₂)

Here, the * superscript is used to denote a measured value of a physical variable, e.g., p_1 is pressure and p_1^* is the measured pressure. Since p_1 is used to compute other variables, it cannot belong to Y and a separation of the variables is required.

The notion of a *causal assignment* is used to specify the computational causality for a constraint c, by defining which $v \in V_c$ is the dependent variable in equation ε_c .

Definition 2 (Causal Assignment). A causal assignment α to a constraint $c = (\varepsilon_c, V_c)$ is a tuple $\alpha = (c, v_c^{out})$, where $v_c^{out} \in V_c$ is assigned as the dependent variable in ε_c .

We write a causal assignment of a constraint using its equation in a causal form, with := to explicitly denote the causal (i.e., computational) direction.

Definition 3 (Valid Causal Assignments). We say that a set of causal assignments A, for a model M^* is *valid* if

- For all v ∈ U ∪ Θ, A does not contain any α such that α = (c, v).
- For all $v \in Y$, \mathcal{A} does not contain any $\alpha = (c, v_c^{out})$ where $v \in V_c - \{v_c^{out}\}$.
- For all $v \in V U \Theta$, \mathcal{A} contains exactly one $\alpha = (c, v)$.

The definition of valid causal assignments states that (i) input or parameter variables cannot be the dependent variables in the causal assignment, (ii) a measured variable can be used as the dependent variable, and (iii) every variable, which is not input or parameter, is computed by only one (causal) constraint.

Based on this, a *causal model* is a model extended with a valid set of causal assignments.

Definition 4 (Causal Model). Given a model $\mathcal{M}^* = (V, C)$, a *causal model* for \mathcal{M}^* is a tuple $\mathcal{M} = (V, C, A)$, where A is a set of valid causal assignments.

For the n-tank system, the causal constraints for tank i are as follows:

$$\dot{m}_{i} := u_{i} + q_{i-1,i} - q_{i} - q_{i,i+1},$$

 $m_{i} := \int_{t_{0}}^{t} \dot{m}_{i} dt,$
 $p_{i} := \frac{1}{K_{i}} m_{i},$

$$q_{i} := \frac{1}{Re_{i}}p_{i},$$

$$q_{i,i+1} := \frac{1}{Re_{i,i+1}}(p_{i} - p_{i+1}),$$

$$p_{i}^{*} := p_{i},$$

$$q_{i}^{*} := q_{i},$$

$$q_{i,i+1}^{*} := q_{i,i+1}.$$

Example 2. The causal model \mathcal{M} is represented by the same variables and constraints as \mathcal{M}^* , along with the set of causal assignments $\mathcal{A} = \{\alpha_1, \alpha_2, \dots, \alpha_{22}\}$, as given below:

$$\dot{m}_1 := u_1 - q_1 - q_{1,2}, \qquad (\alpha_1)$$

$$\dot{m}_2 := u_2 + q_{1,2} - q_2 - q_{2,3},$$
 (\alpha_2)

$$m_3 := u_3 + q_{2,3} - q_3, \qquad (\alpha_3)$$

$$m_1 := \int_{t_0}^t \dot{m}_1 dt, \qquad (\alpha_4)$$

$$m_2 := \int_{t_0}^t \dot{m}_2 dt, \qquad (\alpha_5)$$

$$m_3 := \int_{t_0}^t \dot{m}_3 dt, \qquad (\alpha_6)$$

$$p_1 := \frac{1}{K_1} m_1, \qquad (\alpha_7)$$

$$p_2 := \frac{1}{K_2} m_2, \qquad (\alpha_8)$$

$$p_3 \coloneqq \frac{1}{K_3} m_3, \qquad (\alpha_9)$$

$$q_1 := \frac{1}{Re_1} p_1, \qquad (\alpha_{10})$$

$$q_2 := \frac{1}{Re_2} p_2, \qquad (\alpha_{11})$$

$$q_3 := \frac{1}{Re_3} p_3, \qquad (\alpha_{12})$$

$$q_{1,2} := \frac{1}{Re_{1,2}}(p_1 - p_2), \qquad (\alpha_{13})$$

$$q_{2,3} := \frac{1}{Re_{2,3}} (p_2 - p_3), \qquad (\alpha_{14})$$

$$p_1^* := p_1, \qquad (\alpha_{15})$$

$$p_2^* := p_2,$$
 (\alpha_{16})

$$p_3^{\tau} := p_3,$$
 (α_{17})

$$q_1^* := q_1, \qquad (\alpha_{18})$$

$$q_2 := q_2, \qquad (\alpha_{19})$$

$$q_* := q_* \qquad (\alpha_{19})$$

$$q_3 = q_3,$$
 (a₂₀)
 $q^* = q_3,$ (a₂₀)

$$q_{1,2} = q_{1,2},$$
 (a₂₁)
 $q_{1,2}^* = q_{1,2},$ (a₂₁)

$$q_{2,3} := q_{2,3}. \tag{(a_{22})}$$



Figure 2. Causal graph of the three-tank system.

We can visualize a causal model \mathcal{M} using a directed graph $\mathcal{G} = (N, A)$, where N is the set of nodes corresponding directly to the variables V in \mathcal{M} , and A is the set of arcs, where for every $(c, v_c^{out}) \in \mathcal{A}$, we include an arc (v', v_c^{out}) for each $v' \in V_c - \{v_c^{out}\}$.

Example 3. The causal graph corresponding to the three-tank system model is given in Fig. 2. In the graph, we mark inputs with dashed circles, state variables with dashed squares, and outputs with solid squares.

3.2. Structural Model Decomposition

In our approach, a fault f is modeled as a step change in a system model parameter value, $\theta \in \Theta$. Faults cause changes in observed system behavior from model-predicted behavior. We can detect such changes by computing residuals, defined as the difference between the measured and predicted value of some sensor.

Using the causal model \mathcal{M} of a system, we can predict values of all the sensors in order to compute residuals. However, in the global model, faults are coupled to all the sensors, i.e., they cause deviations in all the sensors eventually. Through structural model decomposition, we can instead define local submodels in which each residual responds to only a subset of the faults, increasing diagnosability (Daigle et al., 2012).

Under this approach, given a (global) model, we can create (local) submodels that use as additional inputs values from the sensors (Roychoudhury et al., 2013). Given the set of potential local inputs (selected from $U \cup Y$) and the set of variables to be computed by the submodel (selected from Y), we create from a causal model \mathcal{M} a causal submodel \mathcal{M}_{Y_i} , in which $Y_i \subseteq Y$ is computed using $C_i \subseteq C$. In this way, each submodel computes its variable values independently from all other submodels. A causal submodel can be defined as follows.

Definition 5 (Causal Submodel). A *causal submodel* \mathcal{M}_{Y_i} of a causal model $\mathcal{M} = (V, C, \mathcal{A})$ is a tuple $\mathcal{M}_{Y_i} = (V_i, C_i,$

$$\mathcal{A}_i$$
), where $V_i \subseteq V$, $C_i \subseteq C$, and $\mathcal{A}_i \cap \mathcal{A} \neq \emptyset$.

When using measurements (from Y) as local inputs for a causal submodel, the causality of these constraints must be reversed, and so, in general, A_i is not a subset of A.

The procedure for generating a causal submodel from a causal model is given as Algorithm 1 (Roychoudhury et al., 2013). Given a causal model \mathcal{M} , and an output variable to be computed y, the GenerateSubmodel algorithm derives a causal submodel \mathcal{M}_i that computes y using as local inputs only variables from $U^* = U \cup (Y - \{y\})$. We briefly summarize the algorithm below.

In Algorithm 1, the *variables* queue represents the set of variables that have been added to the submodel but have not yet been resolved, i.e., they cannot yet be computed by the submodel. This queue is initialized to $\{y\}$, and the algorithm then iterates until this queue has been emptied, i.e., the submodel can compute y using only variables in U^* . For each variable v that must be resolved, we use Subroutine 2 (GetBestConstraint subroutine) to find the constraint that should be used to resolve v in the minimal way.

The GetBestConstraint subroutine (which has been updated from (Roychoudhury et al., 2013)) tries to find a constraint that *completely* resolves the variable, i.e., resolves vwithout further backward propagation (all other variables involved in the constraint are in $V_i \cup \Theta \cup U^*$). Such a constraint may be the one that computes v in the current causality, if all needed variables are already in the submodel (in V_i) or are available local inputs (in U^*); such a constraint may be one that computes a measured output $y^* \in U^*$, in which case the causality will be modified such that y^* becomes an input, i.e., the constraint in the new causality will compute vrather than y^* ; or such a constraint may be one that computes some y^* through some v' in an algebraic relation. If no such constraint exists, then the constraint that computes v in the current causal assignment is chosen, and further backward propagation will be necessary. A preferences list, P, is used to break ties if multiple minimal constraints exist to resolve v.

We assume that the differential constraints in the model are always in integral causality. We assume also that the model \mathcal{M} to be decomposed is free from algebraic loops (which will prevent Algorithm 1 from terminating), otherwise, the constraints may be arbitrarily complex and nonlinear. However, nonlinear constraints may not be possible in all causalities. If causality must be changed in order for the decomposition to proceed, there must be an expression for the constraint in the new causal form. If some constraints are not available in all possible causalities, then this may restrict the possible model decompositions. Algorithm 1 \mathcal{M}_i = GenerateSubmodel (\mathcal{M}, U^*, V^*)

1:	$V_i \leftarrow V^*$
2:	$C_i \leftarrow \varnothing$
3:	$\mathcal{A}_i \leftarrow arnothing$
4:	$variables \leftarrow V^*$
5:	while $variables \neq \emptyset$ do
6:	$v \leftarrow \text{pop}(variables)$
7:	$c \leftarrow \texttt{GetBestConstraint}(v, V_i, U^*, \mathcal{A})$
8:	$C_i \leftarrow C_i \cup \{c\}$
9:	$\mathcal{A}_i \leftarrow \mathcal{A}_i \cup \{(c, v)\}$
10:	for all $v' \in V_c$ do
11:	if $v' \notin V_i$ and $v' \notin \Theta$ and $v' \notin U^*$ then
12:	$variables \leftarrow variables \cup \{v'\}$
13:	end if
14:	$V_i \leftarrow V_i \cup \{v'\}$
15:	end for
16:	end while
17:	$\mathcal{M}_i \leftarrow (V_i, C_i, \mathcal{A}_i)$

3.3. Qualitative Fault Isolation

As mentioned in Section 1, the goal of this work is to solve the sensor placement problem such that all single faults can be uniquely isolated from each other. The solution of this problem depends on the diagnosis framework chosen. In this section, we briefly present our fault isolation approach. For details, please refer to (Mosterman & Biswas, 1999; Bregon et al., 2014).

As previously mentioned, in our approach, a fault f is modeled as a step change in a system model parameter value, $\theta \in \Theta$. Faults are named by the associated parameter and the direction of change, i.e., θ^+ (resp., θ^-) denotes a fault defined as an abrupt increase (resp., decrease) in the value of parameter θ . The complete fault set is denoted as F.

Example 4. In the three-tank system in Fig. 1, the complete fault set F consists of $\{K_1^-, K_1^+, K_2^-, K_2^+, K_3^-, K_3^+, Re_1^-, Re_1^+, Re_2^-, Re_2^+, Re_3^-, Re_3^+, Re_{1,2}^-, Re_{1,2}^+, Re_{2,3}^-, Re_{2,3}^+\}$.

Faults cause transients in the system variables that are observed as deviations of measured values from predicted values. This is captured through the concept of a residual.

Definition 6 (Residual). A *residual*, r_y , is a time-varying signal that is computed as the difference between a measurement, $y \subseteq Y$, and a predicted value of the measurement y, denoted as \hat{y} . A set of residuals is denoted as R.

From the previous subsection, we see that there are several potential submodels that can compute \hat{y} , depending on what local inputs are selected. In the nominal situation all residuals are ideally zero, and when a fault occurs they become nonzero. It is through analysis of the residual signals that fault isolation is performed.

The transients produced in the residuals are captured as qualitative *fault signatures* (Mosterman & Biswas, 1999).

Definition 7 (Fault Signature). A *fault signature* for a fault f and residual r, denoted by $\sigma_{f,r}$, is pair of symbols s_1s_2 representing potential qualitative changes in magnitude and slope of r caused by f at the point of the occurrence of f.

Subroutine 2 $c = \text{GetBestConstraint}(v, V_i, U^*, A)$

1: $C \leftarrow \emptyset$ 2: $c_v \leftarrow \text{find } c \text{ where } (c, v) \in \mathcal{A}$ 3: if $V_{cv} \subseteq V_i \cup U^*$ then 4: $C \leftarrow C \cup \{c_v\}$ 5: **end if** 6: for all $y \in Y \cap U^*$ do $c_y \leftarrow \text{find } c \text{ where } (c, y) \in \mathcal{A}$ if $v \in V_{c_y}$ and $V_{c_y} \subseteq V_i \cup U^* \cup \Theta$ then 7: 8: $C \leftarrow C \cup \{c_y\}$ 9: 10: end if 11: end for for all $y \in Y \cap U^*$ do 12: $c_y \leftarrow \text{find } c \text{ where } (c, y) \in \mathcal{A}$ 13: $\check{V'} \leftarrow V_{c_y} - \{y\}$ 14: for all $v' \in V'$ do 15: $c_{v'} \leftarrow \text{find } c \text{ where } (c, v') \in \mathcal{A}$ 16: if $v \in V_{c_{v'}}$ and $V_{c_y} \subseteq \{v\} \cup U^* \cup \Theta$ then 17: $C \leftarrow C \cup \{c_{v'}\}$ 18: 19: end if 20: end for 21: end for 22: if $C = \emptyset$ then 23: $c \leftarrow c_v$ 24: else if $c_v \in C$ then 25: $c \leftarrow c_v$ 26: else $C' \leftarrow C$ 27: for all $c_1, c_2 \in C$ where $c_1 \neq c_2$ do 28: 29: $y_1 \leftarrow \text{find } y \text{ where } (c_1, y_1) \in \mathcal{A}$ $y_2 \leftarrow \text{find } y \text{ where } (c_2, y_2) \in \mathcal{A}$ 30: if $(y_1 \triangleleft y_2) \in P$ then $C' \leftarrow C' - \{c_1\}$ 31: 32: end if 33: 34. end for $c \gets \texttt{first}(C')$ 35: 36: end if

The set of fault signatures for f and r is denoted as $\Sigma_{f,r}$.

The symbols s_1 and s_2 are selected from $\{0, +, -\}$, denoting no change, increase, and decrease, respectively.

As additional diagnostic information we use also the temporal order of residual deviation, captured through the concept of *relative residual orderings* (Daigle, Koutsoukos, & Biswas, 2007).

Definition 8 (Relative Residual Ordering). If fault f always manifests in residual r_i before residual r_j , then we define a *relative residual ordering* between r_i and r_j for fault f, denoted by $r_i \prec_f r_j$. We denote the set of all residual orderings for f as $\Omega_{f,R}$.

In order to generate signatures and orderings from a model, we extend the definition of a model to include qualitative labels on causal constraints. For each independent variable involved in a constraint, we associate a qualitative label indicating the qualitative direction of influence the independent variable has on the dependent variable. A dt label indicates an integration, a + label indicates that a directly proportional change, and a – label indicates an inversely proportional change. From this representation a Temporal Causal Graph (Mosterman & Biswas, 1999) (TCG) is obtained, and the algorithms described in (Daigle, 2008) may be used to automatically derive the signatures and orderings.¹

Together, fault signatures and relative residual orderings establish an event-based form of diagnostic information. For a given fault, the combination of all fault signatures and residual orderings yields all the possible ways a fault can manifest in the residuals. Each of these possibilities is a *fault trace*.

Definition 9 (Fault Trace). A *fault trace* for a fault f over residuals R, denoted by $\lambda_{f,R}$, is a sequence of fault signatures, of length $\leq |R|$ that includes, for every $r \in R$ that will deviate due to f, a fault signature $\sigma_{f,r}$, such that the sequence of fault signatures satisfies $\Omega_{f,R}$.

The set of all fault traces for a fault constitutes its *fault lan*guage.

Definition 10 (Fault Language). The *fault language* of a fault $f \in F$ with residual set R, denoted by $L_{f,R}$, is the set of all fault traces for f over the residuals in R.

In general, two faults are distinguishable if they always, in finite time, produce different observations. In our diagnosis framework, distinguishability between faults is characterized using fault traces and languages.

Definition 11 (Distinguishability). Given a residual set, R, a fault f_i is *distinguishable* from a fault f_j , denoted by $f_i \approx_R f_j$, if there does not exist a pair of fault traces $\lambda_{f_i,R} \in L_{f_i,R}$ and $\lambda_{f_j,R} \in L_{f_j,R}$, such that $\lambda_{f_i} \sqsubseteq \lambda_{f_j}$.

One fault will be distinguishable from another fault if it cannot produce a fault trace that is a prefix² (denoted by \sqsubseteq) of a trace that can be produced by the other fault. If this is not the case, then when that trace manifests, the first fault cannot be distinguished from the second.

Distinguishability is used to define the diagnosability of a diagnosis model under a given fault isolation framework. A diagnosis model is an abstraction of a system model with only diagnosis-relevant information, and it is defined as follows.

Definition 12 (Diagnosis Model). A *diagnosis model* S is a tuple $(F, Y, R, L_{F,R})$, where $F = \{f_1, f_2, \ldots, f_n\}$ is a set of faults, Y is a set of measurements, R is a set of residuals, and $L_{F,R} = \{L_{f_1,R}, L_{f_2,R}, \ldots, L_{f_n,R}\}$ is the set of fault languages.

If a diagnosis model is diagnosable, then we can guarantee the unique isolation of every fault in the diagnosis model.

Definition 13 (Diagnosability). A diagnosis model $S = (F, Y, R, L_{F,R})$ is *diagnosable* if and only if $(\forall f_i, f_j \in F) f_i \neq f_j \implies f_i \approx_R f_j$.

If S is diagnosable, then every pair of faults is distinguishable using the residual set R. Hence, we can uniquely isolate all faults of interest. If S is not diagnosable, then ambiguities will remain after fault isolation, i.e., after all possible fault effects on the residuals have been observed.

4. PROBLEM FORMULATION

The problem we are trying to solve is one of sensor placement for diagnosability. In our diagnostic framework, diagnosability is based on residuals, and so the sensor placement problem manifests as a residual selection problem. For each set of sensors, there are many potential residuals that can be selected to achieve diagnosability. A solution to the problem is a selection of residuals that achieves diagnosability; an optimal solution is one that satisfies some given criteria the best.

As described in Section 3, residuals are defined from submodel outputs. Given a model \mathcal{M} , there are many submodels that can be defined, and residuals can be derived from each of these. Clearly, this residual space is exceedingly large. However, many of these residuals are not actually unique, i.e., there may be two submodels that use the exact same computations to produce two different residuals; in this case, the residuals are equivalent. We express this property through the concept of *residual equivalence*.

Definition 14 (Residual Equivalence). Given causal submodels \mathcal{M}_i with inputs U_i and output $y_i \in Y_i$, and \mathcal{M}_j with inputs U_j and output $y_j \in Y_j$, the residuals r_i computed from y_i and r_j computed from y_j are equivalent, denoted as $r_i \equiv r_j$ if the causal constraints used to compute y_i are the same as the causal constraints to compute y_j .

We need not consider solutions that contain residuals that are equivalent, and this reduces the search space. We refer to such a residual set as *minimal*.

Definition 15 (Minimal Residual Set). A residual set R is *minimal* if there are no two residuals $r_i \in R$ and $r_j \in R$, $i \neq j$, where $r_i \equiv r_j$.

In fact we need only to search over the space of unique residuals. For a given sensor set, we can define the corresponding *complete residual set*, i.e., the largest set of residuals for a sensor set that is minimal.

Definition 16 (Complete Residual Set). For a set of sensor outputs Y, the *complete residual set* is the minimal residual set R_Y such that there is no residual for an output in $y \in Y$, r_y , such that $R \cup \{r_y\}$ is also minimal.

The complete residual set contains, for a given set of sensors, every possible way of computing residuals for those sensors.

So, the space of the residual selection problem is defined by all combinations of residuals in the unique residual set. We can find the complete residual set by using the model decomposition algorithm. As described in Section 3, to compute a submodel we must define the available local input set U^* and the local output set V^* . For an ouput $y \in Y$, U^* must consist of U and elements from $Y - \{y\}$. For example, say we have a three-tank system where $Y = \{q_1^*, q_2^*, q_3^*\}$. Table 1 lists all possible U^* to compute each output y. Fig. 3 show the causal

¹TCGs can also be derived directly from bond graphs (Karnopp, Margolis, & Rosenberg, 2000). Our modeling approach is more general in that it is not restricted to system topologies imposed by bond graphs.

²A fault trace λ_i is a prefix of fault trace λ_j if there is some (possibly empty) sequence of events λ_k that can extend λ_i such that $\lambda_i \lambda_k = \lambda_j$.

\mathcal{M}_i	U_i^*	V_i^*	U_i
$\overline{\mathcal{M}_1}$	$\{u_1, u_2, u_3\}$	$\{q_1^*\}$	$\{u_1, u_2, u_3\}$
\mathcal{M}_2	$\{u_1, u_2, u_3, q_2^*\}$	$\{q_{1}^{*}\}$	$\{u_1, q_2^*\}$
\mathcal{M}_3	$\{u_1, u_2, u_3, q_3^*\}$	$\{q_{1}^{*}\}$	$\{u_1, u_2, q_3^*\}$
\mathcal{M}_4	$\{u_1, u_2, u_3, q_2^*, q_3^*\}$	$\{q_{1}^{*}\}$	$\{u_1,q_2^*\}$
\mathcal{M}_5	$\{u_1, u_2, u_3\}$	$\{q_{2}^{*}\}$	$\{u_1, u_2, u_3\}$
\mathcal{M}_6	$\{u_1, u_2, u_3, q_1^*\}$	$\{q_{2}^{*}\}$	$\{u_2, u_3, q_1^*\}$
\mathcal{M}_7	$\{u_1, u_2, u_3, q_3^*\}$	$\{q_{2}^{*}\}$	$\{u_1, u_2, q_3^*\}$
\mathcal{M}_8	$\{u_1, u_2, u_3, q_1^*, q_3^*\}$	$\{q_{2}^{*}\}$	$\{u_2, q_1^*, q_3^*\}$
\mathcal{M}_9	$\{u_1, u_2, u_3\}$	$\{q_{3}^{*}\}$	$\{u_1, u_2, u_3\}$
\mathcal{M}_{10}	$\{u_1, u_2, u_3, q_1^*\}$	$\{q_{3}^{*}\}$	$\{u_2, u_3, q_1^*\}$
\mathcal{M}_{11}	$\{u_1, u_2, u_3, q_2^*\}$	$\{q_{3}^{*}\}$	$\{u_3,q_2^*\}$
\mathcal{M}_{12}	$\{u_1, u_2, u_3, q_1^*, q_2^*\}$	$\{q_{3}^{*}\}$	$\{u_3,q_2^*\}$

Table 1. Single-output Submodels

graphs for submodels \mathcal{M}_1 , \mathcal{M}_2 , \mathcal{M}_3 , and \mathcal{M}_4 . The thicker, green arrows in Fig. 3 indicate causal assignments that were reversed to accommodate local inputs.

There are $2^{|Y|-1}$ possible subsets of $Y - \{y\}$ from which to define U^* , and hence $|Y|2^{|Y|-1}$ residuals. However, this residual set may not be minimal. The model decomposition algorithm finds the minimal submodel to compute the given V^* using U^* , therefore, for a given V^* and two different U^* , the derived submodel may have the same U_i and the same causal constraints. This occurs for the example in Table 1. Here, the q_1^* residuals from \mathcal{M}_2 and \mathcal{M}_4 are equivalent. Since the U_i are the same, the submodel must be using the same constraints to compute q_1^* (see Fig. 3). Similarly, the q_3^* residuals from \mathcal{M}_{11} and \mathcal{M}_{12} are equivalent. So, in this case, the complete residual set size is less than $|Y|2^{|Y|-1}$.

So, a solution to the problem will be a selection of residuals from the complete residual set that achieves diagnosability. Among these solutions, we desire only those that require the minimum number of sensors (where measured values may be used to compute residuals and/or as local inputs to submodels). We may prefer some solutions over others for a variety of reasons. We define a relational operator \succ for solutions, describing which solutions are preferred over others and thus obtaining a notion of optimality for solutions. The \succ operator depends on the particular application, and we will describe an implementation of it in the following section. The problem can then be formally defined as follows.

Problem. For a model \mathcal{M} , fault set F, and sensor set Y, the problem is to find a set of residuals R_i such that there is no other $R_j \neq R_i$ where $R_j \succ R_i$.

5. APPROACH

In this section, we introduce three different algorithms to solve the problem stated in Section 4. For validation purposes, we describe an exhaustive search algorithm. We describe also a stochastic search algorithm and a structured search algorithm.

Before defining the \succ operator it is first important to note that residuals can be associated with submodels larger than those computing only themselves. Consider Table 1. For

\mathcal{M}_i	U_i	Y_i
$\overline{\mathcal{M}_1}$	$\{u_1, u_2, u_3\}$	$\{q_1^*, q_2^*, q_3^*\}$
\mathcal{M}_2	$\{u_1, u_2, q_3^*\}$	$\{q_1^*, q_2^*\}$
\mathcal{M}_3	$\{u_2, u_3, q_1^*\}$	$\{q_2^*, q_3^*\}$
\mathcal{M}_4	$\{u_1, q_2^*\}$	$\{q_{1}^{*}\}$
\mathcal{M}_5	$\{u_2, q_1^*, q_3^*\}$	$\{q_2^*\}$
\mathcal{M}_6	$\{u_3, q_2^*\}$	$\{q_3^*\}$

Table 2. Multi-Output Submodels

any U_i that can compute more than one residual, the submodels computing these residuals can be easily merged into a multi-output submodel computing all the residuals. This submodel can be computed by taking the union of the variable and constraint sets of the individual submodels. For example, in Table 1, we see that \mathcal{M}_1 , \mathcal{M}_5 , and \mathcal{M}_9 all have the input set $\{u_1, u_2, u_3\}$; merging these submodels recovers the global model. Also, the input set $\{u_1, u_2, q_3^*\}$ can be used to compute both a residual for q_1^* and one for q_2^* (\mathcal{M}_3 and \mathcal{M}_7 , respectively). So for a given residual set, there is also an associated submodel set, defined by the sets of inputs used to compute the residuals in the set. All the associated submodels for the example in Table 1 are given in Table 2.

For a given set of sensors such that diagnosability can be achieved, what we desire is a solution that corresponds to some notion of the best model decomposition (for the submodel set associated with the residual set). The more independent submodels that are used, the more distributed the solution becomes. Since the submodels are computationally independent, they can be executed in parallel and thus naturally take advantage of distributed computational paradigms. Further, model decomposition can lead to improved diagnosability (Daigle et al., 2012).

We define the \succ operator using five metrics: (*i*) diagnosability, (*ii*) the number of sensors used, (*iii*) the minimality of the involved submodel set, (*iv*) the number of residuals per submodel, and (*v*) the total number of residuals. We explain each of these in turn, starting with the minimality of a submodel set, which is defined as follows.

Definition 17. For a given set of residuals R, the corresponding submodel set M is minimal if for any $\mathcal{M}_i \in M$, there is no other $\mathcal{M}_j \in M$, $\mathcal{M}_i \neq \mathcal{M}_j$, that can be created by decomposing that submodel.

We do not prefer such solutions because they are likely to include residuals that do not improve diagnosability. For example, if the global model is in the submodel set, it is unlikely that adding additional submodels, for which there are already residuals for their outputs, will add diagnosability, since there is much redundant information in a residual for the same output over two different submodels.

We prefer fewer residuals per submodel because this implies a greater level of decomposition, and we prefer fewer residuals, since that implies the solutions are minimal, i.e., they do not include additional residuals that are not needed to obtain



Figure 3. Causal graphs for submodels $\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3$, and \mathcal{M}_4 .

Algorithm 3 $R^* = ExhaustiveSearch(R)$

1:	$\mathcal{R} \leftarrow \operatorname{combos}(R)$
2:	$R^* \leftarrow \mathcal{R}_1$
3:	for all $R_i \in \mathcal{R}$ do
4:	if $R_i \succ R^*$ then
5:	$R^* \leftarrow R_i$
6:	end if
7:	end for

diagnosability.

We next present the three algorithms, in which the inputs will be the complete residual sets as defined here. Other residual sets, computed using different methods, may also be used with no or little changes to the algorithms.

5.1. Exhaustive Search

As described in Section 4, the search space is defined by the complete residual set. The exhaustive search algorithm is shown as Algorithm 3. The combos function returns all possible combinations of the residual set (this is the same as the power set of R, excluding the empty set). The algorithm tries each candidate solution, keeping track of the best solution observed so far. Because it tries all possibilities, it is guaranteed to find the optimal solution, so it can be used to validate the solutions of the other algorithms. However, it is not scalable, as it must consider in the worst case $|Y|2^{|Y|-1}$ candidate solutions.

5.2. Stochastic Search

The stochastic search sacrifices optimality for scalability. It is given as Algorithm 4. It begins with k random candidate solutions generated using the randomCombos function. Beginning with multiple solutions rather than a single solution helps reduce the chances of getting stuck in a local minimum. For each candidate solution, it randomly adds or deletes a

Algorithm 4 $R^* = \texttt{StochasticSearch}(R,k,N)$		
1: $\mathcal{R} \leftarrow \texttt{randomCombos}(R,k)$		
2: for $i = 1$ to N do		
3: for all $R_i \in \mathcal{R}$ do		
4: $R_i' \leftarrow ext{randomModify}(R_i)$		
5: if $R'_i \succ R_i$ then		
6: $R_i \leftarrow R'_i$		
7: end if		
8: end for		
9: end for		
10: $R^* \leftarrow \mathcal{R}_1$		
11: for all $R_i \in \mathcal{R}$ do		
12: if $R_i \succ R^*$ then		
13: $R^* \leftarrow R_i$		
14: end if		
15: end for		

residual using the randomModify function, and, if this improves the solution, then this solution is kept. This process repeats for N iterations, therefore it explores only kN solutions, where both k and N are selected by the user. For larger search spaces, it is more likely to find a good solution with larger values of k and N. If there are many good solutions in the solution space, then this algorithm is likely to find at least one of them, given enough iterations.

5.3. Structured Search

The exhaustive and stochastic search algorithms represent approaches at two opposite ends of the spectrum. We want scalability as well as guarantees of optimality. We can do this by searching through the residual space in a structured way, trying to avoid parts of the search space that we know will not contain optimal solutions.

First, we note that we desire solutions with the minimum number of required sensors. Therefore, as a first stage in the algorithm, we try to find minimum sensor sets that can provide complete diagnosability. To do this, we start with single sensor solutions, one for each potential sensor. The only available residuals for single-sensor solutions are those from the global model. If any of these are diagnosable, then we have found an optimal solution. Otherwise, for each of these candidates, we add a second sensor, and check if the candidate solution containing all available residuals for that sensor set provide complete diagnosability. If so, we add this solution to a set of solutions to analyze later. We continue in this manner, adding sensors, until diagnosability is achieved, thus resulting in initial minimum sensor solutions.

As a second stage, for each of these initial minimum sensor solutions, we select residuals, in a structured way, for the given sensor set. We select residual sets using knowledge of what kind of solutions we consider to be optimal. First, instead of selecting residuals, we select submodels, and for the selected submodels, select all associated residuals for the given sensor set. Since the submodel space is much smaller than the residual space, this shrinks the search space significantly. Second, we know that for a given sensor set, diagnosability cannot be achieved if any one sensor is removed, therefore, we must consider only solutions in which residuals for each sensor are provided. Therefore, we try only combinations that cover all the sensors. So, for each sensor, we select a submodel that computes a residual for that sensor. Over those combinations there are much fewer to consider.

For example, consider again Table 1. Assume the sensors for q_1^* , q_2^* , and q_3^* are all required. There are 6 distinct input sets that can be used to compute the 10 residuals of the complete residual set for this sensor set, and these are shown in Table 2. So, there are only $2^6 - 1 = 63$ combinations of submodels to consider, versus $2^{10-1} = 1023$ combinations of residuals. Now, if we consider only combinations of submodels that cover all the residuals, there are only 36 combinations.

So, in summary, we have at most $|Y|2^{|Y|-1}$ residuals but only at most $2^{|Y|} - 1$ submodels. So there are $2^{|Y|2^{|Y|-1}}$ combinations of residuals, versus $2^{2^{|Y|}-1}$ combinations of submodels, shrinking the search space considerably. By considering only combinations of submodels that cover all residuals, since there are at most $2^{|Y|-1}$ ways to compute each residual, there are only at most $(2^{|Y|-1})^{|Y|} = 2^{|Y|^2 - |Y|}$ such combinations to consider. So we have reduced our search space from $2^{|Y|2^{|Y|-1}}$ residual combinations to $2^{2^{|Y|}-1}$ submodel combinations to $2^{|Y|^2 - |Y|}$ submodel combinations that ensure there are residuals for all sensors. Clearly, this last number grows the slowest, and so we have decreased the search space over the exhaustive search algorithm by a significant factor, offering much improved scalability.

The structured search is described by Algorithm 5. An initial solution queue \mathcal{R} is first constructed using single sensors. Until the initial solution queue is empty, the algorithm pops the first element off the queue, and checks if it is diagnosable. If so, it is added to a new solution set \mathcal{R}' , otherwise, we

create new candidate solutions with one additional sensor, for each of the remaining sensors. Note here that Y(R) is used to denote the sensors involved in residual set R. New candidate solutions are created only if we have not already found a diagnosable solution with smaller size (L^*) . The solutions at this stage include the complete residual set for the minimum sensor sets. The purpose of this stage of the algorithm is to find the minimum sensor sets that can achieve diagnosability.

The purpose of the second stage of the algorithm is, given these minimum sensor solutions, to find optimal residual sets for each sensor set. Given one of these minimum sensor sets, we generate, for each sensor in the set, the list of potential residuals. Note here that $R_{y,Y}$ denotes the set of residuals for y that can be computed using the sensors in Y. We then use the selectCombos function to generate all combinations of residuals from these sets. For example, if we have two sensors y_1 and y_2 where $R_{y_1,Y} = \{r_1, r_2\}$ and $R_{y_2,Y} = \{r_3, r_4\}$, selectCombos would generate four residual sets: $\{r_1, r_3\}, \{r_1, r_4\}, \{r_2, r_3\}, \text{and } \{r_3, r_4\}$. Each of these combinations that result in diagnosability is added to a new solution set \mathcal{R}^* . After this loop, the best solution is picked from \mathcal{R}^* .

6. RESULTS

As a case study scenario, we apply the algorithms to an *n*-tank system with the output flows as the available sensors, and consider as the fault set all K_i^+ , K_i^- , Re_i^+ , Re_i^- , $Re_{i,i+1}^+$, and $Re_{i,i+1}^-$ faults. In this case, the system is only diagnosable if all the output flow sensors are included, and this should be discovered by the algorithms.

The inherent scalability of the system itself is shown in Table 3. As the number of tanks increases, the size of the complete residual set increases, as does the number of unique submodel inputs. Each tank adds a new sensor, so in the worst case, the number of unique residuals is $n2^{n-1}$. For this system, measuring the output flows allows for a substantial amount of model decomposition, so this number is reduced significantly. In fact, $|R_Y|$ increases only polynomially (third order). The number of unique U_i for the submodels grows in the worst case with $2^n - 1$, but because of the decomposition provided by the sensors, it grows only polynomially in this case (second order). Since these parameters of the tank system scale only polynomially, this cuts the worst-case search space size drastically.

Results for exhaustive search are shown in Table 4. The exhaustive algorithm finds the optimal solutions, but quickly becomes unusable due to its poor scalability. For only 4 tanks, the number of solutions that must be searched $(2^{|R_Y|} - 1)$ is already over a million, and the search did not complete within a reasonable amount of time.

For 2 tanks, the optimal solution is to use only the global

Algorithm 5 R*	= StructuredSearch(F, R, Y
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1:	$\mathcal{R} \leftarrow arnothing$
2:	for all $y \in Y$ do
3:	$\mathcal{R} \leftarrow \mathcal{R} \cup R_{\{u\}}$
4:	end for
5:	$L^* \leftarrow \inf$
6:	$\mathcal{R}' \leftarrow arnothing$
7:	while ${\mathcal R}$ not empty do
8:	$R_1 \leftarrow \operatorname{pop}(\hat{\mathcal{R}})$
9:	if diagnosable (F, R_1) then
10:	$L^* \leftarrow R_1 $
11:	$\mathcal{R}' \leftarrow \mathcal{R}' \cup R_1$
12:	else
13:	if $ R_1 < L^*$ then
14:	for all $y \in Y - Y(R_1)$ do
15:	$Y' \leftarrow (Y - Y(R_1)) \cup \{y\}$
16:	$R'_1 \leftarrow R_{Y'}$
17:	$\mathcal{R} \leftarrow \mathcal{R} \cup \{R'_1\}$
18:	end for
19:	end if
20:	end if
21:	end while
22:	$\mathcal{R}^* \leftarrow \{\mathcal{R}'$
23:	for all $R_i \in \mathcal{R}'$ do
24:	$Y_i \leftarrow Y(R_i)$
25:	$\mathcal{R}'' \leftarrow arnothing$
26:	for all $y \in Y_i$ do
27:	$\mathcal{R}'' \leftarrow R_(y, Y)$
28:	end for
29:	$\mathcal{R}'' \leftarrow \texttt{selectCombos}(\mathcal{R}'')$
30:	for all $R_i'' \in \mathcal{R}''$ do
31:	if diagnosable (F,R_i'') then
32:	$\mathcal{R}^* \leftarrow \mathcal{R}^* \cup \{\mathcal{R}'\}$
33:	end if
34:	end for
35:	end for
36:	$R^* \leftarrow \mathcal{R}_1^*$
37:	for all $R_i \in \mathcal{R}^*$ do
38:	if $R_i \succ R^*$ then
39:	$R^* \leftarrow R_i$
40:	end if
41:	end for

model. If we use the submodel that computes q_1^* using q_2^* and the submodel that computes q_2^* using q_1^* , the system is not diagnosable, and so the global model is the optimal solution. For 3 tanks, we can improve over the global model as a solution by using two submodels computing $\{q_1^*, q_2^*\}$ and $\{q_2^*, q_3^*\}$. This decomposition is better than the global model, uses just as many sensors, and obtains complete diagnosability. We find that considering only the pressure sensors gives similar results. When considering both flow and pressure sensors, we still need one sensor for each tank, and the pressure and flow measurements can be interchanged.

The structured search algorithm attempts to avoid searching this entire space by (i) finding only minimum sensor sets required for diagnosability, and (ii) for each of these sets searching only over residual sets in which all sensors are covered. Downselecting to only residuals for a given minimum sensor set reduces the search space significantly, as does, for that given sensor set, considering only the residuals sets that cover all the sensors.

Table 3. Scalability of Tank System

Number	Size	Number of
of Tanks	of R_Y	Unique U_i
2	4	3
3	10	6
4	20	10
5	35	15
6	56	21
7	84	28
8	120	36
9	165	45
10	220	55

Table 4. Exhaustive Search Results.

Number	Solutions	Final
of Tanks	Searched	Solution
2	15	$(\{u_1, u_2\}, \{q_1^*, q_2^*\})$
3	1023	$(\{u_1, u_2, q_3^*\}, \{q_1^*, q_2^*\})$
		$(\{u_2, u_3, q_1^*\}, \{q_2^*, q_3^*\})$
4	1048575	N/A

Results for the structured search algorithm are shown in Table 5. Here, the number of candidates searched grows significantly slower than with the exhaustive search. Once the structured search finds a minimum sensor set from which to select residuals, the remaining search space is searched in a somewhat exhaustive way, i.e., it tries all combinations of residual sets for which the sensors are covered. Therefore, its growth is still exponential although its scalability is much improved over the exhaustive search algorithm.

Upon inspection of the solutions searched by the algorithm, we find that only a small subset are actually only worth searching. All other solutions are considering submodel sets that are not minimal. By the definition of \succ , as long as a solution exists using a minimal submodel set, a solution with a non-minimal submodel set will never be optimal. It is very likely that if there is a solution with a nonminimal submodel set, there is one with a minimal submodel set. If this is true, then the search space of the algorithm can be reduced even more, further improving scalability.

Table 5. Structured Search Results.

Number	Solutions	Final
of Tanks	Searched	Solution
2	7	$(\{u_1, u_2\}, \{q_1^*, q_2^*\})$
3	34	$(\{u_1, u_2, q_3^*\}, \{q_1^*, q_2^*\})$
		$(\{u_2, u_3, q_1^*\}, \{q_2^*, q_3^*\})$
4	277	$(\{u_1, u_2, q_3^*\}, \{q_1^*, q_2^*\})$
		$(\{u_3, u_4, q_2^*\}, \{q_3^*, q_4^*\})$
5	3427	$(\{u_1, u_2, q_3^*\}, \{q_1^*, q_2^*\})$
		$(\{u_3, u_4, q_2^*, q_5^*\}, \{q_3^*, q_4^*\})$
		$(\{u_4, u_5, q_3^*\}, \{q_4^*, q_5^*\})$

Table 6. Stochastic Search	h Results.
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Number	Solutions	Final
of Tanks	Searched	Solution
2	1000	$(\{u_1, u_2\}, \{q_1^*, q_2^*\})$
3	1000	$(\{u_1, u_2, q_3^*\}, \{q_1^*, q_2^*\})$
		$(\{u_2, u_3, q_1^*\}, \{q_2^*\})$
		$(\{u_3, q_2^*\}, \{q_3^*\})$
4	1000	$(\{u_1, u_2, u_3, q_4^*\}, \{q_1^*, q_3^*\})$
		$(\{u_2, u_3, u_4, q_1^*\}, \{q_2^*\})$
		$(\{u_3, u_4, q_2^*\}, \{q_4^*\})$
5	1000	$(\{u_1, u_2, u_3, u_4, u_5*\}, \{q_1^*, q_5^*\})$
		$(\{u_2, u_3, u_4, q_1^*, q_5^*\}, \{q_2^*, q_3^*, q_4^*\})$

Another way to increase scalability is by adding more structure to the search process, in a way that attempts to search first solutions more likely to be optimal, if diagnosable, than others. For example, we can try first the most decomposed solution (single-output submodels with the maximum number of local inputs), and then working up towards the global model. Because \succ prefers more decomposed solutions, if we search candidates solutions with better decomposition first, we can terminate the search once a solution is found (since less decomposed solutions will not then be optimal). The first stage of the algorithm could also be improved by starting first with the maximum sensor set, then reducing it to find minumum subsets that still achieve diagnosability. In this case study, since all sensors are required for diagnosability, this would have resulted in finding the required sensor set much faster. In many cases it is more likely that a large subset of the sensors are needed for diagnosability rather than a small subset.

Scalability can be improved by considering heuristics to guide the search. A greedy search heuristic, for example, can improve significantly the scalability, but the resulting solutions may not be optimal.

The stochastic search algorithm is the most scalable, as the number of solutions it searches are completely defined by the user. Results for the stochastic search are given in Table 6. Here, we used k = 10 and N = 100, so 1000 candidate solutions are always searched independent of n. For 3, 4, and 5 tanks, the optimal solutions are not found. However, the solutions found are still diagnosable and represent a good model decomposition. The solutions found are nonoptimal because the submodel sets are not minimal. So, the solution space is such that there are very few optimal solutions (in this case only 1), but many good solutions. So if optimality is not a requirement, the stochastic algorithm is a suitable choice because it is likely to find a good solution since many exist in the search space. For 5 tanks, the solution is much further from optimal, so since the space is much bigger k and Nshould be increased.

Based on the ideas of the structured algorithm, the stochastic algorithm performance may potentially be improved. For example, it can search only a reduced space in which all sensors required for diagnosability are covered by the residual set. With a reduced space to search, with the same number of iterations it is more likely to find a better solution.

7. CONCLUSIONS

In this work, we have presented a diagnosability-based sensor placement solution by using structural model decomposition. The solution proposed in this paper analyzes the diagnosability of a system to determine the minimum set of sensors required to uniquely isolate all single faults in the system. Then, once the minimum set of sensors for complete diagnosability is computed, several criteria are taken into account to select among the set of equivalent solutions. In particular, we used three different metrics: the minimality of the involved submodel set; the number of residuals per submodel; and the total number of residuals.

In the paper we presented three different solutions for the problem. The first one, an exhaustive search, finds the optimal solutions but is not scalable. A second one, a stochastic search algorithm, sacrifices optimality for scalability. And a third one, a structured search algorithm, is more scalable than the exhaustive search while still guaranteeing optimality.

Experimental results on a multi-tank system demonstrated the performance of the algorithms and suggest possible improvements to the algorithms that will inform future work. In this paper, we considered only single faults and a continuous system for the case study, but, in future work, we will study how the to extend this solutions to multiple fault diagnosis and hybrid systems. Future work will also apply the algorithms to practical large-scale systems.

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REFERENCES

- Basseville, M., Benveniste, A., Moustakides, G., & Rougee, A. (1987, Dec). Optimal sensor location for detecting changes in dynamical behavior. *IEEE Transactions on Automatic Control*, 32(12), 1067-1075.
- Bregon, A., Daigle, M., Roychoudhury, I., Biswas, G., Koutsoukos, X., & Pulido, B. (2014, May). An event-based distributed diagnosis framework using structural model decomposition. *Artificial Intelligence*, 210, 1-35.
- Casillas, M., Puig, V., Garza-Castañon, L., & Rosich, A. (2013). Optimal sensor placement for leak location in water distribution networks using genetic algorithms. *Sensors*, 13(11), 14984–15005. doi:

10.3390/s131114984

- Daigle, M. (2008). A qualitative event-based approach to fault diagnosis of hybrid systems. Unpublished doctoral dissertation, Vanderbilt University.
- Daigle, M., Bregon, A., Biswas, G., Koutsoukos, X., & Pulido, B. (2012, August). Improving multiple fault diagnosability using possible conflicts. In *Proceedings* of the 8th IFAC symposium on fault detection, supervision and safety of technical processes (p. 144-149).
- Daigle, M., Koutsoukos, X., & Biswas, G. (2007, April). Distributed diagnosis in formations of mobile robots. *IEEE Transactions on Robotics*, 23(2), 353–369.
- Debouk, R., Lafortune, S., & Teneketzis, D. (2002). On an optimization problem in sensor selection. *Discrete Event Dynamic Systems*, 12(4), 417–445.
- Eriksson, D., Krysander, M., & Frisk, E. (2012, August). Using quantitative diagnosability analysis for optimal sensor placement. Mexico City, Mexico.
- Frisk, E., Krysander, M., & Åslund, J. (2009). Sensor placement for fault isolation in linear differential-algebraic systems. *Automatica*, 45(2), 364-371.
- Karnopp, D. C., Margolis, D. L., & Rosenberg, R. C. (2000). Systems dynamics: Modeling and simulation of mechatronic systems. New York: John Wiley & Sons, Inc.
- Krysander, M., & Frisk, E. (2008). Sensor placement for fault diagnosis. *IEEE Transactions on Systems, Man,* and Cybernetics – Part A: Systems and Humans, 38(6), 1398–1410.
- Mosterman, P. J., & Biswas, G. (1999). Diagnosis of continuous valued systems in transient operating regions. *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, 29(6), 554-565.
- Narasimhan, S., Mosterman, P. J., & Biswas, G. (1998, May). A systematic analysis of measurement selection algorithms for fault isolation in dynamic systems. In *Proc.* of the 9th international workshop on principles of diagnosis (pp. 94–101). Cape Cod, MA USA.
- Raghuraj, R., Bhushan, M., & Rengaswamy, R. (1999). Locating sensors in complex chemical plants based on fault diagnostic observability criteria. *AIChE Journal*, 45(2), 310–322.
- Rosich, A. (2012). Sensor Placement for Fault Detection and Isolation based on Structural Models. In *Proceedings* of the 8th ifac symposium on fault detection, supervision and safety of technical processes, safeprocess12 (p. 391-396). Mexico City, Mexico.
- Rosich, A., Frisk, E., Aslund, J., Sarrate, R., & Nejjari, F. (2012, March). Fault diagnosis based on causal computations. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 42(2), 371-381.
- Roychoudhury, I., Biswas, G., & Koutsoukos, X. (2009, April). Designing distributed diagnosers for complex continuous systems. *IEEE Transactions on Automation*

Science and Engineering, 6(2), 277–290.

- Roychoudhury, I., Daigle, M., Bregon, A., & Pulido, B. (2013, March). A structural model decomposition framework for systems health management. In *Proceedings of the 2013 IEEE aerospace conference.*
- Said, A., & Djamel, B. (2013). Optimal sensor placement for fault detection and isolation by the structural adjacency matrix. *International Journal of Physical Sciences*, 8(6), 225–230.
- Travé-Massuyès, L., Escobet, T., & Olive, X. (2006, Nov). Diagnosability analysis based on component-supported analytical redundancy relations. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 36(6), 1146-1160.

BIOGRAPHIES



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A Comparison of Methods for Linear Cell-to-Cell Mapping and Application Example for Fault Detection and Isolation

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ABSTRACT

In this paper, the Generalized Cell Mapping (GCM) method for a linear system is compared with a new stochastic method for novel cell-to-cell mapping. The authors presented the new stochastic method in a previous paper last year. The two methods are compared in an application example of a vehicle alternator. The alternator may experience three faults including belt slippage, a broken diode, or incorrect controller reference voltage. Fault detection and isolation (FDI) is performed using the two cell-to-cell mapping methods. The results show that the new stochastic method is more computationally intensive but yields better isolation results than the GCM method.

1. INTRODUCTION

Besides high performance, the other most important and desirable features of modern technological systems are safety and reliability. Owing to their increasing complexity, technological systems are becoming more and more vulnerable to faults. These faults, if not handled timely and properly, may lead to severe failures causing damage to property or even human lives. This is particularly true for the complex dynamic systems made of interconnected components where one faulty component can lead to malfunction of the overall system. Therefore, detection and isolation of the faults is of extreme importance in modern technological systems. Early detection and proper handling of faults essentially improve the dependability of the dynamic system ensuring safe operation.

An important tool for analyzing dynamic systems is cell-tocell mapping as described by Hsu (1980). The dynamic state space of the system is quantized into cells that the system may occupy as time evolves. State variables are considered in intervals instead of a continuum of points. Such a system is justified due to the inherent inaccuracy of physical measurements. Using this framework, the probability of cell transitions can be computed using various approaches such as Monte Carlo and GCM methods.

In the Monte Carlo method, repeated random samplings and deterministic computations are used to find possible outcomes and their associated probabilities (Kastner, 2010). Using this information, a state probability transition matrix for the system can be constructed (Wang, 1999). The more samplings performed, the more accurate the probability transition matrix (Sobol, 1994).

In the GCM method, the boundaries of image cells are important in determining state transition probabilities (Hsu 1981). The image cell of the current cell are found first. Then the boundaries of the image cell are mapped back to locations on the current cell and when linearly connected form an area within the current cell. Now this area is known to transition to a particular image cell area. The probability associated with this transition is calculated given the total area of the current cell.

The main motivation for formulating the GCM method was to analyze global dynamics of a system (Hsu, 1982). The purpose of the method was to find equilibrium states and periodic motions in the system that can be identified after many mapping steps are performed (Hsu & Chiu 1986). This global analysis can yield a stationary probability transition matrix that does not change with time. Stationary transition matrices allow the global behavior of the system to be analyzed through Markov Chain theory where the entire evolution of cell mapping over time is determined by the stationary transition matrix (Hsu & Guttalu, 1980).

The Monte Carlo and GCM method each rely on repetitive simulations during each time step to calculate transition probabilities. Each method effectively uses information about the initial cell and image cell(s). The amount of computation involved could overwhelm a microcomputer trying to calculate transition probabilities in real-time. These methods are most suitable for offline approaches. Therefore, a new method that only uses information about the initial cell would be a beneficial step toward real-time applications.

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The Monte Carlo and GCM approaches can also be computationally burdensome with respect to high dimensional nonlinear systems. Performing the Monte Carlo method on these systems requires huge sampling populations. The GCM method also requires many calculations in order to find image cell boundaries for a nonlinear system. Then all these image cell points must be inversely mapped into the original cell. The feasibility of these methods with nonlinear systems is severely limited.

The new stochastic method proposed by the authors uses the system vector field to calculate state transition probabilities as time evolves without computing image cells. In this paper, the new method will be called the flow method. The flow in/out of a cell through its perimeter is analyzed similar to Green's theorem. The total flow through a cell is comprised of summation of the flow through the sides of the cell. This flow directly impacts the probability of state transition. At each time step, the flow through each side of current state is calculated and then normalized to total flow through whole state perimeter. A time-varying probability transition matrix can be created from these calculations.

Once armed with the above methods for obtaining the probability transition matrices, they can be applied to FDI problems. For example, if an expected state transition has a very low probability, and then the state transitions to this state and possibly continues to transition to low probability states, then this could indicate a fault in the system. This paper applies and compares the GCM and flow methods for fault detection in an alternator system previously described by Mohon and Pisu (2013). Results show that the GCM method yields faster detection time with incomplete isolation of faults. On the other hand, the new stochastic method results in slower detection time and complete isolation at the cost of more computational complexity.

The first section of this paper describes the GCM method. The second section describes the flow method. The third section applies the two methods to an application example with a faulty automotive alternator and compares FDI results. Lastly, some concluding remarks about the usefulness of each method is provided.

2. GENERALIZED CELL MAPPING METHOD

The method for generalized cell mapping is described by C. Hsu in his book (Hsu 1987). Unlike simple cell mapping, where one cell is mapped into a single image cell, generalized cell mapping allows one cell to be mapped to several image cells. Each image cells represents a fraction of the total probability.

Consider the following simple example. Suppose we have a system described by Eq 1. There are two states z1 and z2 and only z2 is observable in output. We can illustrate the state space divided into quantized states 1 through 7 in

Figure 1. We will also assume some maximum and minimum values for z1.

$$\begin{bmatrix} \dot{z}_{1} \\ \dot{z}_{2} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} z_{1} \\ z_{2} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{bmatrix} \begin{bmatrix} u_{1} \\ u_{2} \\ u_{3} \end{bmatrix}$$
(1)
$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} z_{1} \\ z_{2} \end{bmatrix}$$



Figure 1: Quantized states in state space example

Obtaining the image cell boundaries can be thought of as a Monte Carlo exercise. By randomly choosing a large sample of random points within the initial cell (state 4) and applying the dynamic system equations, the new location of the points can be plotted on the 2D state space. Figure 2 and Figure 3 illustrate how the randomly sampled points move in time. A large number of points will clearly delineate the boundary of the new image cell.



Figure 2: Initial cell with randomly sampled points



Figure 3: Image cell containing new position of sampled points after a finite time delta t

The new image cell in this example is clearly a quadrilateral with four vertices. These vertices represent the boundaries of the image cell. Note that the image cell is now spanning states 3, 4, and 5. By using the system dynamic equations, these vertices and other important points can be mapped back into the original cell shown in Figure 4. This will allow us to determine the regions of the original state that map into other states.



Figure 4: Inverse mapping important points on image cell back into original cell

The regions of the area now defined in the original cell can be used to calculate probabilities of transitioning up or down in the system. Region A2 is mapped back into region A1. Region A4 is mapped back into region A3. The probability to transition up, down, or stay in state 4 is given by the following.

$$P_{up} = \frac{A1}{A_{cell}}$$

$$P_{down} = \frac{A3}{A_{cell}}$$

$$P_{stay} = 1 - P_{up} - P_{down}$$
(2)

This process can be repeated as the system's state changes along with input values.

3. PROPOSED FLOW METHOD

The flow method was proposed by the authors in a previous paper (2013). This method uses the system's vector field F to determine flow into and out of the current state/cell. The method exploits the divergence theorem and determines the total potential of flow through the cell as the sum of flows through the perimeter of the cell.

A two-dimensional form of the divergence theorem is defined in Eq. (3). We define C as a closed curve, A as the 2D region in the plane enclosed by C, \bar{n} as the outward pointing normal vector of the closed curve C, and \bar{F} as a continuously differentiable vector field in region A. A graph of the 2D divergence theorem for the same 2D system in Eq. 1 is shown in Figure 5.



Figure 5. Graph of 2D Divergence Theorem for 2D state space system

We consider that the vector field \overline{F} describes transition flow in and out of the current state along the state boundaries. For the DC electric machine model, \overline{F} is defined as Eq. (4) where \hat{i} and \hat{j} are coordinates of vector field F and functions f_1 and f_2 are defined by states z_1 and z_2 from the state space model in Eq. (1).

$$\vec{F} = f_1 \hat{i} + f_2 \hat{j}
\dot{z}_1 = f_1(z_1, z_2, u_1, u_2, u_3)
\dot{z}_2 = f_2(z_1, z_2, u_1, u_2, u_3)$$
(4)

The flow through the left and right sides of the area A in Figure **5** will be assumed zero for the alternator system shown in Figure **6**. The line integrals along the state z boundaries will determine flow in and out of the state. The vector field F is illustrated by grey slope field in Figure **6**. Flow out of state z is defined as a positive value ϕ^+ and flow into state z is a negative value ϕ^- . Since each side may have flow in and flow out sections, the flow transition point z** or z* is found if necessary and the appropriate limits of integration for flow in and flow out are integrated for each side. Transition points are shown in Figure **6**. Without loss of generality assume $f_2 < 0$ if $z_1 < z^*$, z^{**} and $f_2 > 0$ if $z_1 > z^*$, z^{**} such that Eq. (5) holds. The upward and downward flow through each side of state z is given by Eq. (6).



Figure 6. Graph of quantized DC electric machine system with flow definitions

$$f_{2}(z^{*}, z_{2}^{(1)}, u_{1}, u_{2}, u_{3}) = 0$$

$$f_{2}(z^{**}, z_{2}^{(2)}, u_{1}, u_{2}, u_{3}) = 0$$
(5)

$$\varphi_{1}^{+} = -\int_{z_{1}^{\min}}^{z_{1}^{+}} f_{2}(z_{1}, z_{2}^{(1)}, u_{1}, u_{2}, u_{3}) dz_{1} > 0$$

$$\varphi_{1}^{-} = -\int_{z_{1}^{*}}^{z_{1}^{\max}} f_{2}(z_{1}, z_{2}^{(1)}, u_{1}, u_{2}, u_{3}) dz_{1} < 0$$

$$\varphi_{2}^{-} = \int_{z_{1}^{*}}^{z_{1}^{*}} f_{2}(z_{1}, z_{2}^{(2)}, u_{1}, u_{2}, u_{3}) dz_{1} < 0$$
(6)

$$\varphi_2^+ = \int_{z_1^{\text{min}}}^{z_1^{\text{min}}} f_2(z_1, z_2^{(2)}, u_1, u_2, u_3) dz_1 > 0$$

Next we define ϕ_{in} , ϕ_{out} , and ϕ_{total} in Eq. (7) in order to build probabilities. The sum of the absolute value of all inward flow in defined as ϕ_{in} . The sum of all outward flow is defined as ϕ_{out} . The total flow ϕ_{total} is the sum of ϕ_{in} and ϕ_{out} .

$$\begin{aligned}
\varphi_{in} &= \left| \varphi_{1}^{-} + \varphi_{2}^{-} \right| \\
\varphi_{out} &= \varphi_{1}^{+} + \varphi_{2}^{+} \\
\varphi_{total} &= \varphi_{1}^{+} + \left| \varphi_{1}^{-} \right| + \left| \varphi_{2}^{-} \right| + \varphi_{2}^{+}
\end{aligned} \tag{7}$$

The notion of probability can be interpreted as counting types of occurrences and then normalizing the count of each type by the total occurrences. Suppose the occurrences of outward and inward flow defined in Eq. (6) are normalized by the total flow defined in Eq. (7). For example, the probability to transition up will be defined as the outward flow through side 2, φ_2^+ , divided by the total flow φ_{total} . We can then define z^+ as the state above current state z and define z^- as the state below current state z. Equation (8) gives the probability to transition up or transition down to an adjacent state. Uniform probability distribution is assumed along the borders of each state.

$$1 = \frac{\varphi_{in}}{\varphi_{total}} + \frac{\varphi_{out}}{\varphi_{total}}$$

$$1 = \frac{\left|\varphi_{1}^{-} + \varphi_{2}^{-}\right|}{\varphi_{total}} + \frac{\varphi_{2}^{+}}{\varphi_{total}} + \frac{\varphi_{1}^{+}}{\varphi_{total}} \qquad (8)$$

$$1 = \Pr(z' = z \mid z) + \Pr(z' = z^{+} \mid z)$$

$$+ \Pr(z' = z^{-} \mid z)$$

At each time step the probability to stay or transition up or transition down is calculated using the current state boundaries and the current input. This information builds a time-varying probability transition matrix named L that can be constructed as shown in Table 1 for the example of current state z=2 at time t.

Table 1. Example of	probabil	lity trar	nsition matrix L for
current	state z=	2 at a t	ime t
			_

_

		Future State z'			
		1	2	3	4
z	1	0	0	0	0
t State	2	$\Pr(z' = z^- \mid z)$	$\Pr(z' = z \mid z)$	$\Pr(z' = z^+ \mid z)$	0
urrent	3	0	0	0	0
С	4	0	0	0	0

Thus far, the new method formulation has shown the 2D case. The new method can also be extended for the 3D case using 3D divergence theorem defined in Eq. (3). Define V as a closed volume, A as the surface area of V, \bar{n} as the outward pointing normal vector of the closed volume V, and \bar{F} as a continuously differentiable vector field in volume V. A picture for a cubic volume is shown in Figure 7.

$$\iiint\limits_{V} \left(\nabla \cdot \vec{F} \right) dV = \iint\limits_{A} \left(\vec{F} \cdot \vec{n} \right) dA \tag{3}$$



Figure 7. Graph of 3D Divergence Theorem This method can also be extended to higher dimensions as well using the same procedure.

4. APPLICATION EXAMPLE: EPGS SYSTEM

Today's vehicles require higher electrical demands than ever before due to more mandated safety technology and popular consumer technology integrated within the vehicle. The purpose of the vehicle's electrical power generation storage (EPGS) system is to maintain the necessary electrical power needed to start the vehicle and keep it running smoothly. A healthy EPGS system is crucial for proper operation of a vehicle and have been investigated in previous literature.

Scacchioli, Rizzoni, and Pisu (2006) proposed a fault isolation approach for an EPGS system using two equivalent alternator models. One equivalent model for a healthy alternator and one equivalent model for an alternator with one broken diode. Parity equations and three residuals with constant thresholds were used for fault isolation. The approach assumed a 3000 second Federal Urban Driving Schedule (FUDS) cycle.

Zhang, Uliyar, Farfan-Ramos, Zhang, and Salman (2010) proposed a fault isolation approach for an EPGS system using parity relations trained by Principal Component Analysis (PCA). Three residuals with constant thresholds were used for isolation. The approach assumed a staircase profile for both load current and alternator speed input, which is not a realistic scenario.

Hashemi and Pisu (2011) proposed a fault isolation approach for an EPGS system using two observers and three residuals. The approach assumed a staircase profile for load current and a portion of the FUDS cycle for alternator speed. Adaptive thresholds were used for isolation. In other similar work, Hashemi and Pisu (2011) showed the same approach but created a reduced order adaptive threshold model using Gaussian fit of data. The second approach was less computationally intensive. Scacchioli, Rizzoni, Salman, Onori, and Zhang (2013) proposed a fault isolation approach for an EPGS system using one equivalent EPGS model that used parity equations to produce three residuals for fault isolation. The approach used a staircase profile for both load current and alternator speed input.

As stated, previous work for fault isolation in an EPGS system has included observers and parity relations. The approaches with observers were built for linear systems that approximate the nonlinear behavior of the EPGS system. These approaches cannot be extended for direct use on the nonlinear system itself. At least three residuals are required for all previous approaches. It is also concerning that some approaches were not validated using real driving situations. Therefore these approaches have limited scopes.

4.1. Model for EPGS System

This paper analyzes the EPGS system shown in Figure 8 as modeled by Scacchioli et al. (2006). It consists of a voltage controller, alternator, and battery. The controller can be an electronic control unit or a voltage controller on the alternator itself. In this paper, the controller is a part of the alternator to regulate field voltage. The alternator model consists of an AC synchronous generator, three phase full bridge diode rectifier, voltage controller, and excitation field.

The engine crankshaft mechanically spins the generator's rotor by use of a belt and pulley. The rotor is a ferrous metal wrapped with a single conductive winding. When the controller applies a small field voltage to the winding, a small field current flows through the winding. The flow of current through the winding produces a magnetic rotor with a north and south pole. However, the stator is composed of three phase stationary windings. As the magnetic rotor moves relative to the conductive stator windings, an electromotive force is induced in the stator windings. If the stator windings are connected to an electrical load, then AC current will flow in each of the three stator windings. The three currents are sent to a diode bridge rectifier to produce DC current for electrical loads or for recharging the battery. Therefore, the alternator takes mechanical energy of the engine and produces electrical energy for the battery or loads of the vehicle.



Figure 8. EPGS model

The model for the EPGS system results in a complex nonlinear system but can be more easily modeled by an equivalent DC electric machine as described by Sacchioli et al. (2006). The dashed line in Figure 8 encompasses the components represented by the DC model.

The DC electric machine is modeled by the state space system in Eq. (9) as shown by Hashemi (2011).

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \begin{bmatrix} 0 & a_{12}(\omega_e) \\ 1 & a_{22}(\omega_e) \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11}(\omega_e) & b_{12}(\omega_e) & b_{13}(\omega_e) \\ 0 & b_{22}(\omega_e) & b_{23}(\omega_e) \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \quad (9)$$
$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

Equation (9) has two states z_1 and z_2 and inputs u_1 , u_2 , and u_3 . The system inputs represent the alternator field voltage V_f , angular frequency of alternator ω_e , and dc voltage of the battery V_{dc} also shown in Eq. (10). The coefficients a_{12} , a_{22} and $b_{11}...b_{23}$ are functions of engine speed and were found using system identification by Hashemi (2011) using test data at different constant engine speeds. In this model, state z_2 is the measurable quantity I_{dc} which is the rectified output current of the alternator.

$$y_2 = I_{dc} = z_2$$

$$u_1 = V_f$$

$$u_2 = \omega_e$$

$$u_3 = V_{dc}$$

(10)

4.2. Possible Faults in EPGS System

The EPGS system is important in every vehicle and faults in the system need to be detected and isolated as quickly as possible to prevent costlier damage. This paper considers three common faults that occur in an EPGS system. Possible fault locations in EPGS system are bolded in Figure 9.

- 1. Voltage controller fault: This fault occurs when the reference voltage V_{ref} is incorrectly raised or lowered by a percentage of the nominal V_{ref} . The fault can cause the alternator to overcharge or undercharge the battery.
- 2. Open diode rectifier fault. This fault occurs when a diode in the diode bridge rectifier breaks. The fault results in a large ripple in battery voltage V_{dc} and alternator output current I_{dc} thereby decreasing the efficiency of alternator output.
- 3. Belt slip fault. This input fault occurs when the belt between the engine crankshaft and alternator pulley slips due to insufficient tension. The belt slip causes a decrease in alternator rotational speed ω_e and a decrease in alternator output voltage. To compensate, the voltage controller increases the field voltage and/or the battery must discharge more often to meet load demand. This can age the battery prematurely. Belt slip can signify the belt is worn and needs to be replaced.



Figure 9: Possible faults in EPGS model

4.3. Simulation Results

Previous work by Scacchioli et al. (2006) yielded a complete nonlinear EPGS model. This nonlinear model uses ω_e , I_{load} , and V_{ref} as inputs and yields V_f , V_{dc} , and battery dc current I_{dc} as output. Diagnostics for the belt fault case, diode fault case, and voltage controller fault case are accomplished by using the flow model and GCM model. The flow model procedure is illustrated in Figure **10** and the GCM model procedure is illustrated in Figure **11**.



Figure 10. EPGS model with flow method



Figure 11: EPGS model with GCM method

The inputs for the nonlinear EPGS Simulink model are provided in Mohon et al (2013).

Table 2 details the selected injection time and magnitude of fault relative to nominal that were injected during simulation. In other words, the nominal inputs were modified to simulate a fault.

Table 2. Fault injection time and magnitude

Fault	Injection time (s)	Modified Input	Resulting % drop with respect to nominal
Belt Slip	10	ω _e	80
Open Diode	10	V _{dc}	N/A (one broken diode)
Voltage Controller	10	V _{ref}	30

Output z_2 range for nominal and faulty cases must be quantized into rectangles to find the probability transition matrix over time. Output z_2 is quantized into 12 states with names 1-12. The same boundaries and names will be used for faulty cases as well.

The z_1 range for this simulation is z_1^{min} is -2.210e+06 and z_1^{max} is 6.683e+06. Given the z_1 range, the quantized states, and u_1 , u_2 , and u_3 , the probability transition matrix can now be calculated using the f_2 function from Eq. (1).

The probability transition matrix L contains the prediction of the most likely quantized state $z' = z_L$ and its probability $P(z' = z_L)$ at the next time step. The most likely probability and most likely predicted state can be compared with the quantized output state $[I_{dc}]$ that actually occurs. If there is a relatively high probability of a particular state transition occurring and that state transition does not occur, then a fault may be present. An example of predicted state probabilities, predicted states, and output states over time for belt fault case is shown in Figure **12** and Figure **13**.

Disagreement between predicted and output states are clear after calculating the difference of quantized output state $[I_{dc}]$ and the predicted state. This difference is defined as the residual r in Eq. (11). The residual results for each fault case using flow method are shown in Figure 14 through Figure 16. The residual results for each fault case using GCM method are shown in Figure 17 through Figure 19.







Figure 13: Belt fault outputs for GCM method

$$r = [I_{dc}] - [I_{dc, predicted}]$$
(11)



Figure 14. Belt fault residual for flow method



Figure 15. Diode fault residual for flow method



Figure 16. Voltage controller fault residual for flow method



Figure 17: Belt fault residual for GCM method



Figure 18: Diode fault residual for GCM method



Figure 19: Voltage controller fault residual for GCM method

4.3.1. Analysis of Flow Method Results

All three fault cases using the flow method show a shortterm disagreement $r \neq 0$ between predicted and output states at time t=0.2 seconds but returns to agreement r = 0immediately at t=0.3 seconds. The disagreement occurs before a fault is injected at time t=10 seconds. This disagreement at t=0.2 could trigger a false alarm during fault detection. Similar rapid switching behavior also occurs in the diode fault residual in Figure 17. То distinguish between the similar switching behavior of false alarms with real faults and to build confidence in the diagnostic algorithm, a fault will only be detected if the residual shows disagreement for at least 0.2 seconds. The belt fault will be detected at t=38.4 seconds. The diode fault will be detected at t=10.7 seconds. The controller fault will be detected at 10.2 seconds.

Isolation of a detected fault will be achieved by monitoring the switching behavior during a finite time window following detection. The belt fault appears in the residual when the load current increases or decreases. Due to the quick duration of load current change, the belt fault is also present for a short time in the residual lasting between two to four seconds. The diode fault causes a large ripple in the alternator output current. This ripple causes frequent and rapid switching behavior from agreement to disagreement in the residual. The controller fault is the only fault case where there is residual disagreement for the entire duration of the fault. Therefore, the mean \overline{r} of the absolute value of the residuals during a finite time window can be used to isolate each fault as defined in Eq. (12). The time window is chosen based on data behavior. For the data in this paper, a six second window was used. Table 3 shows the mean value calculations for each fault using the six second window immediately after fault detection.

$$\overline{r} = \frac{\sum_{i=1}^{n} |r_i|}{n} \tag{12}$$

Table 3. Mean \overline{r} for six second window using flow method

Fault	Mean \bar{r}
Belt Slip	0.75
Open Diode	0.08
Voltage Controller	1

Appropriate constant thresholds for \overline{r} can isolate the fault. For this paper, if \overline{r} is between 0.5 and 1 the fault is due to belt slip. If \overline{r} is 1 the fault is due to the controller. Otherwise, the fault is due to an open diode.

Based on this approach, the belt fault will be isolated at t=44.4 seconds; the diode fault will be isolated at t=16.7

seconds; the controller fault will be isolated at time t=16.3 seconds.

4.3.2. Analysis of GCM Method Results

The GCM method residuals show similar behavior compared to the flow method residuals. For the GCM method, fault detection will occur when the residual shows disagreement for at least 0.2 seconds. The belt fault will be detected at t=10.1 seconds. The diode fault will be detected at t=52.5 seconds. The controller fault will not be detected or isolated because the residual never deviates from zero. The controller fault causes the output to transition to a nonadjacent cell and GCM method allows for nonadjacent cell transitions. Therefore, the residual of controller fault is always zero.

Isolation of the detected fault can be attempted by Eq. (12) with using a six second window immediately after fault detection. Table 5 shows the mean value calculation for each fault. The belt slip fault can be isolated if \bar{r} is between 0.1 and 0.2. The open diode fault can be isolated if \bar{r} is between 0 and 1. However, the voltage controller fault cannot be isolated. The residual never deviates from zero during the entire dataset. Therefore, the voltage controller fault cannot be isolated using GCM method.

Table 4. Mean \bar{r} for six second window using GCM method

Fault	Mean \bar{r}
Belt Slip	0.15
Open Diode	0.08
Voltage Controller	0

4.3.3. FDI Summary

Table 5 contains the detection and isolation times for both flow and GCM methods. The flow method can isolate all three faults while the GCM method can isolate only belt slip and open diode faults. The flow method can isolate the open diode fault faster than the GCM method. The GCM method can isolate the belt slip fault faster than the flow method. It is clear that the flow method gives best results since all fault detection and isolation is achievable.

		Belt	Onen	Voltage
	Fault	Slip	Diode	Controller
	Injection	10	10	10
	time (s)			
Flow Method	Detection	38.4	10.7	10.2
	time (s)			
	Isolation	44.4	16.7	16.3
	time (s)			
GCM Method	Detection	25.6	52.5	N/A
	time (s)			
	Isolation	31.6	58.5	N/A
	time (s)			

Table 5. Fault injection time and magnitude

Different fault magnitudes might require different isolation thresholds. This paper only considers three discrete fault modes.

5. CONCLUSION

This paper compares the GCM method and a new stochastic method for calculating state transition probabilities within a dynamic system. The methods are compared by detecting and identifying faults in a vehicle alternator system. The methods vary based on computational complexity and the ability to isolate all faults. The GCM method could not detect the controller reference fault but did isolate the belt fault faster than the new stochastic method. Overall, the new stochastic method is preferred since it can complete the FDI analysis even at the cost of computational effort.

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and conclusions Any opinions, findings, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

NOMENCLATURE

- ω_{m} engine rotational speed
- alternator rotational speed ω_{e}
- battery DC voltage V_{dc}
- V_{f} field voltage
- voltage controller reference V_{ref}
- alternator output current I_{dc}
- vehicle load current Iload
- battery charging current IB
- first state space state \mathbf{Z}_1
- second state space state and output \mathbf{Z}_2
- state space input u
- $a(\omega_e)$ state space parameter dependent on alternator rotational speed

$b(\omega_e)$	state space parameter dependent on alternator
	rotational speed
Z	current state
z'	possible future state
z_1^{min}	minimum z_1 value
z_1^{max}	maximum z_1 value
z*	flow transition point on z_1 axis on side 1 of state z
Z**	flow transition point on z_1 axis on side 2 of state z
$z_2^{(1)}$	upper boundary of state z
$z_2^{(2)}$	lower boundary of state z
ϕ^+	flow up
φ	flow down
f	general function
\overline{F}	Field vector
\overline{n}	normal vector
С	general closed curve
А	area within curve C
r	line integral direction along curve C
ϕ_{in}	total flow into state z
ϕ_{out}	total flow out of state z
ϕ_{net}	net flow for given state z
z^+	state above state z
z	state below state z
L	time varying probability transition matrix
$[I_{dc}]$	quantized alternator output current
r	residual
\overline{r}	mean of absolute value of residual
n	number of data points in residual

REFERENCES

- Chiu, H. M. & Hsu, C. S. (1986). A Cell Mapping Method for Nonlinear Deterministic and Stochastic Systems-Part II: Examples of Application. ASME Journal of Applied Mechanics. September Vol. 53. pp. 702-710. Doi: 10.1115/1.3171834
- Hashemi, A., & Pisu, P. (2011). Adaptive Threshold-based Fault Detection and Isolation for Automotive Electrical Systems (pp. 1013-1018), World Congress on Intelligent Control and Automation. June 21-25, Taipei, Taiwan. doi: 10.1109/WCICA.2011.5970668
- Hashemi, A., & Pisu, P. (2011). Fault Diagnosis in Automotive Alternator System Utilizing Adaptive Threshold Method. Annual Conference of Prognostics and Health Management Society. September 25-29, Montreal, Canada.
- Hashemi, A., (2011). Model-Based System Fault Diagnosis Utilizing Adaptive Threshold with Application to Automotive Electrical Systems. Masters dissertation. Clemson University, Clemson, South Carolina, USA. http://etd.lib.clemson.edu/documents/1314212419/Hash emi clemson 0050M 11327.pdf
- Hsu, C. S. (1980). A Theory of Cell-to-Cell Mapping Dynamical Systems. ASME Journal of Applied Mechanics. December Vol. 47. pp. 931-939. Doi:10.1115/1.3153816

- Hsu, C. S. & Guttalu, R. S. (1980). An Unravelling Algorithm for Global Analysis of Dynamical Systems: An Application to Cell-to-Cell Mappings. ASME Journal of Applied Mechanics. December Vol. 47. pp. 940-948. Doi: 10.1115/1.3153817
- Hsu, C. S. (1981). A Generalized Theory of Cell-to-Cell Mapping for Nonlinear Dynamical Systems. *ASME Journal of Applied Mechanics*. September Vol. 48. pp. 634-642. Doi: 10.1115/1.3157686
- Hsu, C. S. (1982). A Probabilistic Theory of Nonlinear Dynamical Systems Based on the Cell State Space Concept. ASME Journal of Applied Mechanics. December Vol. 49. pp. 895-902. Doi: 10.1115/1.3162633
- Hsu, C. S. & Chiu, H. M. (1986). A Cell Mapping Method for Nonlinear Deterministic and Stochastic Systems— Part I: The Method of Analysis. *ASME Journal of Applied Mechanics*. September Vol. 53. pp. 695-701. Doi: 10.1115/1.3171833
- Hsu, C. S., John F., Marsden, J. E., & Sirovich, L. (Eds.). (1987). Cell-to-Cell Mapping: A Method for Global Analysis for Nonlinear Systems. New York: Springer.
- Kastner, M. (2010). Monte Carlo Methods in Statistical Physics: Mathematical Foundations and Strategies. Communications in Nonlinear Science and Numerical Simulation. June Vol. 15. pp. 1589-1602. Doi: 10.1016/j.cnsns.2009.06.011
- Mohon, S., & Pisu, P. (2013). A Stochastic Modeling Approach of Quantized Systems with Application to Fault Detection and Isolation of an Automotive Electrical Power Generation Storage System. *Annual Conference of the Prognostics and Health Management Society*, October 14-17, New Orleans, Louisiana.
- Scacchioli, A., Rizzoni, G., & Pisu, P., (2006). Model-Based Fault Detection and Isolation in Automotive Electrical Systems, ASME International Mechanical Engineering Congress and Exposition (pp. 315-324), November 5-10, Chicago, Illinois, USA. doi: 10.1115/IMECE2006-14504
- Sobol, I. (1994). *A Primer for the Monte Carlo Method*. Boca Raton: CRC Press.
- Wang, J. (1999). Transition Matrix Monte Carlo Method. Proceedings of the Europhysics Conference on Computational Physics (CCP). September Vol. 121. pp. 22-25. Doi: 10.1016/S0010-4655(99)00270-2

BIOGRAPHIES



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Pierluigi Pisu was born in Genoa, Italy in 1971. He received his Ph.D. in Electrical Engineering from Ohio State University (Columbus, Ohio, USA) in 2002. In 2004, he was granted two US patents in area of model-based fault detection and isolation. He is currently an Associate Professor in the Department of

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Identification and classification protocol for complex systems

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ABSTRACT

This paper proposes a test protocol for drift identification and classification in a complex production system. The key objective here is to develop a classifier for failure causes where variables depend on a set of measured parameters. In the context of our work, we assume that the drift problem of a production system is generally observed in control products phase. The model proposed in this paper for failure causes classification is structured in the form of a causeseffects graph based on Hierarchical Naïve Bayes formalism (HNB). Our key contribution in this is the methodology that allows developing failure causes classification test model in the complex and uncertain manufacturing context.

1. INTRODUCTION

Nowadays, the industrial market is characterized by capital investment and growing international competition. In this scenario, success depends on the competitiveness of products. In order to achieve this, manufacturers aim to maximize the performance and quality of services through three criteria: cycle time, costs and productivity (Kunio et al, 1995). These can only be achieved by improving manufacturing equipment availability. The manufacturing processes have become very complex and automated (Zio, 2009), and requires accuracy while executing production steps in the context of automated manufacturing systems (AMS), especially for the production equipment.

The equipment act directly on the product and they can be represented according to three parts: (i) the product flow that includes processed product, assembled product, finished product, etc., (ii) the controlled system including actuators, sensors and effectors, and (iii) the supervision, monitoring and control system (detection, diagnosis, prognosis, etc.), as shown in the Figure 1.

However, sensors are not directly positioned on the product for technical reasons. Therefore, the manufacturing process has the risk of not observing perturbation that affects the product quality. Also, the production equipment do not have internal mechanism to confirm that recipe applied to the product has been carried out correctly (Bouaziz et al., 2013). Therefore, many drifts are unavoidable in the production process.



Figue 1. Internal structure of the production equipment. (Bouaziz et al., 2013).

This article is structured as follows: in section 2, we present the approaches details of the identification and classification processes. Section 3 is devoted to present state of the art in the field of classification (main techniques). In section 4, we propose an introduction to Hierarchical Naïve Bayes technique. Then in section 5, we present an application of our approach on the Tennessee Eastman Process example.

2. IDENTIFICATION AND CLASSIFICATION PROCESS

In this section, we present the four steps of our methodology. The process of identification and classification is performed according to Figure 2.

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Figure 2. Identification and classification process.

2.1. Definition of the production context

This phase presents the production system context that is characterized by high complexity and uncertainty. Industrial production system is even more complex with multiple manufacturing processes running on the same production line and competing for available production resources. It means that there are a large number of elementary operations to manufacture a finished product (especially in the semiconductor and the pharmaceutical industries) and long production periods (8 to 10 weeks in semiconductor production). Also, the industrial production environment is naturally uncertain (equipment drifts, human errors...) that can impact the process control and maintenance contexts.

2.2. Definition of modeling techniques

In this second step, we analyze several methods based on the criteria defined within the production context. We analyse in particular if the model can:

- Manage diversity of the parameter types (discrete, continuous, qualitative and quantitative). Examples: time, digital measurements, samples ...
- Manage multiple hierarchical classes of equipment parameters (sensors, motors...) and products.
- Manage diversity of variables: (observed variables and unobserved variables).
- Take into account correlation between variables or causal events.
- Deal with uncertain data and/or missing data (complete data and incomplete data).

- Be suitable: It is defined as the flexibility of the model for different purposes and problems (diagnosis, prognosis...).
- Be efficient: it is defined as the computation time of variables distributions (performance).

After making a synthetic comparison between the different methods (Neural networks, Decision trees, BN...), we found that modeling technique must be suitable to the context of production; and, this study is oriented towards probabilistic method: Bayes Network.

2.3. Analysis of causality (FM/RC)

The FMECA (Failure Modes, Effects and Criticality Analysis) approach is used to identify a list of failure modes (FM) and root causes (RC) by the expert. It is based on the priorities which are identified for the qualitative classification of failure modes by experts based on their knowledge. It results in the list of causalities (correlation between variables) (Bouaziz et al., 2013).

2.4. Modeling

In this last phase, we propose a mechanism to verify the causalities proposed by experts and/or find new causalities (Zaarour et al., 2004). An automated tool is proposed for this purpose that searches correlations by classification (Bouaziz et al., 2013) by learning them from a historical database.

The classifiers inputs (parameters and graphical structure) are calculated from the measured data and experts' knowledge. The output tool helps to make decisions to

either verify and/or find existing or new causalities by calculating various probability distributions of the graphical model. In our case, as we propose to work in both diagnosis and prognosis; hence, we present a generic methodology for developing a simulation tool to assist this decision making.

3. THE TECHNIQUES IN THE FIELD OF CLASSIFICATION

Thereafter this section is designed to introduce techniques in the field of classification. It is necessary to know that in our case the classification phase is used for diagnosis/prognosis aspects. That is to say, the objective of this phase is to present a study of different types of classifiers with their advantages and disadvantages in the context that there is no single classifier that is better in all applications. We distinguish the classification algorithms in two categories as supervised and unsupervised classification. This section is dedicated to introduce some techniques often used in the each of these categories.

3.1. The supervised classification

In the process, when a failure causes are diagnosed, we classify the collected data according to different causes associated with degradation. The key purpose of supervised classification is to find, from the examples already classified (training sets), a model to predict the classes for new data. Following is the list of supervised classification methods used more often:

- K-nearest neighbors (k Nearest Neighborhood or kNN): The idea of this method is to observe the k nearest neighbors of a new observation to determine the class membership of this new observation (Belur, 1991). To predict the class of a new variable, the algorithm finds the K nearest neighbors of the new cases and predicts the most common response of them. This method is used on continuous data. It is possible to take into account binary data (discrete variable with 2 modalities), but not multinomial (discrete variable with n modalities) (Cover & Hart, 1967). It is difficult to find the class in case of insufficient data because it also needs a lot of examples for learning.
- Decision trees data set: It is a recognized discrimination between different classes tools. The main advantage of decision trees is that they can be easily used with the understandable rules. If the attribute is binary, we have two possible decisions, whereas if the attribute has k modalities, we have k possible decisions. Indeed, although the execution is fast, but the construction of the tree uses much more time. Also, it do not actually support the continuous values. In addition, it is always possible to discretize but the problem here is how to optimize discretization (lose the least amount of information compared to the original variable). So the decision trees work well with criteria to manage

diversity parameters and variables whereas with others, they are not accurate (Verron et al, 2010).

• SVM Support Vector Machines: These are binary classifiers. The purpose of this technique is to find wide margin classifier to separate the data and maximize the distance between two classes. This linear classifier is called "hyperplane". The closest points are called Support Vector (Verron et al, 2010). That "hyperplane" must be optimal which passes through the middle among the "hyperplanes" valid. This method has shown its effectiveness in many fields of applications such as image processing and medical diagnosis with large dimension datasets. However, the SVM application is not effective with the incomplete data.

3.2. The unsupervised classification

As we have discussed, when classes exist and that we have a large number of data already classified, we can classify new data (supervised classification). Unlike this technique, unsupervised classifications do not have a training set. There are two main families of unsupervised classification methods.

Hierarchical classification: Its purpose is to create a hierarchy in groups of variables. It means that identified classes of variables are assigned different levels.

Non-hierarchical classification: The hierarchy is not presented in this type of classification. The algorithms of this type produce classes but without forming a hierarchy (all classes are created in the same level).

- Agglomerative Hierarchical Clustering (AHC): It is a method of classification based on simple principle. We begin by calculating dissimilar objects among N. Then we combine the two objects according to criterion aggregation, thus creating a class for these two objects. We then calculate the dissimilarity between this class with other N-2 objects using this criterion to create another class. Then the two classes of objects or grouping minimizing the aggregation criterion objects are grouped.
- Divisive Hierarchical Clustering (DHC): It is the inverse of the previous method where classes are created step by step. We initially assume that all individuals belong to the same class, and in turn we cut into two. This step is repeated until you get as many classes as individuals.
- Bayesian Networks (BN) (Pearl, 1988): This method can be used on both discrete and continuous variables. Indeed, we can build a BN model with a graph that reflects the discrete or continuous data, modeled in the probability tables. The extracted data are used for learning and the level of complexity for the

computation depends on the amount of data. A BN may represent variables by nodes and prioritization of classes with a Hierarchical Naïve Bayes networks HNB. The probabilities calculations can be provided by Maximum Likelihood Estimation / Expectation– Maximization algorithm (MLE/EM) and are used to represent correlations between nodes. Moreover, the advantage of Bayesian Networks is its adaptability. A Bayesian Network allows the consideration of the temporal dimension using Dynamic Bayesian Networks DBN (Verron et al., 2010).

In this paper, we want to remind that our study is directed towards the probabilistic methods, so it is really a method that can fulfill all of these criteria. Moreover, in our study, data is not supervised with the need for Hierarchical priorities, we would present the following details of this method in the next section.

4. INTRODUCTION OF THE HNB TECHNIQUE

4.1. Background and principle

A Bayes Network is a system representing knowledge and to calculate conditional probabilities providing solutions to different kinds of problems. The structure of this type of network is simple: a graph in which nodes represent random variables and arcs are connected by conditional probabilities (uncertainty knowledge) (Jensen, 1996). These variables may be discrete or continuous, observable or unobservable, detected or not detected.

In the general case, $X = \{X_1, X_2, ..., X_n\}$, the joint probability distribution P(X) is written as follows:

$$P(X) = \prod_{i=1}^{n} P(X_i / Parents(X_i))$$
(1)

The calculation of BN is based on the Bayes theory (Bayes, 1763):

$$P(X_{2} / X_{1}) = \frac{P(X_{1} / X_{2}) \cdot P(X_{2})}{P(X_{1})}$$
(2)

- $P(X_i)$ is the a priori probability (or Marginal) of X_i .
- P(X₂/X₁) is the posterior probability of X₂ (knowing X₁).
- $P(X_1/X_2)$ is the likelihood function of X_1 (knowing X_2).

The marginal distribution $P(X_2)$ is calculated by the formula:

$$P(X_2) = P(X_2 / X_1)P(X_1) + P(X_2 / \overline{X}_1)P(\overline{X}_1) \quad (3)$$

The Naïve Bayes Network also called Bayes classifier is the Bayes classifier with the simplest structure. This classifier is very famous because of its performance, especially in the case where all variables are discrete (Verron et al., 2010). Naïve Bayes networks have a simple and unique structure that includes two levels. The first level contains a single parent node and the second is several children with high hypothesis of conditional independence of children (*X*) to the parent. Nodes $X_1...X_n$ are independent conditional on X_c class. They are widely used to solve classification problems expressed by Eq. (4) and Figure 3:

$$P(X_c, X_1, X_2 \dots X_n) = P(X_c) \prod_{i=1}^n P(X_i / X_c)$$

$$(4)$$





Figure 4. Hierarchical Naïve Bayes models.

In fact, the knowledge provided by an expert can also result in the creation of latent variables between two or more nodes. This is the case for example unsupervised problems where the class is never measured. Therefore, it is possible to provide the equivalent of a Naïve Bayesian network, the latent model, where classes (shown in blue in the following figure) are not part of the measured variables. A latent class (LC) model includes X_c , X_1 and X_2 latent and manifest variables Y_1 , Y_2 ... Yn. Latent Hierarchical models illustrated in Figure 4 have been proposed by (Bishop & Tipping, 1998) for data visualization and unsupervised classification.

4.2. Learning and inference

Different families of learning and inference algorithms are proposed in the literature (Naïm et al., 2007) with three criteria of classification:

- Objective: learning or inference.
- Data: Complete or incomplete.
- Judgments of the expert: with or without the expert knowledge.

In this paper, we are working with two criteria (objective and data availability). (Bouaziz et al., 2013) presents a synthesis for probabilistic algorithms mostly used for Bayes networks. For a more detailed description, we recommend reading (Heckerman, 1998), (Neal & Hinton, 1998), (Pearl, 1988), (Jensen, 1996) and (Kappen, 2002).

These learning methods find the structure of Bayes network (structure learning) and estimate conditional probabilities (parameter learning) or acquire knowledge (experts' judgments). The inference algorithms are used for very large networks. There are many libraries for Bayes networks (BNT Matlab, BNJava, Java- Bayes, PNL...) and quality software (ProBT, BayesiaLab, Netica, Elvira...) that are useful (Naim et al., 2007).

The conditional probabilities of variables are computed based on the Bayes theory for TEP model. These results can help to make decision support components for metrology and maintenance (Bouillaut et al., 2008).

5. APPLICATION TO TENNESSEE EASTMAN PROCESS

5.1. Description

Tennessee Eastman Process (TEP) is a complex process developed by Eastman Company to provide a simulation of a real industrial process to test process monitoring methods. There are reactive gases A, C, D, E and inert gas B in the reactor. G and H are two products (liquid). The chemical reactions of the method are given by the equation system in Eq. (5).

$$\begin{array}{ll} A(g) + C(g) + D(g) & \rightarrow G(liq) \\ A(g) + C(g) + E(g) & \rightarrow H(liq) \\ A(g) + E(g) & \rightarrow F(liq) \\ 3D(g) & \rightarrow 2F(liq) \quad (5) \end{array}$$

TEP has five elements: Reactor, Condenser, Compressor, Separator and Stripper. At first, the products leave the reactor while catalyst remains in there. Then the product gas is cooled through a condenser that moved to the vapor liquid separator. The uncondensed vapors in the separator return to the reactor via compressor. The inert gas B and derivative F are purged from the separator in this process. At last, the condensed stream into the separator is sent to the stripper to remove the last traces of reagents (Figure 5).

The TEP includes 53 variables: 41 measurements and 12 manipulated variables. Among these 41 variables, there are

22 continuous variables (these are the values of the sensors of the process), while other measures are compositions such as concentrations, which are not readily available but continuously sampled. TEP is subjected to 20 different faults. These faults are of different natures: step, random variation (the increasing level variability of certain variables) or other actuators such as a blocked valve. The description of these 20 mistakes and 53 variables is presented in detail in (Li & Xiao, 2011). Furthermore, we propose to work on the faults that cannot be observed (F_{16} to F_{20}).

5.2. Modeling

In our work, we propose to determine a set of variables representing the case study TEP according to steps 3 and 4 (see Figure 2). Therefore, the variables used in the illustrative models, we describe in this section, are inherently based on the experience and inference (Verron et al., 2010). Through this model, our objective is to describe the evolution and identify one or more failures in the system. We identified four distinct categories of variables:

- Failure modes of the process *FM*: We assume that the states of the variable *(FM)* takes two possible values (detected, not detected).
- Primary failure causes (level 1) *RC_i* (*i*= 1→6): these are quantitative variables defined by expert opinion. They correspond to six elements of process TEP (see table 1). All variables have a binary mode (observed or unobserved).

Node	Variables
RC_{I}	Reactor feed flow
RC_2	Reactor temperature
RC_3	Reactor pressure
RC_4	Condenser cooling water
RC_5	Separator temperature
RC_6	Stripper valve

Table 1. Primary failure causes.

- Intermediate failure causes (level 2) F_j ($j=1\rightarrow 20$). In our work, the failure causes are defined by the experts; however, for detailed description, we recommend to read (Verron et al, 2010). All faults have a binary mode (observed or unobserved).
- Parameter descriptions X_m ($m=1\rightarrow 53$): they are determined by the real process. We have 53 variables that correspond to the measurement and manipulated variables in TEP. Each variable has either a binary mode true or false.



Figure 5. TEP flow sheet adopting control structure proposed by (Lyman & Georgakis, 1995).

In follows, we propose a graph structure of the model and calculate the probability distributions associated with each of variable in the graph. A classification structure from RC_i with the known observation parameters X_m and structure prognosis/diagnosis of FM based on the observations on RC_i is shown in Figure 6 below.



Figure 6. Identification and classification model by Hierarchical naïve Bayes network.

This model offers to classify failures causes in 2 hierarchicals RC_i and F_j . At the same time, we specify which are failures causes of the *FM* and predict the future state of the system or a component. To continue, our result would be presented in the next section.

6. RESULTS

In this section, first we present the preliminary results of learning with simulation in two cases complete and incomplete data. At first, a square matrix (80 x 80) corresponding to 80 variables (53 parameters X_m + 20 variables F_j + 6 variables RC_i + 1 variable FM) and 80 samples for learning the probabilities are created by BNT Matlab © library (Murphy, 2001). The calculation of probabilities is done by MLE (Maximum Likelihood Estimation) algorithm that is a statistical estimate of the probability based on its occurrence (frequency of occurrence) in the dataset. Similarly, we have created incomplete data by adding many hidden variables in complete data.

Columns represent probabilities of variables. With FM (failure mode) variable we have 2 largest columns that represent probabilities of detected and undetected failure. We found that there are few different probability variables (Figure 7). This is unavoidable with incomplete data. However, we saw probabilities FM (failure mode) in two cases (0.77 and 0.74) is similar which is an acceptable result.



Figure 7. The results of learning algorithme.

Thereafter, we present the simulation results for the failure causes classification and prognosis after the appearance of failure. In the framework of this paper, we present un simple exemple model in Figure 8 to calculate probability distributions with the failure causes cooling water in condenser process (TEP) and related parametres.



Figure 8. Exemple model to calculate probability distributions.

Figures 9 and 10 present results of two scenarios with complete data (result with incomplete data is not shown in figures). These are cleary illustrative examples of inference. We presented only probability distributions with known observation of some variables (Figure 8).

• P(*FM*/*RC_i*): Variable observation in the example is *RC₄*. We used Bayes formula to calculate the probability failure mode based on this observation. Thus, the FM process is defined (predicted) from the calculation of probabilities. This is the classification model for prognosis (Figure 9).



Figure 9. Probability of variables in prognosis case.

• P(*RC_i/FM*): Similarly, we establish the diagnosis model when we know the observation of a failure mode. This is to calculate probabilities of the causes (for example *RC*₄). This is the model of classification for diagnosis (Figure 10).



Figure 10. Probability of variables in diagnosis case.

Base on learning results, a predicted result of failure mode of process *FM* is calculated from the observed failures causes RC_4 and F_{15} (see Figure 9). We found similar inferences in both cases. Indeed, probabilistic inference is essentially a matter of calculation. This shows that learning with whether complete or incomplete data (0.81 & 0.84), we also have close probabilities to make a decision. Similarly, in diagnosis case, we found probabilities of these variables (see Figure 10) from a failure mode of process *FM* which is detected. Therefore, we can compare between probabilities to make a correct decision. So these results show that the proposed method performs good detection capability.

However, it should be mentioned that classifiers could not make choice easy if there are too many variables in the manufacturing process. This implies that we must have weights primarily depending on the differences between each variables to propose the optimal distribution.

7. CONCLUSION AND PERSPECTIVES

Our work presented in this paper deal with the identification and classification of failure causes in the context of complex industrial production. We first presented complex industrial manufacturing processes along with detailed steps of our methodology and in particular approaches for Bayes network. In the end, we presented simulation results on our TEP case study.

We showed thereafter an international benchmark that our approach propose a solution in terms of classification. In particular, we have presented a failure causes classification method based on a set of measured parameters. The resulting model, developed using Bayesian approach, allows diagnosis or prognosis in a context of complete/incomplete data. Nevertheless, this proposed model is a testing protocol for failures causes classification. Therefore, certain aspects in this model could be improved. In future, we shall propose the learning of the proposed model on real set of data that requires validation. On the other side, a development will be directed to a new configuration which is the application of a heuristic that quickly finds weights by the optimal structure of VIP classifier. In addition, an extension of the temporal Bayes network will improve dynamic monitoring for decision making.

REFERENCES

- Bayes T., (1763). An Essay towards solving a Problem in the Doctrine of Chances. Philosophical Transactions of the Royal Society of London, vol. 53, pages 370-418.
- Belur V. D, (1991) Nearest Neighbor: *Pattern Classification Techniques*, IEEE Computer Society.
- Bouaziz. M.-F, Zamaï. E, Duvivier. F. (2013). Towards Bayesian Network Methodology for Predicting the equipment Health Factor of Complex Semiconductor Systems. International Journal of Production Research, Volume 51, Issue 15, 4597-4617.
- Bouillaut L., Leray P., Aknin P., François O., Dubois S., (2008). Dynamic Bayesian Networks Modelling Maintenance Strategies: Prevention of Broken Rails. WCRR'08 World Congress on Railway Research, Séoul. Corea.
- Bishop, C. M. and Tipping M. E., (1998). A hierarchical latent variable model for data visualization. IEEE Transactions on Pattern Analysis and Machine Intelligence 20(3), 281–293.
- Cover.T.M and Hart. P.E, (1967). *Nearest neighbor pattern classification*, IEEE Transactions on Information Theory, 13 :21–27.
- Heckerman D., (1998). A Tutorial on Learning with Bayesian Network. JORDAN M. I., Ed., Learning in Graphical Models, Kluwer Academic Publishers, Boston.
- Li H. and Xiao D-Y., (2011). Faut diagnosic of Tennessee Eastman process using signal geometry matching technique. EURASIP Journal on Advance in Signal Processing 2011:83.
- Jensen F.V., (1996). Introduction to Bayesian networks, UCL Press, London.
- Kappen H., (2002). *The cluster variation method for approximate reasoning in medical diagnosis*. Eds., Modeling Bio-medical signals,World-Scientic.
- Kunio S., Mitsugu K., Yoshifumi K., (1995). An Advanced step in TPM Implementation. (pages 64-65). Paris, France.
- Lyman. PR, Georgakis. C. (1995). *Plan-wide control of the Tennesse Eastman problem*. Comput Chem Eng, 19(3), 321-331. USA.
- Murphy K., (2001). *The BayesNet Toolbox for Matlab*. Computing Science and Statistics: Proceedings of Infence, vol. 33.
- Naim P., Wuillemin P.H., Leray P., Pourret O., (2007). *Bayesian Network*. 3e édition, Eyrolles (eds).

- Neal R.M., Hinton G.E., (1998). A View of the EM algorithm that justifies incre-mental, sparse and other variants. JORDAN M. I., Ed., Learning in Graphical Models, Kluwer Academic Publishers, Boston.
- Pearl J., (1988). Probabilistic reasoning in intelligent systems: Networks of plausible inference. Morgan – Kaufmann, San Diego.
- Verron. S., Li. J., Tiplica, T. (2010). Fault detection and isolation of faults in a multivariate process with Bayesian network. Journal of Process Control 20 (8), 902-911.
- Zio, E. (2009). *Reliability engineering: Old problems and new challenges*. Reliability Engineering and System Safety journal. Volume 94, pp. 125-141.
- Zaarour I., Heutte L., Leray P., Labiche J., Eter B., Mellier D., (2004). Clustering And Bayesian Network Approaches For Discovering Handwriting Strategies Of Primary School Children. IJPRAI 18(7):1233-1251.

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Dynamic Weighted PSVR-Based Ensembles for Prognostics of Nuclear Components

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ABSTRACT

Combining different physical and / or statistical predictive algorithms for Nuclear Power Plant (NPP) components into an ensemble can improve the robustness and accuracy of the prediction. In this paper, an ensemble approach is proposed for prediction of time series data based on a modified Probabilistic Support Vector Regression (PSVR) algorithm. We propose a modified Radial Basis Function (RBF) as kernel function to tackle time series data and two strategies to build diverse sub-models of the ensemble. A simple but effective strategy is used to combine the results from submodels built with PSVR, giving the ensemble prediction results. A real case study on a power production component is presented.

1. INTRODUCTION

Combining various data-driven approaches into an ensemble is a relatively recent direction of research, aimed at improving the robustness and accuracy of the final prediction. The models which compose the ensemble are called sub-models. Various strategies have been proposed for building sub-models, including error-correcting output coding, Bagging, Adaboost, and boosting (Kim, Pang, Je, Kim & Bang, 2003; Hu, Youn, Wang & Yoon, 2012). Similarly, several methods for aggregating the prediction results of the sub-models have been proposed, such as majority vote, weighted vote, Borda count, Bayes and probabilistic schemes, etc (Polikar, 2006).

Support Vector Machine (SVM) is a popular and promising data-driven method for prognostics. SVM-based ensemble models have been proposed for classification. Chen, Wang and Zuylen (2009) use ensemble of SVMs to detect traffic incidents. The sub-models use different kernel functions and parameters, and their outputs are combined to improve the classification performance. Acar and Rais-Rohami (2009) treat the general weighted-sum formulation of an ensemble as an optimization problem, and then minimize an error metric to select the best weights for the sub-models of SVM. Kurram and Kwon (2013) try to achieve an optimal sparse combination of the sub-model results by jointly optimizing the separating hyperplane obtained by each SVM classifier and the corresponding weights of sub-decisions. Valentini and Dietterich (2003) prove that an ensemble of SVMs employing bagging of low-bias algorithms improves the generalization power of the procedure with respect to single SVM. The ensemble of SVMs built with bagging and boosting can greatly outperform a single SVM in terms of classification accuracy (Kim et al., 2003).

SVM can also be treated as a Bayesian inference problem with Gaussian priors. The Maximum A Posteriori (MAP) solution to this problem can contextually give an estimate of the model parameters and also of the underlying function (Sollich, 1999). Within the Bayesian treatment of SVM, an error bar for the prediction, i.e. the variance of the predicted outcome, can also be obtained (Liu *et al.*, 2012). This

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Bayesian interpretation of SVM for regression is called Probabilistic Support Vector Regression (PSVR).

In this paper, we focus on the combination of multiple PSVR sub-models (Liu, Seraoui, Vitelli & Zio, 2012). The case study addressed in this paper concerns the monitoring of a component in the Reactor Coolant Pump (RCP) of a Nuclear Power Plant (NPP), with real data collected from a sensor.

An ensemble model of PSVRs is proposed in this paper with a dynamic weighting strategy. The elements of novelty of the method here proposed are various. In the previously mentioned ensembles of SVMs, all the weights were calculated during the training part and fixed for testing. However, a sub-model may perform well only on a part of the data set. Hence, the weights need to be updated considering the different data sets involved in the case study, and even different input vectors. A dynamic weighting strategy, based on local fitness calculation (Baudat & Anouar, 2003) is proposed in this paper. A dynamic weighting method is also used in Muhlbaier, Topalis and Polikar (2009), Yang, Yuan and Liu (2009) and Razavi-Far, Baraldi and Zio (2012), to add a new classifier to the ensemble model, but weights are not adjusted to the different input vectors. Moreover, in order to build an ensemble of PSVRs on different failure scenarios, a modified Radial Basis Function (RBF) is also proposed and used in this paper. In addition, a simple but efficient aggregating method is proposed to combine the outputs of the sub-models, including predicted values and associated error bars. Finally, two different strategies are proposed to form the training data set of each sub-model on the basis of the characteristics of the data. All the novel strategies are tested in the case study concerning a component of the RCP in a NPP.

The rest of the paper is organized as follows. Section 2 gives details about the proposed ensemble approach and a modified RBF. Section 3 illustrates the case study, the available data and how the two proposed ensemble models are constructed. Section 4 presents the experimental results from the PSVR ensemble models and describes the comparison with a single PSVR model. Finally, conclusions with some considerations are drawn in Section 5.

2. DYNAMIC-WEIGHTED PSVR-BASED ENSEMBLE

The strategy underlying the use of ensemble-based methods in prediction problems is to benefit from the strength of different sub-models by combining their outputs to improve the global prediction performance if compared to the result of a single sub-model.

In this section, we give details about the proposed Dynamic-Weighted PSVR-based Ensemble (named DW-PSVR-Ensemble in short).

2.1. Probabilistic Support Vector Regression

Depending on the choice of the loss function, we can define different Gaussian versions of PSVR. The PSVR approach proposed in the previous work (Liu *et al.*, 2012) and used in the ongoing research makes use of the ε -insensitive Loss Function, which enables a sparse set of support vectors to be obtained.

2.1.1. PSVR with ε-Insensitive Loss Function

With limited length of the paper, we do not give mathematical details on the derivation of the PSVR approach that can be found in Gao, Gunn, Harriset and Brown (2002). But it is very important to recall that the output of PSVR is a Gaussian distribution of the predicted value.

2.1.2. Modified Radial Basis Function Kernel

The kernel function enables the mapping of an input vector in a higher-dimensional Reproducing Kernel Hilbert Space (RKHS). By calculating pairwise inner products between mapped samples, kernel functions return the similarity between different samples. In fact, only kernels that fulfill Mercer's Theorem (i.e. the kernel matrix must be positive semi-definite) are valid ones and, thus, can be used in SVM (Minh, Niyogi and Yang, 2006). The most common kernel functions include the linear kernel function, the polynomial kernel function and the Radial Basis Function (RBF).

In all these popular kernel functions, different inputs, i.e. different elements of x(t), are treated equally in computing the inner product involved in RBF. For time series data, H historical values of the time series are normally chosen as inputs according to the partial autocorrelation analysis results. These values have, of course, different correlation structures with respect to the output. In order to reflect this difference, a modified RBF is proposed in this paper.

Supposing two input vectors x(i) and x(j), in order to calculate the inner product of these two input vectors in RKHS, the traditional RBF is $K(\mathbf{x}(i), \mathbf{x}(j)) = \exp(-\frac{\|\mathbf{x}(i)-\mathbf{x}(j)\|^2}{2\gamma^2})$, with γ the width of the kernel given by particular optimization algorithm, and the proposed modified RBF is $K(\mathbf{x}(i), \mathbf{x}(j)) = \exp\left(-\frac{\langle C_a^2, (\mathbf{x}(i) - \mathbf{x}(j))^2 \rangle}{2\gamma^2}\right)$. In general, $C_a =$ $(C_1, ..., C_H)$ denotes the correlation between each input and the output, in our case between different temporal lags and the output of time series data. Suppose $A_i = [x_i(t)], B =$ [y(t)], with $x_i(t)$ the i-th input of x(t) and t = 1, ..., M. Then, C_i is the correlation between A_i and B, and so the correlation between $x_i(t)$ and y(t). As C_a is constant for each sub-model, it is easy to prove that the modified RBF satisfies Mercer's Theorem. Thus, the modification of the RBF does not change the theoretical results on which the PSVR method is based.

By giving different weights to different inputs in the input vector, we can reduce the influence of the inputs less correlated with the output and make the more correlated ones more significant in the relation between the inputs and the output. Another advantage of the modified RBF is illustrated in Section 3, when dealing with multiple time series data.

2.2. Ensemble-Based Approach

An ensemble-based approach is obtained by training diverse sub-models and, then, combining their results with given strategies. It can be proven that this can lead to superior performance with respect to a single model approach (Bauer & Kohavi, 1999). A simple paradigm of a typical ensemblebased approach with N sub-models is shown in Figure 1. Ensemble models are built on three key components: a strategy to build diverse models; a strategy to construct accurate sub-models; a strategy to combine the outputs of the sub-models in a way such that the correct predictions are amplified, while the incorrect ones are counteracted. We focus here on the latter. Proper strategies to build diverse and accurate sub-models are described in relation to the case study.

In the DW-PSVR-Ensemble that we are proposing, the submodels are built using the PSVR model presented in Liu *et al.* (2012). The reason for not using other data-driven approaches, including other SVMs, lies on the special output structure of PSVR. The output of each sub-model built with PSVR contains a predicted value and the associated variance, assuming that the predicted value follows a Gaussian distribution.



Figure 1. Paradigm of a typical ensemble method.

A dynamic weighted-sum strategy is proposed to combine the outputs of the sub-models. As mentioned in Section 1, different methods can be applied to calculate the weights for the sub-models. In the methods that can be found in the literature, the weights are normally fixed after the ensemble model is built. They are only updated when new sub-models are added to the ensemble or when some sub-models are changed. In some real applications with fast changing environmental and operational conditions, the performance of the ensemble model may degrade rapidly. This degradation is not always caused by the low robustness or capability to adapt of the ensemble model, but can be due to the fact that the best sub-models are not given proper weights. In this paper, a dynamic weighting strategy is thus proposed. The weights are no longer constant during the prediction, but dependent on the input vector. They are recalculated each time a new input vector arrives. Inspired by the work of Baudat and Anouar (2003) and considering the characteristics of PSVR, a local fitness calculation is implemented in this paper to calculate weights of different sub-models for each input vector.

2.2.1. Local Fitness Calculation

In Baudat and Anouar (2003), the authors define a global and local criterion to characterize the feature space in SVM. The proposed local fitness can describe the linearity between the mapping of a new input vector and the mapping of all the Feature Vectors (FVs) of the model: if a linear combination of the mapping of the FVs can better approach the mapping of the new input vector, the model gives better approximation of the output of the new data point; otherwise, the model performs worse for this data point. Thus local fitness can be implemented to derive the weight of each submodel for each input vector.

Suppose (x_i, y_i) , for i = 1, 2, ..., M are the training data points, and the mapping $\varphi(x)$ maps each input vector x_i into RKHS with the mapping φ_i , for i = 1, 2, ..., M. $k_{i,i} =$ $k(\mathbf{x}_i, \mathbf{x}_i)$ is the inner product between $\boldsymbol{\varphi}_i$ and $\boldsymbol{\varphi}_i$. The FVs of this model, selected with the method proposed in Baudat and Anouar (2003), are $\{x_1, x_2, ..., x_L\}$, with the corresponding mapping $S = \{ \boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, ..., \boldsymbol{\varphi}_L \}$. $\boldsymbol{\varphi}_N$ is the mapping of the new input vector x_N . According to Baudat and Anouar (2003), the calculation of the local fitness of new input this vector amounts to finding $\{a_{N,1}, a_{N,2}, \dots, a_{N,L}\}$, which gives the minimum of Eq. (1).

$$\delta_N = \frac{\|\boldsymbol{\varphi}_N - \boldsymbol{\Sigma}_{i=1}^L \boldsymbol{a}_{N,i} \boldsymbol{\varphi}_i\|}{\|\boldsymbol{\varphi}_N\|} \tag{1}$$

The minimum of δ_N can also be expressed with an inner product as shown in Eq. (2).

$$\min \delta_N = 1 - \frac{\kappa_{S,N}^{t} \kappa_{S,S}^{-1} \kappa_{S,N}}{\kappa_{N,N}} = J_S \tag{2}$$

where $K_{S,S} = (k_{i,j}), i, j = 1, 2, ..., L$ is the kernel matrix of S and $K_{S,N} = (k_{i,N}), i = 1, 2, ..., L$ is the vector of the inner product between $\boldsymbol{\varphi}_N$. J_S is the local fitness of \boldsymbol{x}_N for this model.

With Eq. (2), for a new coming data point at time *t*, we can calculate the local fitness $J_i(t)$ for the *i*-th sub-model. And the weight of the *i*-th sub-model for this data point is calculated as $\omega_i(t) = \frac{1/I_i(t)}{\sum_{i=1}^N 1/I_j(t)}$.

2.2.2. Combining Sub-Models Outputs

Figure 2 shows the paradigm of DW-PSVR-Ensemble, where *N* is the number of sub-models, $\mathbf{x}(t)$ is a new input vector arriving at time *t*, $w_j(t)$ is the weight assigned to the *j*-th sub-model for the new input vector, $\hat{y}_j(t)$ and $\sigma_j^2(t)$ are the predicted value and corresponding variance for the *j*-th sub-model given by PSVR, and $\hat{y}(t)$ and $\sigma^2(t)$ are the final outputs of the ensemble model.



Figure 2. Paradigm of the proposed DW-PSVR-Ensemble.

The output of each PSVR-based sub-model is a Gaussian distribution predicted value. The proposed simple but efficient strategy for combining sub-models results is by taking a weighted-sum of Gaussian distributions, which means that $N(\hat{y}(t), \sigma^2(t)) = \sum_{j=1}^N \omega_j(t)N(\hat{y}_j(t), \sigma_j^2(t))$, with $N(\hat{y}(t), \sigma^2(t))$ denoting a Gaussian distribution with mean value $\hat{y}(t)$ and variance $\sigma^2(t)$. From this, we can derive the fact that $\hat{y}(t) = \sum_{j=1}^N \omega_j(t)\hat{y}_j(t)$ and $\sigma(t) = \sqrt{\sum_{j=1}^N \omega_j^2(t)\sigma_j^2(t)}$, if we assume sub-models results to be uncorrelated.

Note that all the sub-models weights and outputs are a function of t, which means that they are all dependent on the input vector of the ensemble model.

3. CASE STUDY DESCRIPTION

The real case study considered in this paper concerns the 1day prediction of leak flow of the first seal of the RCP of a NPP.

In this section we describe the time series data and briefly recall the data pre-processing steps. We also detail the strategies to build accurate and diverse sub-models.

3.1. Data Description and Pre-Processing

In the data provided, there are 20 failure scenarios concerning the leak flow from 10 different NPPs. Each failure scenario contains a time series data of the leak flow. They are named Scenario 1, Scenario 2, ..., Scenario 20 in the following sections of the paper. These data are monitored every four hours. As these data are time-

dependent and recorded within different time windows, only failure scenarios coming from the same NPP have the same size. From the second column of Table 1, we can see that the size of the failure scenarios can vary from 389 to 3129 data points. In some of the scenarios, there are missing data points and outliers.

Table 1. C	haracteristics	of raw	and	reconstru	icted
	scona	rios			

		Beenarios	
Scenario	Size of Raw Data	Best Number of Historical values H	Size of Reconstructed Data
1	2277	17	2265
2	385	3	373
3	385	3	373
4	2027	14	2015
5	2027	8	2015
6	2027	8	2015
7	1391	13	1379
8	1391	4	1379
9	1391	4	1379
10	1391	4	1379
11	3124	12	3112
12	562	7	550
13	562	9	550
14	562	9	550
15	964	2	952
16	2767	8	2755
17	2767	7	2755
18	1061	7	1049
19	1061	12	1049
20	861	9	849

Since the dataset we are going to analyze contains both missing data and outliers, we have to deal with both these issues. First of all, we will remove anomalous data, since their extreme values would affect the results of the analysis. Outliers can be easily detected by deciding some constraints, e.g. the limits $\overline{x} \pm 3 * \sigma_x$ where \overline{x} is the mean of all the data points and σ_x is their standard deviation. These limits are needed to detect the outliers, selected as those data points bigger than $\overline{x} + 3 * \sigma_x$ or smaller than $\overline{x} - 3 * \sigma_x$, and subsequently removed. Note that we used such constraints, rather than the usual ones based on the median and the InterQuartile Range (IQR), to be more conservative in the outlier selection, due to the dependence among data.

Secondly, we want to reconstruct missing data. Note that, after the outlier selection and elimination procedure, the number of missing data has increased. A possible way to deal with the reconstruction of missing data is the local polynomial regression fitting. This local least squares regression technique estimates effectively the values when there are missing data points. Moreover, it can also be used to perform the smoothing of the available observations, in order to reduce noise. We will thus use this technique both to reconstruct data where missing, and to obtain a smoother and less noisy time series in all remaining time instances. All details can be found in Liu *et al.* (2012).

All the time series data of all failure scenarios are, then, normalized from 0 to 1.

3.2. Strategies to Build Sub-Models

Since we have a time series data set and since there is no other information available related to the target except for a set of monitored data directly related to the condition of the component of interest, the input vector of the model can only be a set of historical values. Before building the submodels of the ensemble, we, thus, need to decide the best number of historical values to be used as inputs.

3.2.1. Sub-Model Identification

For time series data, the inputs are normally a number of historical target values. Suppose a(t) represents an instance of the time series data of one failure scenario. For 1-day ahead prediction, the output y(t) is a(t+6), because the signals are monitored every four hours. In order to decide the best H for selecting the input vector $\mathbf{x}(t) =$ (a(t - H + 1), ..., a(t)) most related to the output, a partial autocorrelation analysis is carried out on each failure scenario, i.e. the correlation between the output and different temporal lags is computed. Figure 3 shows the results of this analysis on Scenario 1, where the x and y axis represent, respectively, the temporal lag (a multiple of four and the corresponding empirical hours) partial autocorrelation. The bounds of a 95% confidence interval are also shown with dashed lines in the Figure. The correlation decreases with the lag (although not linearly). and after a lag of 17 time steps, for Scenario 1 it is no longer comparable with the values observed for lags smaller than 17, i.e. the best choice is $H_1 = 17$.

A best value H_i is, thus, found for Scenario *i*, for i =1, 2, ..., 20; but this value is not the same for all scenarios, as shown in the third column of Table 1. When building an ensemble model, however, a unified size of input vector would simplify the model, since a single value of H is applied for all scenarios to reconstruct the data. If we choose a small H, some useful information would be ignored for those scenarios with larger best H; in contrast, choosing a large H would bring some perturbations to scenarios with smaller best H. In order to solve this problem, we propose the modified RBF, where C_a , calculated by partial autocorrelation analysis, controls the contribution of each variable of the input vector, when H is chosen as the largest of all the failure scenarios. For one scenario with smaller best H_i , the values for the last $H - H_i$ elements of the vector C_a are very small compared to the first H_i elements, because their correlations with the output are very weak. In this case study, we choose the biggest time step H of all the scenarios, i.e. H = 17.





3.2.2. Two Strategies to Build Sub-Models

Bagging and boosting are two of the most popular strategies to build diverse sub-models of an ensemble. However these methods are more suitable with scarce data. In our case, there are enough data (20 failure scenarios), so that two simple but efficient and reasonable strategies can be proposed.

Thanks to the sub-model identification process described before, the data for each failure scenario has been reconstructed with same structure, where the input vector is $\mathbf{x}(t) = (a(t-16), ..., a(t))$, and the corresponding output is y(t) = a(t+6), and t takes every possible value in each scenario. The size of each failure scenario after reconstruction is listed in the fourth column of Table 1.

With multiple failure scenarios available, the simplest and most immediate strategy is to build a sub-model on each failure scenario, so that the number of sub-models equals the number of failure scenarios. Because of the frequently changing operational and environmental conditions in NPP, each scenario can represent a specific process, and thus submodels built in such a way show enough diversity between each other. Another simple but effective strategy is to mix all the data points from all failure scenarios, and then divide them into different groups according to their target values y(t). A sub-model is, then, trained on each group. This strategy is inspired by the intrinsic structure of SVM/PSVR. Performance of SVM depends highly, although not only, on the training data set (or support vectors). Sub-models built on training data set considering different ranges of output values can strengthen the specialty of each sub-model on particular characteristics of the input vectors. This strategy can make the sub-models perform well on different text examples but worse on others. The proposed weighted-sum strategy to combine the outputs of sub-models will be shown to outperform the individual model. These two strategies are named Ensemble 1 and Ensemble 2, for convenience.

3.2.3. Comparison of DW-PSVR-Ensemble with Single PSVR

The ensemble model is expected to give better results than a single PSVR model. To verify this claim, a comparison between a single PSVR model and the proposed DW-PSVR-Ensemble is carried out on the considered case study.

Each time one out of 20 failure scenarios is chosen as the test data set (named Observed Scenario), the other 19 failure scenarios (named Reference Scenarios) are used to construct the ensemble model with the two previously proposed strategies. A PSVR model is also trained on the Observed Scenario for comparison (it is named Single PSVR to be distinguished from the two ensemble models). The size of the training data set for all PSVR models is fixed at 200 for the fairness of comparison. The choice of the size is decided by trial and error in order not to increase too much the computational complexity in time and storage, which increases exponentially with the size of the training data set, and in order to guarantee the accuracy of the model.

The steps of comparison are the following:

- 1. Choose the training data set for Ensemble 1: 200 data points equidistantly distributed for each Reference Scenario are selected. Totally, 19 sub-models can be trained with PSVR, each trained on 200 data points from each scenario.
- 2. Choose the training data set for Ensemble 2: the normalized data of 19 Reference Scenarios are sorted according to the output value of each data point and then divided into 10 groups, with the output value in the intervals of [0, 0.1], [0.1, 0.2], ..., [0.9, 1]. For each group, if the size is bigger than 200, 200 data points equidistantly distributed in the group are chosen, if not, all the points in the group are used in the training data set. For the first eight groups, the size of training data set is 200, while for the last 2, the training data sets contain only 90 and 33 data points. Ten sub-models are built with PSVR on these training data sets.
- 3. Choose the training data set for the single PSVR: the first 200 data points of the Observed Scenario are chosen to train one single PSVR model for regression on it.
- 4. Calculation of Mean Absolute Error (MAE), Mean Relative Error (MRE), width of Prediction Intervals (PIs) with 95% confidence level (PI_Width), and coverage percentage of PIs with 95% confidence level (PI_Coverage) of the outputs of Ensemble 1, Ensemble 2 and Single PSVR.

5. Comparison of Ensemble 1, Ensemble 2 and Single PSVR considering prediction accuracy, uncertainty of estimation and robustness.

The results and comparisons between these three models are presented in the next section.

4. RESULTS

In this section, the results from Ensemble 1, Ensemble 2 and Single PSVR are compared with respect to different aspects.



Figure 4. MAE of prediction results of Ensemble 1, Ensemble 2 and Single PSVR, for all 20 failure scenarios.



Figure 5. MRE of prediction results of Ensemble 1, Ensemble 2 and Single PSVR, for all 20 failure scenarios.



Figure 6. Width of PIs with 95% confidence level of prediction results of Ensemble 1, Ensemble 2 and Single PSVR, for all 20 failure scenarios.



Figure 7. Coverage of PIs with 95% confidence level of prediction results of Ensemble 1, Ensemble 2 and Single PSVR, for all 20 failure scenarios.

4.1. Prediction Accuracy and Uncertainty Estimation

Figures 4, 5, 6 and 7 are the prediction results (including MAE, MRE, width and coverage of PI with 95% confidence level, i.e. $[\hat{y} - 1.97\sigma, \hat{y} + 1.97\sigma]$, where σ is the variance of the assumed Gaussian distribution of the predicted value), respectively from Ensemble 1, Ensemble 2 and Single PSVR. It is clear that Single PSVR gives worst results in this case study, i.e. on average, the MSE and MAE are bigger than the ensembles and PI Coverage is lower compared to the ensembles. There is no such problem with Ensemble 1 and Ensemble 2, because the training data set contains more information than that of Single PSVR. Moreover, Ensemble 1 gives better results than Ensemble 2 considering the prediction accuracy, with more stable PIs. This is caused by the scarceness of the training data set for the last two sub-models of Ensemble 2, which are supposed to be experts on the prediction of the data points with output values in the intervals of [0.8, 0.9] and [0.9, 1.0].

We also notice that Single PSVR can give comparable prediction accuracy to the ensemble models for some failure scenarios, but not for all of them. The bad results of Single PSVR are caused by the fact that the prediction results are highly dependent on the training data set. Moreover, the hyperparameters optimization is also critical to the performance of PSVR. Well-chosen hyperparameters values can improve the performance of PSVR. However, the optimization method can easily converge to a local extreme, which results into a good performance at the beginning but very bad at the end of the scenario.

These unstable results from the Single PSVR prove the necessity of the ensemble approach for avoiding the limits of Single PSVR in attaining the desired accuracy and robustness of the model. The prediction results from Ensemble 1 and Ensemble 2 confirm the practicability and efficiency of the DW-PSVR-Ensemble approach.

4.2. Robustness

From Figures 4, 5, 6 and 7, it is seen that the ensemble models give more stable prediction results compared to the Single PSVR model. Single PSVR model cannot properly handle the noise in the data and it is difficult to find the global optimal values of the hyperparmeters, even with the modified RBF proposed in this paper. The weighted-sum ensemble models can decrease the influence of the noise by combining the prediction outputs of the sub-models; this is one reason for which ensemble models can give stable results, i.e. the ensemble models are more robust compared to the Single PSVR.

5. CONCLUSION

In this paper, we have proposed an innovative dynamicweighted PSVR-based ensemble approach for short-term prediction (1-day ahead prediction) with multiple time series data. Local fitness calculation is integrated to calculate the specific weights of the sub-models of the ensemble for each new input vector without bringing too much computational burden. A modified RBF kernel is used to discriminate the different correlation of the different inputs with the output.

According to the characteristics of the available time series data in the case study, two strategies are proposed to form an ensemble model: one considering different scenarios and the other selecting different ranges of output values. In both cases, the proposed ensemble approach performs well in the real case study of signals recorded on a NPP component. Compared to the single model PSVR, the proposed ensemble models outperform on prediction accuracy, robustness and adaptability. This ensemble approach demands enough data on different pattern drifts.

Further research needs to be carried out, for optimizing the numbers of sub-models and for obtaining a more careful tuning of the hyperparameters.

REFERENCES

- Acar, E., & Rais-Rohani, M. (2009). Ensemble of metamodels with optimized weight factors. *Structural* and Multidisciplinary Optimization, 37(3), 279-294.
- Bauer, E., & Kohavi, R. (1999). An empirical comparison of voting classification algorithms: Bagging, boosting, and variants. *Machine learning*, 36(1-2), 105-139.
- Baudat, G., & Anouar, F. (2003). Feature vector selection and projection using kernels. *Neurocomputing*, 55(1-2), 21-38.
- Chen, S., Wang, W., & Van Zuylen, H. (2009). Construct support vector machine ensemble to detect traffic incident. *Expert systems with applications*, 36(8), 10976-10986.
- Gao, J. B., Gunn, S. R., Harris, C. J., & Brown, M. (2002). A probabilistic framework for SVM regression and error bar estimation. *Machine Learning*,46(1-3), 71-89.
- Gurram, P., & Kwon, H. (2013). Sparse kernel-based ensemble learning with fully optimized kernel parameters for hyperspectral classification problems.*Geoscience and Remote Sensing, IEEE Transactions on*, 51(2), 787-802.
- Hu, C., Youn, B. D., Wang, P., & Taek Yoon, J. (2012). Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. *Reliability Engineering & System Safety*, 103, 120-135.
- Kim, H. C., Pang, S., Je, H. M., Kim, D., & Yang Bang, S. (2003). Constructing support vector machine ensemble. *Pattern recognition*, 36(12), 2757-2767.
- Liu, J., Seraoui, R., Vitelli, V., & Zio, E. (2013). Nuclear power plant components condition monitoring by probabilistic support vector machine. *Annals of Nuclear Energy*, 56, 23-33.
- Minh, H. Q., Niyogi, P., & Yao, Y. (2006). Mercer's theorem, feature maps, and smoothing. In *Learning theory* (pp. 154-168). Springer Berlin Heidelberg.
- Muhlbaier, M. D., Topalis, A., & Polikar, R. (2009). Learn. NC: Combining Ensemble of Classifiers With Dynamically Weighted Consult-and-Vote for Efficient Incremental Learning of New Classes. *Neural Networks, IEEE Transactions on*, 20(1), 152-168.
- Polikar, R. (2006). Ensemble based systems in decision making. *Circuits and Systems Magazine*, *IEEE*, 6(3), 21-45.
- Razavi-Far, R., Baraldi, P., & Zio, E. (2012). Dynamic Weighting Ensembles for Incremental Learning and Diagnosing New Concept Class Faults in Nuclear Power Systems. *Nuclear Science, IEEE Transactions* on, 59(5), 2520-2530.
- Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. Statistics and computing, 14(3), 199-222.
- Sollich, P. (1999). Probabilistic interpretations and Bayesian methods for support vector machines. In *Artificial Neural Networks*, 1999. ICANN 99. Ninth International

Conference on (Conf. Publ. No. 470) (Vol. 1, pp. 91-96). IET.

- Valentini, G., & Dietterich, T. G. (2003, August). Low bias bagged support vector machines. In *ICML* (pp. 752-759).
- Yang, X., Yuan, B., & Liu, W. (2009, November). Dynamic Weighting Ensembles for incremental learning. In *Proc.* of *IEEE conference in pattern recognition* (pp. 1-5).

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Remaining Useful Life Estimation for Air Filters at a Nuclear Power Plant

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ABSTRACT

The exhaust ventilation air from nuclear power plants and other nuclear facilities is carefully filtered, as aerosols are a potential vector of contamination. Monitoring the condition of the air filters improves radiation safety. In this paper the progression of differential pressures over air filters at a nuclear research reactor have been studied. Technical properties and possible environmental influences have been checked in order to understand the variation of the pressure over time. The differential pressure has been decomposed into different components as a result of an analysis of environmental conditions. The gradually increasing component, representing gradual accumulation of aerosol particles in the filter, is modeled as a gamma process and an estimate for determining the remaining useful life of the air filters has been computed.

1. INTRODUCTION

At most nuclear power plants there are relatively long periods of operation, typically about one year, before the plant is shut down for an outage period of several weeks for inspection, maintenance and possibly also refueling. For economical and safety reasons it is desirable to avoid unplanned shutdowns and keep the outage period as short as possible. The estimation of the remaining lifetime for air filters at a nuclear facility can therefore help in planning the optimal outage period for changing air filters. In addition to advancing safety and improving maintenance planning, this also helps to minimize radioactive waste. The OECD Halden Reactor project is an international research program with 20 member countries. One of the research themes deals with condition based maintenance at nuclear power plants. This paper describes methods developed within this project for estimating the remaining useful life (RUL) of air filters at nuclear power plants.

The air filter data described in this paper is measured at one of the two research reactors belonging to the institute. The data contains measurements of the differential pressure over the air filters for air originating at two different locations in the reactor building. One of the locations is the reactor hall, and the other location is a laboratory where radiation experiments are held.

2. TOWARDS RISK-INFORMED DECISION MAKING

Filtration of exhaust air from nuclear facilities forms a barrier against nuclear contamination. High-efficiency particulate air (HEPA) filters are used as the final filtration stage due to their high particle removal efficiency. Another requirement for filters in these applications is durability even in unlikely scenarios, including e.g., earthquakes and explosions. Glass fiber media in HEPA filters is brittle and loses strength with aging (First, 1996; Winegardner 1996). With the current state of the art filter changes are based on conservative pressure difference and age limits (e.g., 10 years from the date of manufacture) defined with the main focus of maintaining adequate physical strength. (U.S. Department of Energy, 2003). This is in contrast to most air filtration applications, where the energy cost of ventilation is a major factor in determining filter replacement policies (Gustavsson, Ginestet, Tronville & Hyttinen, 2011).

As aerosol particles are accumulated in a filter, its permeability decreases, and consequently forces acting on the aging material increase (Brown, 1993). As increasing forces due to filter loading and the weakening of the

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material aren't considered jointly in the current state of the art (Gustavsson et al., 2011), filter replacement limits have to be set quite conservative. Prediction of pressure drop development, and consequently RUL facilitates time-based maintenance procedures to be superseded by condition based maintenance. As a further advantage, comparing actual pressure drop to predicted development facilitates monitoring of increased aerosol emissions.

Prediction of pressure drop development is also a step towards risk-informed decision making. In this approach, complex safety-related issues are evaluated where probabilistic risk assessment is used as a tool in design, operation, and regulation to achieve an acceptable overall risk level (U.S. Nuclear Regulatory Commission, 2011; Varde & Pecht, 2012). In the case of air filtration this would involve, e.g., defining monitoring and replacement procedures based on predictions of filter strength and permeability developments combined with estimated probabilities of pressure shocks and evaluated consequences of mechanical failures.

3. COLLECTED AIR FILTER DATA

3.1. How the air is filtered at the reactor site

The inlet air is split in three tubes where the air is filtered and heated or cooled down before it is sent to the destination rooms. The target temperature is regulated and supposed to be constant at 20°C all year, which means that the air is cooled down occasionally during summer and heated otherwise. In addition to the reactor hall and laboratory, the air is sent to adjacent rooms, but data in this paper is collected only for air from the reactor hall and laboratory.

The outlet air is filtered through three types of filters; a coarse filter, a fine filter and a micro filter (HEPA filter). All three filters are changed at the same time based on the value of the pressure difference, dP(t), which is measured over all three filters.

3.2. Differential pressure

The collected data are from 1974 until now (2014) and are written down on paper schemas. In this first phase, data from the end of 2000 until the end of 2013 have been converted to digital form suitable for computer analysis.

The differential pressures over the air filters from the two different locations, plotted in Figures 1 and 2, have different signatures. The differential pressure over the air filters for the laboratory has clear seasonal variation, so that the pressure drop decreases each spring. This is especially visible when the air filters have a high load of particles, with pressure drop decreasing up to about 20 % from winter to the following summer.

The two locations are used very differently. While the entrance and exits to the reactor hall are practically sealed,

the laboratory is a working environment with direct exits to the outdoor area where unfiltered air from the external environment can enter the room. To prevent leakage of radioactive particles, the indoor air pressure is kept adequately below the outdoor air pressure.

Filter changes can be seen in the pressure difference graphs as sharp drops down to ca. 20 mmH₂O and are indicated with vertical dashed lines in Figures 1 and 2. The filter pack was changed only once for the reactor hall and twice for the isotope laboratory during the studied period.



Figure 1. The differential pressure over air filters for air coming from the reactor hall.



Figure 2. The differential pressure over air filters for air coming from the isotope laboratory.

Some step-like increases of the differential pressure occur occasionally at both locations. It is not known what is causing these jumps, but it can be e.g. maintenance operations that contribute to extra loading of the filters.

The differential pressure for air filters is commonly assumed to be monotonically increasing as particles accumulates in the filters under constant environmental conditions. The observed data, however, is clearly non-monotonic. The decreases in the data are assumed to be caused by both changing environmental conditions (especially humidity), measurements errors, and possible variations in air flow.

3.3. Air quality

As changing environmental conditions were hypothesized to influence the observed pressure drop, measurement data from a nearby weather station was retrieved. Available data included time series of outdoor air pressure, temperature, and humidity (Norwegian Meteorological Institute, 2014). Indoor humidity was estimated by computing the absolute amount of water in the incoming air and transforming it to relative humidity at 20 °C, which was the regulated indoor temperature.

Data on particle concentrations in the outdoor air in the vicinity of the studied facility was not available. Availability of such data would have aided in understanding the observed phenomena. However, its interpretation wouldn't have been trivial due to both the large number of different particles assumedly present and most of the particle concentrations showing a seasonal variability that correlates with the seasonal variability in the pressure drop data.

3.4. Radioactivity measurements

Radioactivity is also monitored in addition to differential pressures. It is measured at four different locations in the vicinity of the metal casings of the air filters. As particles accumulate in the air filters, the radioactivity readings will increase. The activity measurements can give an indication of unusual radioactive pollution in either location.

4. METHODS USED FOR RUL ESTIMATION

In RUL estimation the development of the differential pressure dP(t) is modeled as an aggregation of three phenomena, each occurring at different time scale:

$$dP(t) = dP_1(t) + dP_2(t) + dP_3(t) + dP_0 + \varepsilon(t)$$
(1)

The modeled phenomena are:

- 1. $dP_1(t)$: Gradual accumulation of aerosols
- 2. $dP_2(t)$: Sporadic large aerosol emissions.
- 3. $dP_3(t)$: Seasonal variation.
- 4. dP_0 : Differential pressure of a new clean filter.

5. $\varepsilon(t)$: Residual variation, comprising e.g. measurement errors.

Gradual accumulation of aerosols causes the differential pressure to increase with a functional form that is characteristic to each combination of (not fully known) aerosol and filter characteristics. This phenomenon is modeled as a stochastic gamma process, where the gradual development of the pressure drop dP(t) is identified as a large number of small mutually independent gamma distributed increments (van Noortwijk, 2003):

$$dP_1(\tau) - dP_1(t) \sim \operatorname{Ga}(v(\tau) - v(t), u) \ \forall \ \tau > t \ge 0$$
(2)

The shape function $v(\tau)$ of the gamma process represents the above mentioned functional form. Utilizing data from preceding filter lifetimes in shape function identification improves the reliability of the RUL estimates especially for long prediction horizons (Saarela, Nystad, Taipale & Ventä, 2013). In this study a fit that was subjectively considered as adequately good (see discussion in Section 5.2) was achieved with a power law shape function

$$v(t) = ct^b \tag{3}$$

where parameters c and b are identified from measured data. The expected value of the gamma process can then be calculated as

$$E\{dP_1(t)\} = \frac{v(t)}{u} = \frac{c}{u}t^b$$
(4)

which is then extrapolated to future time values in RUL prediction.

Sporadic large aerosol emissions are caused by, e.g., some maintenance operations. They are modeled as stepwise increments in the differential pressure. A statistical identification of these larger increments could be based on, e.g., identifying a probability distribution of the observed increments and determining a classification threshold based on a predefined significance level (Box, Hunter & Hunter, 2005). Instead of such a data-driven approach, however, classification based on a priori knowledge (especially times of maintenance operations) was seen as preferable. These sporadic phenomena were modeled as

$$dP_2(t) = \sum_{i} dP_{2,i} * (t > t_i)$$
(5)

where t_j are the times and $dP_{2,j}$ the magnitudes of these sporadic large increases of the pressure drop. The logical expression $(t > t_j)$ is here interpreted to produce a value 1 for true and 0 for false.

Seasonal variation of the pressure drop is hypothesized to be caused by changes in relative air humidity as the heating of the input air varies. In filter loading laboratory experiments an increasing humidity has been observed both to decrease differential pressure (by facilitating especially larger particles already captured in the filter to rearrange) and to increase differential pressure (due to particles of various hygroscopic salts expanding especially in high humidity) (Joubert, Laborde, Bouilloix, Chazelet & Thomas, 2011; Miguel, 2003).

A detailed modeling of humidity-related air filtration phenomena would require comprehensive data of, e.g., the time history of aerosol composition. Most importantly, distributions of the hygroscopic properties of the particles would have to be known for past and assumed to remain relatively unchanged for the future. As such information was unavailable, seasonal variation observed in the data was modeled with a data-driven approach. Applying the principle of Occam's razor (Burnham & Anderson, 2002), the simplest possible model with adequate modeling accuracy was sought for. A simple, yet reasonably accurate (see discussion in Section 5.2) model found turned out to be a sinusoid whose amplitude was directly proportional to $dP_1(t)$:

$$dP_3(t) = e * dP_1(t) * \sin(2\pi t_d/365 + t_{d0})$$
(6)

where t_d indicates the number of the day from the beginning of each year. Coefficient *e* and day offset t_{d0} were identified from data using differential evolution (Storn & Price, 1997) to minimize least squares cost function. In this optimization, term $dP_1(t)$ in Eq. 6 was replaced by its expected value (Eq. 4) identified from the same data set.

5. ESTIMATED LIFETIMES FOR THE AIR FILTERS

5.1. Reactor hall

Three distinctive steps were identified from the historical data for the differential pressure over the filters for air from the reactor hall. Their magnitudes were determined by visual inspection to be 3 mmH₂O, 3 mmH₂O, and 5 mmH₂O. After the last step the differential pressure had increased by 11 mmH₂O due to sporadic stepwise changes since the start of the data series.

The stepwise increase of the data was subtracted from the data before a median filter was applied to reduce the effect of noise and to have a monotonically increasing data series.

The data then looks to be close to a parabolic curve. The actual form of the curve is not known since it is expected to change depending on the type distribution, size distribution and amount of particles in the air and the total airflow. A RUL estimation of the data using the gamma process model (Eq. 2) with power law shape function (Eq. 3) was carried out using the algorithms described in (van Noortwijk, 2003; Saarela et al., 2013). Values for the shape function parameters c and b were identified using the maximum likelihood approach, giving:

$$c \approx 0.066, \ b \approx 1.92 \tag{7}$$

Figure 3 shows the data series after subtracting the stepwise increases and applying the median filter (solid line). The predicted power law function v(t) is plotted as a dotted line.

The threshold for the end of life should be determined from the recommended maximum pressure or operational performance in the specification of the filters. This information has not been obtained and it is set to 24 mmH₂O (dashed line), which corresponds to the threshold when the filter is changed.

At filter age 3600 days, the model gives a predicted end of life at filter age 4580 days with a 95 % confidence interval of [4160, 5120]. This prediction was made more than a year before the filters were changed.



Figure 3. Predicted power law function, differential pressure and a RUL threshold.

5.2. Isotope laboratory

The differential pressure measured at the isotope laboratory exhaust air filter had a distinct seasonal component. This data was modeled as a sum of the three components discussed above. The identified components, representing phenomena of different time scales are plotted in Figure 4. The identified seasonal variation $dP_3(t)$ has its minima at each summer, when input air is not heated and consequently indoor humidity is high. The straight line segments in the seasonal variation are time intervals for which original measurement data was not available.



Figure 4. Three components of pressure drop development identified from the data measured at the isotope laboratory exhaust air filter.

The modeled differential pressure, i.e., the sum of the three identified components is plotted together with measured data in Figure 5. The standard deviation of the residual $\sigma(\varepsilon(t))$ was $\approx 2.6 \text{ mmH}_2\text{O}$ for six months preceding the RUL prediction time. The reading-to-reading variability in the measured data had roughly an equal standard deviation $\sigma(dP(t_{i+1}) - dP(t_i)) \approx 2.8 \text{ mmH}_2\text{O}$ in the same time interval. This was subjectively considered as accurate enough to represent the pressure drop trend, while keeping the number of identified parameters reasonably small to reduce the risk of overfitting. This assessment also implies that the used functional forms (seasonal sinusoid and power law shape function) were considered as adequately applicable. However, the impact of modelling accuracy to the RUL estimation accuracy (Saxena, Celaya, Saha, Saha & Goebel, 2010) must be studied in further phases of this work.

Identified values for the shape function parameters

$$c \approx 0.017, \ b \approx 2.45$$
 (8)

differ from those identified from the reactor hall data. Since the filtration system is equivalent, the difference reflects the dissimilarities of aerosol concentration and composition.

Figure 6 depicts RUL estimation using the data series after subtracting the identified seasonal variation and the stepwise increase and applying the median filter (solid line). The predicted power law function v(t) is plotted as a dotted line.



Figure 5. Measured and modeled differential pressure at the isotope laboratory exhaust air filter.

RUL was estimated at filter age 2600 days, assuming 45 mmH_2O as the filter change threshold. The gamma process model representing gradually accumulating aerosols gives a predicted end of life at filter age 3040 days with a 95 % confidence interval of [2760, 3500] days.



Figure 6. Predicted values of the power law function at the isotope laboratory exhaust air filter.

The seasonal variation is predicted simply by extrapolating the identified sinusoid and using the prediction from the gamma process model in computing the increasing amplitude. For final prediction, depicted in Figure 7, these predicted pressure drop components are added together. The 95 % confidence interval in Figure 7 was computed from the identified gamma process model, Eq. 2. In this simplified approach the uncertainties of the identified seasonal and sporadic component were not considered separately. Further study is required for understanding their impact on the reliability of the RUL estimate. Especially, inaccuracies in the identification of the seasonal component influence the identification of the gamma process in a way that is not compliant with the assumption of mutual independency of increments made in the theory of gamma processes.



Figure 7. Predicted values of the pressure drop development at the isotope laboratory exhaust air filter.

6. CONCLUSIONS

Historically HEPA filters were developed for the removal of radioactive particles from air streams in nuclear facilities. Monitoring the loading of the air filters and estimating their remaining useful life can enhance the facilities ability to plan ahead and optimizing their maintenance schedule.

In this study the measured differential pressure was decomposed into components representing phenomena of different time scales. RUL was estimated from the decomposed time series. The results suggest the applicability of this approach for estimation of RUL of air filters. Gamma process models are seen suitable for modelling gradual lifetime expenditure, especially as it easily adapts to the steeper increase of the differential pressure towards the end of filter life. Naturally the shape function representing the functional form of differential pressure development and values for model parameters have to be identified for each application separately.

In this analysis, measured differential pressure at one location was found to have a strong seasonal variation. The amplitude of this variation increased as more particles accumulated in the filter. The phase of this variation was such that its minima coincided with the highest values of relative humidity of the indoor air.

Modeling large sporadic aerosol emissions and seasonal variations separately facilitated increased accuracy in modeling the gradual pressure drop development. Evaluation and quantification of the RUL prediction accuracy will be topics in further phases of this work, where data from multiple filter life times will be utilized.

Besides more accurate RUL estimates, modelling relevant phenomena separately allows more reliable detection of sporadic aerosol emissions when actual pressure drop deviates significantly from what is predicted. Consideration of high humidity values in pressure drop calculation is also relevant to fault scenarios involving release of steam.

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REFERENCES

- Box, G. E. P., Hunter J. S., & Hunter, W. G. (2005). *Statistics for experimenters*. Hoboken, NJ, USA: John Wiley & Sons.
- Brown, R. C. (1993). Air filtration An integrated approach to the theory and applications of fibrous filters. Oxford, UK: Pergamon Press.
- Burnham, K. P., & Anderson, D. R. (2002). Model selection and multimodel inference. New York, NY, USA: Springer Verlag.
- First, M. W. (1996). Aging of HEPA filters in service and in storage. *Journal of the American Biological Safety Association*, 1 (1).
- Gustavsson, J. (ed.), Ginestet, A., Tronville, P., & Hyttinen, M. (2011). Air filtration in HVAC systems. REHVA Guidebook 11. Brussels: REHVA.
- Joubert, A., Laborde, J. C., Bouilloix, L., Chazelet, S., & Thomas, D. (2011). Modelling the pressure drop across HEPA filters during cake filtration in the presence of humidity. *Chemical Engineering Journal*, 166 (2).
- Miguel, A. F. (2003). Effect of air humidity on the evolution of permeability and performance of a fibrous filter during loading with hygroscopic and non-hygroscopic particles. *Journal of Aerosol Science*, 34 (6).
- Norwegian Meteorological Institute (2014). Weather data in <u>http://eklima.met.no/</u> accessed 3.1.2014.
- van Noortwijk, J. M. (2003). A stochastic deterioration process for time-dependent reliability analysis. *The Eleventh IFIP WG 7.5 Working Conference on Reliability and Optimization of Structural Systems*, November 2-5, Banff, Canada.

- Saarela, O., Nystad, B. H., Taipale, A., & Ventä, O. (2013). Selection and identification of a shape function for modeling degradation as a gamma process. *International Workshop on Structural Health Monitoring*, September 10-12, Stanford, CA, USA.
- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2010). Metrics for offline evaluation of prognostic performance. *International Journal of Prognostics and Health Management*, 1(1).
- Storn, R., & Price, K. (1997). Differential evolution a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11 (4).
- U.S. Department of Energy (DOE) (2003). *Nuclear air cleaning handbook*. DOE technical standards, DOE-HDBK-1169-2003. Washington: DOE.
- U.S. Nuclear Regulatory Commission (NRC) (2011). An approach for using probabilistic risk assessment in risk-informed decisions on plant specific changes to the licensing basis. Regulatory Guide 1.174, Revision 2. Washington: NRC.
- Varde, P. V., & Pecht, M. G. (2012). Role of prognostics in support of integrated risk-based engineering in nuclear power plant safety. *International Journal of Prognostics and Health Management*, 3 (1).
- Winegardner, W. K. (1996). Phase I aging assessment of nuclear air-treatment system high efficiency particulate air and adsorbers. *Nuclear Engineering and Design*, 163 (3).

BIOGRAPHIES

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Prognostics for Light Water Reactor Sustainability:

Empirical Methods for Heat Exchanger Prognostic Lifetime Predictions

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ABSTRACT

As the licenses of many nuclear power plants in the US and abroad are being extended, the accurate knowledge of system and component condition is becoming more important. The US Department of Energy (DOE) has funded a project with the primary goal of developing lifecycle prognostic methods that generate accurate and continuous remaining useful life (RUL) estimates as components transition through each stage of the component lifecycle. These stages correspond to beginning of life, operations at various expected and observed stress levels, the onset of detectable degradation, and degradation towards the eventual end of life. This paper provides an overview and application of a developed lifecycle prognostic approach and applies it to a heat exchanger fouling test bed under accelerated degradation conditions. The results of applying the lifecycle prognostic algorithms to the heat exchanger fouling experiment are given, followed by a discussion of the strengths and shortcomings of the developed techniques for this application.

1. INTRODUCTION

The field of systems and component level prognostics focuses on the determination of overall system health and RUL to provide safety, reliability, and financial benefits. The interest in this field is growing as more commercial reactor licenses seek to extend operations past original design lifetimes. As the operating life of the nuclear plant is increased, concern for the reliability and safety of the system components also grows. Development of online prognostic models for the RUL of many components can lead to more efficient maintenance scheduling, and when used for on-line monitoring, can reduce sudden loss of operations from unexpected component failure. The goals of well-made prognostic models are to lessen plant down time and the related loss of revenue.

Current research focuses on the development of prognostic methods and models for estimating RUL throughout the lifetime of a component. To validate the developed methods, three accelerated degradation test beds have been constructed. These test beds include setups for induction motor degradation, pump impeller degradation, and heat exchanger fouling. Nuclear Power Plants (NPP) contain many heat exchangers, each of which is crucial to the overall performance of the plant. This is why accurate monitoring and modeling of the RUL for these heat exchangers is so important. Possibly the most important heat exchanger for maintenance purposes is the NPP condenser. Failure to remove waste heat in the system by the condenser can significantly reduce plant capability to maintain vacuum resulting in derating the NPP, which has occurred during hot summer months at several NPPs, including Watts Bar, resulting in a derating from loss of efficiency (Buecker 2009). Between 2008 and 2010, the North American Electric Reliability Corporation (NERC) stated that condenser associated performance issues were responsible for the removal of over 9.1 million megawatt hours from the energy grid (Fayard 2011). In an effort to reduce the effects of this efficiency loss for NPPs, the analysis given in this paper is implemented on the data collected from the small scale heat exchanger fouling experiment onsite at the University of Tennessee. This paper presents the development of a data-driven model for degradation detection methods, collection of system health indicators, and finally lifecycle prognostic prediction model development.

The structure of this paper is as follows: A brief discussion of the background for heat exchanger fouling research and

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the steps necessary to develop a lifecycle prognostics model for a heat exchanger system with a short explanation of each step. Next is a description of the heat exchanger setup and operating procedure used to generate the data for lifecycle prognostics model generation. This will be followed by a detailed report of the steps taken to develop the lifecycle model such as signal/feature selection, auto-associative kernel regression model development, prognostic parameter generation, general path model generation and Bayesian updating implementation. These methodologies will be followed by the lifecycle prognostics model results and a conclusion.

2. BACKGROUND

Research into heat exchanger degradation modeling is focused mainly on simulated heat exchanger system data, such as plate heat exchanger with simulated milk fouling (Georgiadis and Macchietto 2000). Unlike the physical heat exchanger test bed, simulated models provide the ability to quickly generate large sample data sets with multiple failure modes. Ardsomang et al. (2013) utilizes physics models for heat transfer and effectiveness to estimate the RUL of simulated heat exchanger data. Physics based methods for detecting fouling in heat exchangers, such as Kalman filtering utilizing first principles models, are also currently used (Jonsonn et al. 2007). Because the models are physics based, some of the parameters used for development are dependent on the heat transfer coefficient of the heat exchanger. For example, when significant fouling occurs, there is a reduction in heat transfer, which can be seen as changes in model parameters over time. This application of extended Kalman filtering is also sensitive when moderate fouling is introduced, showing this as a physics based approach that is well suited for on-line fouling detection in heat exchangers. The use of extended Kalman filters with temperature and flow rate sensor data shows an example of a state spaced model that can implement physics based approach to effectively detect heat exchanger fouling.

Alternatively, a physical test bed allows for validation of the degradation models with real world signals collected from the heat exchanger. Simulated models must be designed to include a robust set of different conditions and failure mechanisms, whereas with real world experimentation different natural failure mechanisms, operations, and noise are inherent to the physical setup. Another inherent advantage of test beds is that unexpected developments in testing may not be considered when designing simulation models. For example, if a simulation of an induction motor system is developed to model the conditions of onset bearing failure, there may actually be several different failure modes, such as electrical, shaft or bearing, which the simulation will not implement. Using test bed data prevents the need for additional concerns in design. Simulated heat exchanger modeling is presently used mainly for on-line

monitoring, diagnostics and fault detection (Upadhyaya et al., 2004). Unlike many first principle models, empirically driven models are developed almost exclusively on historic unfaulted data. Real-time data can be passed through to these models and monitored for deviations from expected normality.

One type of empirical modeling technique is based on the auto-associative kernel regression (AAKR) (Wand and Jones 1995). AAKR models are built using vector selection techniques on unfaulted data to construct a memory matrix. The AAKR model in this study is an error correction model constructed using fault free data built off of methods developed by Yang et al (2006). When faulted data is input to the model, the output is a corrected version of the faulted input data. When the corrected data is compared to the actual data, the difference between them is termed residuals. As a component degrades, the residuals will increase until failure. Figure 1 shows the basic arrangement of the AAKR based prognostic system. Operational data is input and residuals are calculated. These residuals can be combined into a prognostic parameter, which is related to the health of the system. A prognostic model is developed to explain the degradation process and predict the system RUL. These four steps, AAKR modeling, prognostic parameter generation and prognostic modeling, are discussed in subsequent sections.



Figure 1 – Basic arrangement of an AAKR based prognostic system.

Prognostic models can be classified into three types based on the type of data used in the model (Hines et al. 2007). The first of these, Type I, or simple time-to-failure distribution models, are used to estimate the failure times of a system, generally before operation begins or if there is no information available from the query system other than run time. Stressor information such as the flow rates for heat exchangers can be used to improve the estimates starting at the early stages of operation when expected or continuing stress levels are known with the second type of model, a Type II prognostic model. When quantifiable measured or inferred degradation is detected in the system, Bayesian techniques can be used to further transition to a Type III model, such as the general path model, for more accurate RUL estimates.

The general path model (GPM) was first proposed by Lu and Meeker (1993), and was first used for prognostics by

Upadhyaya et al. (1994). GPM is commonly used to extrapolate some measure of system health, called the prognostic parameter, built from degradation data by means of a regression fit. For prognostics, past degradation cycles can be analyzed, and an appropriate functional fit type (linear, quadratic, etc.) can be determined and applied to an unfailed case with detectable levels of degradation. The regression model is then extrapolated to some failure threshold and the time to failure (TTF) is calculated. This method of utilizing GPM, along with Bayesian inference, is applied to the heat exchanger test bed.

Bayesian methods for including prior information are based on Bayes' theorem and can be used for regression problems. It has been shown by Coble and Hines (2011) that Bayesian inference for application in prognostics problems can be successfully used to update GPM regression weights based on prior information. By appending weighted inputs to the matrices, GPM regression can be purposefully biased towards historical paths or failure times. This method of Bayesian updating for use on the heat exchanger experiment data is discussed in section 4.

3. EXPERIMENTAL SETUP AND DATA ACQUISITION

The heat exchanger fouling test bed experiment was designed to increase the rate of fouling degradation of a tube and shell heat exchanger by expedited process side fouling. The system contains 8 sensors to monitor temperature, flow, and pressure within the 64 tube cross-flow heat exchanger, shown in Figure 2 and summarized in Table A1.



Figure 2 - Schematic of heat exchanger physical setup

As seen in Figure 2, there are thermocouples at each of the four entrances and exits of the heat exchanger used to measure the incoming and outgoing temperature of the hot and cold legs: sensors 1, 2, 3, and 4, respectively. Pressure transducers are at both ends of the heat exchanger hot leg to measure the pressure variation (sensors 7 and 8). There are two turbine style flow meters to measure flow velocity of the hot and cold legs (sensors 5 and 6, respectively). A

LabVIEW data acquisition (DAQ) system is used to sample and record the signals at 0.1 Hz. Three 250 watt heaters are used to heat the reservoir water for the hot leg supply, and a 0.5 horsepower (HP) pump is used to facilitate flow. The heat exchanger used for this test bed is the Basco 64 tube and shell. Each hot leg tube is 0.25 inches in diameter and 24 inches in length. A full list of system components is given in Table 1.

	Component	Brand	Location
	Thermocouple	Omega	Hot Leg Inlet Hot Leg Outlet Cold Leg Inlet Cold Leg Outlet
nsors	Turbine Flow Meter	Blancett	Hot Leg Inlet Cold Leg Outlet
Se	Pressure Transducer	Dwyer	Hot Leg Inlet Hot Leg Outlet
	Data Acquisition System	Texas Instruments	N/A
	Heat Exchanger	Basco	N/A
nents	250 Watt Heater	Tempco	Two on top of tank One on bottom of tank
Compo	15 Gallon Reservoir Tank	McMaster- Carr	Hot Leg - Below Heat Exchanger
	0.5 HP Pump	Berkeley	Below Tank

Table 1 - Major systems components, brand, and location

Tube and shell heat exchanger degradation occurs most commonly as continuous fouling within the tubes, that results in a reduction in heat transfer to the point where it no longer meets specifications (Upadhyaya et al. 2004). For the scope of this experiment, this reduction in heat transfer is due to particulate fouling inside the process side tubes. To accelerate fouling of the test bed experiment, kaolin (china clay) is added to the hot leg water. At startup, a mixture of water and 105 grams of clay is added to the system, with additions of 75 grams of clay in solution every 48 hours during the cycle. This regular addition of clay helps to maintain a consistent clay density in solution within the system. Without these regular additions, the clay has a tendency to fall out of solution and settle in the reservoir tank. The typical cycle is 14 days of continuous operation at 1 gallon-per-minute in the hot and cold legs (excluding down time during clay addition).

Operational data have been collected for eight cycles run at one gallon-per-minute. For the purposes of this paper, the average flow rate can be considered a stress related variable as it is directly related to the fouling rate. The flow rate is important for the stressor-based prognostic algorithms, and in future research will be varied during a data collection cycle; for the extent of this paper, each cycle is held at near constant flow rate.

4. MODEL DEVELOPMENT

To determine an optimal lifecycle prognostic method, multiple competing models were created. Four signal sets were selected to build the models, and ordinary least squares regression of each residual set was used to produce prognostic parameters. For the GPM, a linear and quadratic fit was used for each case, and Bayesian updating was applied. These will be further discussed in the following sections.

4.1. Signal and Feature Sets

From the data, certain features such as log mean temperature difference (LMTD), heat rate, and delta temperatures are calculated. The two features used in the prognostics models are heat rate and overall heat transfer coefficient given by equations 1 and 2b respectively.

$$\dot{Q}_{h/c} = \dot{m}C_p(T_1 - T_2) \tag{1}$$

$$LMTD = \frac{(T_{h1} - T_{c2}) - (T_{h2} - T_{c1})}{\log(\frac{T_{h1} - T_{c2}}{T_{h2} - T_{c1}})}$$
(2a)

$$U_{h/c} = \frac{\dot{Q}_{h/c}}{LMTD*A}$$
(2b)

where A is the surface area of heat transfer.

These signals and features define the state of the system and are selected for inclusion into the AAKR models. When cleaning the training data for the AAKR model, it is important that the data is fault-free and the test cases operate in the same conditions. To reduce system noise, especially for the mass flow rates, a median filter was applied to remove outliers exceeding three standard deviations. This procedure removed many of the large spikes seen in the mass flow rate signals, which should have been in near steady state.

It is important to develop AAKR models with groups of related variables. Therefore, the linear relationships between the signals and features were analyzed via correlation coefficients. Absolute coefficient values of greater than 0.7 correspond to strong correlations between signals, and coefficients of 0.25 and below are considered to show no significant linear correlation. Figure 3 shows a plot of the correlation coefficients of the raw data and calculated feature indices, with indices summarized in Table A1.

Figure 3 shows that there is a strong correlation between signal indices 1 to 4 (measured temperatures). There is also a strong correlation between signals 1 and 2 and features 13 to 15 (LMDT and heat transfer coefficients). There are moderate correlations between signals 1 to 6 (5 and 6 are the flow rates) and 13 to 15.



Figure 3 – Correlation coefficients of signals and features

Four sets of related variables were chosen based on correlation coefficients and understanding of the system processes. Other signal sets were tested during initial modeling attempts, but did not return desirable residual values and trends, and therefore were not considered for final lifecycle prognostic methods. The selected signals and features were chosen either for being moderately-to-highly correlated to one another or for the strong trend observed in them, such as the increasing trend of the hot leg temperatures and the decreasing trend of the heat transfer coefficients. The indices chosen for each signal set are given in Table 2.

Table 2– Signal sets used for modeling

Signal Set	Signal/Feature Indices Used
1	2, 3, 11, 12, 14, 15
2	1, 2, 3, 4, 11, 12, 14, 15
3	1, 2, 3, 4
4	1, 2, 3, 4, 14, 15

In signal sets one, two, and four, the heat transfer coefficients, heat rates, and temperature signals are used. Since the overall heat transfer coefficients (indices 14-15) are calculated from first principles models that are dependent on temperature signals (Schmidt et al. 1993), including them in an empirical AAKR model has the effect of increasing both the model's and prognostic parameter's weightings toward the temperature signals. This may improve modeling attempts when the temperature signals have strong increasing trends, and is expected to be more effective than other methods of artificially increasing the weightings, as it collapses signals to known, important dimensionalities.

4.2. Auto-Associative Kernel Regression

After feature selection is completed, the unfaulted heat exchanger data is divided into three data sets termed training, testing, and validation. Training data is used to train the model and should consist of unfaulted data that covers the range of operating values. Testing data is used for bandwidth optimization, which will be deferred to later discussion, and validation data is used to validate the performance ability of the model. AAKR models for the heat exchanger were developed and evaluated with the PEM toolbox (Hines and Garvey 2006). Kernel regression requires a parametric kernel function, in this case a Gaussian function, defined by a bandwidth that specifies the region of localized weighting for an input vector to the memory matrix output. An optimal bandwidth can be selected by altering it to minimize the error between known unfaulted observations and the model output. This method of determining the bandwidth increases the accuracy of the kernel regression model (Wand and Jones 1995). The training residuals from an AAKR model of signal set 2 are shown in Figure 4.



Figure 4 – Training residuals for signal set 2.

For this experiment, the training residuals of the temperature signals are desired to be less than 1°C since the temperature signals change less than 10°C over the faulted range. The training residuals of the heat rate should optimally be less than 50 *W*, and the heat transfer coefficient residuals should be less than 10 W/m^2K . These levels were chosen based off knowledge of signal and feature operating ranges over normal cycles. After the model is built, faulted data is passed through and residuals for each faulted cycle are calculated. An example of faulted residuals for the temperature sensors in signal set 2 is plotted in Figure 5.



Figure 5 – Faulted residuals of temperature signals (indices 1-4) using the signal set 2 model

From the failure residuals shown, strong increasing trends can be seen for the hot leg temperature signals. Dominantly monotonic trends are important when combining residuals to make a prognostic parameter. When combining the residuals, the objective is for the resulting health indicator to increase or decrease over the lifecycle to help indicate the degree of system or component degradation. If the observed trends of the residuals show a strong increasing/decreasing trend then the resulting prognostic parameter will also have a strong trend and be more useful for RUL predictions.

4.3. Prognostic Parameter Generation

The prognostic parameter is a single metric of the amount of deviation from normal behavior of the system and is ideally linked to the overall health of the system. In this project, it is calculated as a linear combination of the residuals from the AAKR model. While Coble (2010) used a genetic algorithm to find a linear combination of weights for the residuals, the algorithm is computationally expensive. Instead, an ordinary least squares (OLS) regression is applied that mimics the optimization and is less computationally intensive for smaller data sets. The monitoring model residuals of multiple runs to failure are collected into a single matrix by concatenating each test case. This creates an **n** x **s** matrix, **X**, where **n** is total data points in all test cases, and s is the number of signal residuals output from the model. This X matrix is regressed against the $n \ge 1$ vector y where each y_i corresponds to the percent of the total unit life at that observation. This means that the residuals of each test case are fitted to a linear curve from 0 to 1. The linear weights are then

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{3}$$

where $\hat{\beta}$ is an **s** x 1 vector.

4.4. General Path Model and Bayesian Updating

When using the GPM approach, a parametric function is fit to the degradation parameter, and extrapolated until it crosses a predefined failure threshold. Typically, the failure threshold is based on historical failures but need not directly indicate a point of catastrophic failure. The failure threshold can be set as any point where a system no longer conforms to the necessary specifications and demands placed upon it.

Because of the limited number of test cases, the GPM and all components are created by the use of a leave one out cross validation (LOOCV) technique. Hence, to calculate the RUL of a specific case, every other case is used to build the model. This avoids invalidating a model by keeping training and testing data separate, yet general enough to compare over all cases. With more data an alternative approach could be to simply divide the cases in half and build one model.

The degradation path is assumed to have the general linear form that is shown in equation 4:

$$\mathbf{y}|\boldsymbol{\beta}, \mathbf{X}, [\boldsymbol{[\sigma]]}^{2} \sim \mathbf{N}(\mathbf{X}\boldsymbol{\beta}, \sigma^{2} \mathbf{I})$$
(4)

where y is the response a vector, X is the input data matrix, and β is the vector of regression parameters. This model assumes normally distributed errors with variance σ^2 .

Development of failure thresholds had to be generated with respect to the data. The values were chosen as a reflection of an unacceptable amount of degradation, limited by the least degraded cycle for any given model. Any data collected after this point was considered past failure and removed from the data analysis. A histogram plot of failure times for the lifecycle prognostics models is shown in Figure 6.



Figure 6 – Histogram of failure thresholds

If the test case data is censored such that only data before a time step is available, then the RUL can be calculated at each time step by extrapolating the current path to the threshold. To do this, a suitable parametric fit must be chosen. The fit can be of any linearly separable form such as, linear, quadratic, exponential, etc. The OLS method is used for regression of the parametric fittings because the OLS regression on a joint Gaussian distribution of parameters gives the maximum likelihood estimate. This method assumes that the error is normally distributed around zero. The OLS solution can be found using the pseudo-inverse given in equation 3.

By adjusting the functions in the columns of the input matrix \mathbf{X} , different fits can be applied to any test path. It is assumed that for a certain failure mode the degradation paths will follow similar fits. Therefore once a suitable fit is chosen for the failed data, it is assumed the censored faulted data will follow the same fit.

Bayesian priors can also be incorporated into the OLS model (Gelman et al. 2004) to reduce the uncertainty and increase the stability of RUL estimates. Bayesian statistics combines prior distributions with sampling data to create a posterior distribution. When few data points are available, without incorporating any form of Bayesian prior estimations, the model can easily be affected by noise and give widely varying predictions of time to failure. Coble and Hines (2011) use Bayesian methods to incorporate prior knowledge of regression parameters in the GPM. This approach requires historical run-to-failure data in order to evaluate the prior distributions of regression parameters. An alternative approach instead uses RUL estimates from Type I prognostic models as prior information (Nam 2013). In this approach, the Type I RUL distribution is treated as an additional data point in the OLS regression. The measured data are augmented with the distribution according to equation 5:

$$Y = \begin{bmatrix} y \\ thresh \end{bmatrix}, X = \begin{bmatrix} X \\ MTTF \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma_y & 0 \\ 0 & \Sigma_{RUL} \end{bmatrix}$$
(5)

where *y* is the observed prognostic parameter, *thresh* is the failure threshold, *x* is the timestamps (or appropriate transformation thereof), *MTTF* is mean failure time from the Type I distribution (or appropriate transformation thereof), Σ_y is the noise or uncertainty associated with the observed prognostic parameter, and Σ_{RUL} is the uncertainty in the Type I RUL estimate. The OLS regression is then solved according to equations (6) – (8):

$$\hat{\beta} = \left(X^{\mathrm{T}} \Sigma^{-1} X \right)^{-1} X^{\mathrm{T}} \Sigma^{-1} y \tag{6}$$

$$V\sigma^{2} = (X^{T}\Sigma^{-1}X)^{-1}$$
 (7)

$$\sigma^{2} = \frac{1}{n \cdot k} \left(y \cdot X \hat{\beta} \right)^{T} \Sigma^{-1} \left(y \cdot X \hat{\beta} \right)$$
(8)

where k is the degree of the parametric function used in the GPM.

The weight of the prior information in the OLS regression depends on two main factors: the variance of the prior relative to the variance of the data, and the number of observations collected. If the variance of the prior is small compared to the noise of the data, the prior β_0 will be weighed more heavily. However, no matter the difference in variance, with enough observations, the data should eventually swamp out the prior in calculating the posterior.

4.5 Bayes Method Implementation

For each of the four AAKR models, two prognostic modeling methods are used:

GPM Method 1: No Bayesian updating

GPM Method 2: Type 1 Bayes priors

To compare the two methods, plots of the predicted TTF versus the actual TTF are examined. In each plot, the multiple blue lines correspond to the determined TTF of each cycle over time. Figure 7 shows a plot of the TTF comparison when no Bayesian updating is used.



Figure 7 – Plot of the GPM method 1 TTF predictions across cycles without Bayesian updating

Without Bayesian updating, TTF prediction times have large spikes, and prediction accuracy is reduced. While some peaks are due to the noise and artifacts in the heat exchanger data acquisition system, the somewhat larger and broader peaks at regular intervals are most likely the result of the regular additions of clay into the hot fluid. The extra clay would change the thermodynamics as well as mass flows of the otherwise closed system. In an attempt to improve TTF estimation, past cycle failure times are incorporated as prior information (Type I) as shown in Figure 8.



Figure 8 - Plot of the GPM method 2 TTF predictions across cycles with Type I Bayesian updating

The predictions using Type I prior information show visual improvement over those with no Bayesian updating.

5. RESULTS AND DISCUSSION

Initial modeling attempts revealed that using a quadratic fit is more accurate than using a linear fit; therefore, to conserve space, results will be confined to quadratic fit models. The different GPM methods and signal sets (models) are compared using several performance metrics.

The first model comparison metric used is the absolute error mean (AEM), which returns the average absolute difference between the predicted RUL and the true RUL in real time units, shown in Figure 9. Signal sets 1 and 3 have the lowest AEM, and GPM method 2 further improves the predictions. Signal set 1 with GPM method 2 results in the most accurate RUL predictions for this data set.



Figure 9 – Absolute error mean for four signal set models and two GPM methods

The second metric used to evaluate the prognostic models is the absolute error standard deviation (AES), which is a measure of the variation in error through time of each model and GPM method, shown in Figure 10. Again, the model using signal set 1 and GPM method 2 shows the best performance, with highest precision in estimating the RUL.



Figure 10 – Absolute error standard deviation for four signal set models and two GPM methods.

To quantitatively compare the different GPM methods, the AEM, AES, spread, and coverage metrics are used (Saxena et al. 2010). A plot showing the results of these metrics for each GPM method for signal set 1 is shown in Figure 11 and the unnormalized metric scores are shown in Table 3.



Figure 11 – Plot of normalized performance metrics for two GPM methods and signal set 1

These metrics indicate that the Bayesian updating method (GPM Method 2) is more accurate for predicting RUL for this data set.

GPM-1	AEM	1.7026E4	
	AES	9.6206E3	
	Spread	131.135	
	Coverage	83	
GPM-2	AEM	1.1441E4	
	AES	5.1395E3	
	Spread	70.767	
	Coverage	99	

Table 3 – Performance Metrics Scores

6. CONCLUSION AND FUTURE WORK

In analyzing the fouling of a heat exchanger, a method for the development of a lifecycle prognostics model was presented that spans from empirical modeling of the system to TTF calculations using the GPM. Across all test cases, the Bayesian transition using a type I prior outperformed the GPM with no Bayesian updating.

The prognostics method presented here can be improved in several ways. The noise of the prognostics parameter can be reduced by improved filtering or prognostics parameter optimization. A more optimized prognostics parameter with a more well-defined degradation threshold could increase the prognosability and decrease the end of life RUL and TTF prediction errors. A crucial future implementation is the application of a fault detection method to cut beginning of life test data before a fault is detectable. Cutting data that is similar to clean or unfaulted data would increase trendability, particularly for linear GPM fits that would not accommodate a sudden increase in degradation. A mitigating factor to this is that all test cases are initially run with clay in the system. Therefore, physically, some form of degradation should be manifest from the beginning.

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References

- Ardsomang, T., Hines, J.W., & Upadhyaya, B.R. (2013). Heat Exchanger Fouling and Estimation of Remaining Useful Life, Annual Conference of Prognostics and Health Management Society.
- Buecker, B. (2009). Save Big Bucks with Proper Condenser Performance Monitoring, Energy Tech Magazine, April 2009.
- Coble, J.B., & Hines, J.W. (2011:2). Applying the General Path Model to Estimation of Remaining Useful Life, International Journal of Prognostics and Health Management.
- Fayard, E.C. (2011). Improving Condenser Reliability and Availability Through Effective Offline Cleaning and Nondestructive Testing, Proceedings of Electric Power Research Condenser Technology Conference, July 2011.
- Garvey, D., & Hines, J.W. (2006). Traditional and Robust Vector Selection Methods for use with Similarity Based Models, by 5th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology (NPIC&HMIT '05), Albuquerque, NM.
- Gelman, A., Carlin J., Stern, H., & Rubin, D. (2004). Bayesian Data Analysis 2nd ed. Boca Raton: Chapman and Hall/CRC, Boca Raton, USA.
- Georgiadis, M. C., & Macchietto, S. (2000). Dynamic modelling and simulation of plate heat exchangers under milk fouling, Chemical Engineering Science, 55(9).
- Hines, J.W., Garvey, D., Preston, J., & Usynin, A. (2007). *Empirical Methods for Process and Equipment Prognostics*, Tutorial presented at the IEEE Reliability and Maintainability Symposium (RAMS).
- Hines, J.W., & Garvey, D. (2006). *Process and Equipment Monitoring Toolbox Tutorial*, Nuclear Engineering Department, University of Tennessee.
- Jonsonn, G.R., Lalot, S., Palsson, O.P., & Desmet, B. (2007). Use of extended Kalman filtering in detecting fouling in heat exchangers, In the International Journal of Heat and Mass Transfer (IJHMT).
- Lu, C.J., & Meeker, W.Q. (1993). Using Degradation Measures to Estimate a Time-to-Failure Distribution, Technometrics, Vol 35, No 2, pp. 161-174.
- Nam, A., Sharp, M., Hines, J.W., & Upadhyaya, B. (2013). Lifecycle Prognostic Algorithm Development and Application to Test Beds, Chemical Engineering Transactions, Vol. 33.
- Saxena, A., et al. (2010). Metrics for Offline Evaluation of Prognostics Performance, In the Internation Journal of Prognostics and Health Management (IJPHM), vol. 1(1) 001, pp. 20.
- Sharp, M. (2013). Simple Metrics for Evaluating and Conveying Prognostic Model Performance To Users With Varied Backgrounds, Annual Conference of the

Prognostics and Health Management Society. New Orleans, LA.

- Schmidt, F.W., Henderson, R.E., & Wolgemuth, C.H. (1993). Introduction to Thermal Sciences: Thermodynamics, Fluid Dynamics, Heat Transfer. Canada: John Wiley & Sons, Inc.
- Upadhyaya, B.R., Naghedolfeizi, M., & Raychaudhuri, B. (1994). *Residual Life Estimation of Plant Components*, P/PM Technology 7 (3), 22 29.
- Upadhyaya, B.R., Hines, J.W., et al. (2004). On-Line Monitoring and Diagnostics of the Integrity of Nuclear Plant Steam Generators and Heat Exchangers, Final Report: Volume 1, Experimental and Hybrid Modeling Approach for Monitoring Heat Exchanger System Performance, prepared for the DOE-NEER Program by the University of Tennessee, Knoxville, Report No. DE-FG07- 01ID14114/UTNE-07.
- Wand, W.P., & Jones, M.C. (1995). *Kernel Smoothing*, London: Chapman & Hall.
- Yang, D., Usynin, A., & Hines, J.W. (2006). Anomalybased intrusion detection for SCADA systems, 5th Intl. Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technologies (NPIC&HMIT 05).

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APPENDIX

Table A1 – Measured signals and calculated features and their indices $% \left({{{\rm{A}}_{\rm{B}}}} \right)$

Signal Index	Signal/Feature		
1	Hot Leg Inlet Temperature		
2	Hot Leg Outlet Temperature		
3	Cold Leg Inlet Temperature		
4	Cold Leg Outlet Temperature		
5	Hot Leg Flow Rate		
6	Cold Leg Flow Rate		
7	Hot Leg Inlet Pressure		
8	Hot Leg Outlet Pressure		
9	Delta Hot Leg Temperature		
10	Delta Cold Leg Temperature		
11	Hot Leg Heat Rate		
12	Cold Leg Heat Rate		
13	Log Mean Temperature Difference		
14	Hot Leg Overall Heat Transfer Coefficient		
15	Cold Leg Overall Heat Transfer Coefficient		

A Data-Driven Approach for on-line Gas Turbine Combustion Monitoring using Classification Models

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ABSTRACT

Given the critical nature of Gas Turbines in most industrial plants, it is a high priority to find ways of reducing maintenance costs and increasing the availability. Quickly detecting and identifying combustion anomalies enables the choice of an appropriate recovery strategy, potentially mitigating the consequences of unscheduled down time and increased maintenance costs. Monitoring the Exhaust Gas Temperature (EGT) profiles is a good means of detecting combustion problems: plugged nozzles and/or combustor and transition piece failures will always result in distorted exhaust gas temperature patterns. However the conventional monitoring systems do not allow robust discrimination between instrumental failures and real gas turbine issues; furthermore weak diagnostic methods can be source of numerous false alarms.

In this paper, we investigate the problem of monitoring the combustion chambers of a gas turbine and we attempt to address this issue by introducing a strategy for automatic and efficient patterns recognition by using Machine Learning Classification algorithms. Some historical events have been firstly retrieved and analyzed to discover which features are useful for classification. Based on the observations, two multiclass classification algorithms, one based on logistic regression, the other on Artificial Neural Networks (ANN), have been developed. Finally, real-world datasets have been used to benchmark the performance of the proposed algorithms against a traditional physics-based approach.

1. INTRODUCTION

Today industrial gas turbines are one of the most widely-used prime movers for power generation and mechanical drive applications. In the Oil&Gas field these engines are often used to drive compression trains (for example in gas pumping or injection stations or in natural gas liquefaction plants) and to provide power for the plant. Maintenance costs and availability are two of the most important concerns to a heavy-duty gas turbine equipment owner. Gas turbines have to be built and operated with higher availability, reliability, and performance in order to ensure the customer with sufficient operating revenues and minimal fuel costs. Therefore, Remote Monitoring & Diagnostics (RM&D) of equipment like heavy duty gas turbine has become increasingly important and popular in the industry since it's considered a critical process in preventing costly unplanned maintenance and secondary damage.

To achieve this goal, a large number of critical parameters such as engine vibration, bearing temperature, combustion profile, etc. are continuously acquired to detect any changes in the normal operating conditions of the gas turbine engine. This large number of operational data from the everyday operation of a gas turbine is usually collected and analyzed as soon as new data sets arrive in the monitoring center. Anomaly detection rules and models are designed to scan through the data and notify the monitoring and diagnostic engineers, if any novelties or emerging problems are detected.

For example every day of the year, the RM&D center of General Electric Company in Florence (GE Oil&Gas), Italy collects more than 3,850 operating hours of data from a fleet of more than 700 globally installed equipment (gas turbines, compressors, steam turbines and electric generator assets). More than 70,000 signals are processed by automatic diagnostic rules and about 2,300 recommendations per year are sent to customers. Therefore in recent years, in parallel with the operational diagnostic service, it has become increasingly important the challenge of transforming big data into knowledge (Jlang & Foster, 2013) and to detect emerging problems at nearly real-time (early warning) with the development of advanced analytics. In a great number of industrial applications, this continuous supervision of critical parameters is driving the gradual transition from systematic maintenance to conditional maintenance strategies (Vachtsevanos, Lewis, Roemer, Hess, and WU, 2006).

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2. COMBUSTION MONITORING

The diagnosis of any malfunction of the combustion system of a gas turbine is of great importance for long term engine reliability and availability. Main causes of damage of hotsection components are imbalanced fuel distribution and combustion instabilities.

Some of the common problems experienced in gas turbines operation are: random re-ignition, combustor blowout, abnormal combustion dynamics, and non-compliant emissions. Modern dry low NOx combustors can target very low emissions levels, but need to operate within very narrow equivalence ratio. Premixed combustors are often susceptible to thermoacoustic combustion instability, which can lead to large pressure oscillations in the combustor and decreased durability of components.

Other causes of combustion issues are clogged or loose fuel nozzles, which may lead to severe burning problems. Abnormal fuel mass distribution among nozzles may cause high emissions of either NOx (due to hot spots in the combustion zone) or CO and unburned hydrocarbons (due to cold spots and poor mixing or atomization). Those hot spots reduce the time taken for failure in creep (phenomenon of plastic deformation) of the combustion liners, transition pieces, turbine nozzles and blades. In fact creep life of metal components in the hot section of a gas turbine is extremely sensitive to metal temperature.

The consequences of hot-section component failures caused by overheating might be quite costly. In extreme cases, combustion liner failures can allow hot flames to impinge on the turbine pressure casing, which can result in catastrophic combustion casing failure (Figure 1). Even before casing failure occurs, broken pieces of the liner can pass into the expander section and cause extensive blade damage.

Monitoring the gas turbine exhaust temperature spread via thermocouples mounted at the gas turbine exhaust section (i.e. maximum - minimum) is a good means of detecting combustion problems. In fact, almost all gas turbine control systems monitor this parameter and issue an alarm when it reaches an OEM-specified value. However most modern diagnostic systems often do not display expected exhaust gas turbine spread profiles (EGT spread) and do not figure out the source of the high-temperature spread. Moreover many false alarms are often triggered as a result of instrumental problems.

In this paper, we discuss the application of a pattern recognition technique to the monitoring of the exhaust gas turbine temperature profile. Although physical insight is without any doubt an important step to enhance knowledge of the processes within the combustion chamber, large datasets can also be exploited with data-mining techniques based on black box models, such as classifiers or artificial neural networks (Hannes, Deneve, Vanderhaegen, & Museur, 2009).



Figure 1. Broken liner as the result of cracks propagation

The data-driven approach to fault diagnosis and prognosis is usually preferred when system models are not available or not robust enough (e.g., when the physics underlying is too complex to be modeled), but instead system monitoring data is available (Namburu, Azam, Luo, Choi, & Pattipati, 2007).

The key challenge in implementing this kind of approach is developing an algorithm that can flag anomalies without also sending out false alarms when something else changes such as engine operating conditions. Pure data-driven modeling techniques work well if sufficient labeled data are available. However in real-world applications like in gas turbine monitoring, obtaining sufficient labeled data is laborintensive, if ever possible. In particular, true positive cases might be sparse or noisy and using small set of labeled data may cause model over-fitting or ill-formed model representation (Yan, Yu, Sherbahn, and Brahmakshatriya, 2013).

In this paper, an anomaly detection method based on classifiers technology is discussed in detail and implemented on E-class gas turbines. These black box models, trained on historical data (training set), are used to detect the presence of anomaly patterns in unseen data of the EGT profile (test set). These specific signatures not only can alert the operator to a possible problem, but they also identify its severity and can guide in understanding the possible root cause.

3. CLASSIFICATION

In machine learning and statistics, classification is the problem of identifying to which of a set of categories a new observation belongs, on the basis of a training set of data containing observations whose category membership is known. Example of classification would be to predict whether a patient has a given disease or not, classifying a given email as "spam" or "non-spam", an online transactions as fraudulent or not, etc. It's worth noting that the response variable y is qualitative instead of quantitative. All these cases above are examples of binary classification problems because the variable y that we'd like to predict admits only two possible outcomes (usually coded as "0" or "1"), but the same concept can be extended to multi-class cases to deal with situations where the outcome can have three or more possible types (e.g., "disease A" vs. "disease B" vs. "disease C").

There are many possible classification techniques, or classifiers, that one might use to predict a qualitative response. Some of these are: logistic regression, Artificial Neural Networks, K-nearest neighbors, decision tree and Support Vector Machines (James, Witten, Hastie, and Tibshirani, 2013).

In this work, logistic regression and artificial neural networks techniques are investigated. Today logistic regression is one of the most popular and most widely used learning algorithms thanks to the interpretability of model parameters and ease of use. On the other hand, neural networks can be seen as nonlinear generalizations of logistic regression, and thus they are considered more flexible algorithms (Dreiseitl & Ohno-Machado, 2002).

3.1. LOGISTIC REGRESSION

In a binary classification problem, where the response *y* falls into one of two categories, 0 or 1, logistic regression models the probability that *y* belongs to a particular category. The surface that partitions the vector space into two sets, one for each class, is called decision boundary.

The function that satisfies the property that a prediction is between 0 and 1 is the hypothesis function $0 \le h_{\theta}(x) \le 1$, defined as $h_{\theta}(x) = g(\theta^T x)$, where the function g is the logistic or sigmoid function $g(z) = \frac{1}{1+e^{-z}}$, that takes the shape of the S-curve shown in Figure 2 for values of z in the range of real numbers from $-\infty$ to $+\infty$. Putting these two equations together, we obtain an alternative form of the hypothesis function.

$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}} \tag{1}$$

The output value of the hypothesis function is the estimated probability that the variable y is equal to 1 on a new input example x.

Suppose that the hypothesis output is 0.7, the interpretation is that for a patient with features *x*, the patient has a 70% chance of having a specific disease. More formally we can write this as $h_{\theta}(x) = P(y = 1|x; \theta)$ probability that y = 1, given feature *x*, parameterized by θ .



Figure 2. Sigmoid function

The parameter vector θ is the vector of unknown linear regression coefficients of the *n*th order polynomial $\theta_0 x_0 + \theta_1 x_1 + ... + \theta_n x_n = \theta^T x$. High-dimensional vector can be used in non-linear problems to get more complex decision boundary, but the model will be more susceptible to overfitting, which means that it may fit the training set very well, but fail to generalize to new examples.

In every supervised learning problem, a training set of m training examples is required

$$\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \cdots, (x^{(m)}, y^{(m)})\}$$

where each example is represented by an N+1 dimensional feature vector x, and its associated label y can be either 0 or 1.

$$x \in \begin{bmatrix} x_0 \\ x_1 \\ \dots \\ x_n \end{bmatrix} \quad x_0 = 1, \qquad y \in \{0, 1\}$$

The training process of a classifier involves finding the best parameter θ vector for the logistic regression cost function $J(\theta)$, given the dataset of x and y values. This optimization problem consists in minimizing the sum of the square difference between the output of the hypothesis $h_{\theta}(x)$ and class label y, which is finding parameters θ that minimize the function:

$$J(\theta) = \frac{1}{2m} \left[\sum_{i=1}^{m} (h_{\theta}(x^{i}) - y^{i})^{2} + \lambda \sum_{j=1}^{n} \theta_{j}^{2} \right]$$
(2)

where λ is the regularization parameter. This optimization problem can be solved with any standard numerical optimization algorithm, like the gradient descent or more advanced methods.

3.2. ARTIFICIAL NEURAL NETWORKS

In computer science and related fields, Artificial Neural Networks are computational models inspired by the neural structure of the brain that are capable of machine learning and pattern recognition. Due to their high connectivity and parallelism, ANNs are able to link, in a non-linear way, a multi-dimensional input space with a multi-dimensional output space, allowing very high computational speed (Haykin, 1999).

The neural network architecture used in this paper for gas turbine combustion monitoring is the multilayer feedforward neural network (see Figure 3), in which the artificial neurons are arranged in layers, and the neurons of a layer are linked to all the neurons of the following layer, while, there are no links among neurons of the same layer. The input layer consists of a set of nodes (where no data processing occurs) equal to the number of ANN inputs, while the number of neurons in the output layer is equal to the number of ANN outputs.



Figure 3. Artificial Neural Network architecture

Feedforward networks often have one or more hidden layers of sigmoid neurons also called activation functions (Eq. (1)) followed by an output layer of linear or sigmoid neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems, while sigmoid transfer function is used to constrain the outputs of a network (such as between 0 and 1). This is the case when the network is used for pattern recognition problems (in which a decision is being made by the network). All the calculations are performed in hidden and output layers. In particular, if x_{ii} is the *i*th input of the *j*th neuron and w_{ij} is the weight of x_{ij} , the neuron output y_j is determined by means of an activation function f applied to the weighted sum of the inputs plus the bias b.

$$y_i = f\left(\sum_{i=1}^{m_j} w_{ij} x_{ij} + b\right)$$
, $j = 1, ..., n_N$ (3)

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, which generally is the mean square error *mse*, namely the average squared error between the

network outputs y and the target outputs t. It is defined as follows:

$$F = mse = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (t_i - y_i)^2 \qquad (4)$$

For training multilayer feedforward networks, any standard numerical optimization algorithm can be used to optimize the performance function, but there are a few key ones that have shown excellent performance for neural network training. These optimization methods use either the gradient of the network performance with respect to the network weights, or the Jacobian of the network errors with respect to the weights. The gradient and the Jacobian are calculated using a technique called backpropagation algorithm, which involves performing computations backward through the network.

Although the functional forms for logistic regression and artificial neural network models are quite different, a network without a hidden layer is actually identical to a logistic regression model if the logistic (sigmoidal) activation function is used.

Since artificial neural networks are aggregations of nonlinear functions (neurons), in classification problems ANNs are able to represent complex models that form non-linear hypotheses, differently from logistic regression that is only a linear classifier. The type of decision boundary that the network can learn is determined by the number of hidden layers.

4. MODEL DEVELOPMENT

The first step towards the development of a classifier for gas turbine combustion monitoring is the definition of the categories to be classified.

Polar plot of EGT profiles is often used in diagnostics to identify uneven temperature distributions. The calculation of the exhaust swirl angle is then used to map temperatures back to the originating combustion chamber. Based on experience, the 4 classes of Figure 4 have been identified, each of which is characterized by a specific temperature distribution in the polar plot.

For example, in a fault-free case (Class 1) the exhaust temperature profile is expected to be quite regular; it will be peaked on the abnormal thermocouple in presence of a sensor anomaly (Class 2) and asymmetric with more than one thermocouple far from the average temperature in the case of a cold (Class 3) or hot spot (Class 4).

The underlying idea in this paper is that a classification model can be trained on real cases of normal behavior, sensor anomaly, cold spot and hot spot to recognize their specific patterns when new data are presented.



Figure 4. Polar plots of exhaust gas temperature profiles

This would allow greater performance than traditional diagnostic systems that are simply based on the monitoring of the exhaust spread.

4.1. REGULARIZED LOGISTIC REGRESSION TRAINING AND VALIDATION

For the 4-classes classification problem presented here, a multi-class classification algorithm called "one-vs-all" is implemented. This algorithm handles the training set as 4 separate binary classification problems, where each class *i* is separated from the remaining ones. In other words the logistic regression classifier $h_{\theta}^{(i)}(x)$ is trained for each class *i* to predict the probability that y=i, $h_{\theta}^{(i)} = P(y=i|x;\theta)$. To make the final prediction, the 4 classifiers are run simultaneously on the input *x*, and the class with the highest probability max $h_{\theta}^{(i)}(x)$ is then selected.

For the creation of the training dataset, historical events ground truth data have been primarily collected from RM&D issue database. Operating data of about 150 heavy-duty gas turbines in a period of 2 years operation are available for the analysis. Since we focus on anomaly detection algorithm, these data include both abnormal units and normal units, which are referred as positive and negative cases respectively. Secondly, time series of classifier input data x of some historical cases are extracted from the data historian and analyzed to generate the training dataset as explained below.

The most reliable way to get a high performance machine learning system is to take a low bias learning algorithm and to train it on a massive training set. However in real-world applications true positive cases are sparse and only small labeled training set are available. An artificial data synthesis method can be used to create new data from scratch or to amplify a given dataset. The second case has been put in place to turn the relative small training set available into a larger training set. For intellectual property protection, we are not allowed to give details and how this procedure was carried out and the number of feature x considered for the model.

Through the procedure explained above, a dataset of 11000 samples was generated and divided in three subsets for training, validation and test with following ratio 0.7, 0.15 and 0.15 respectively.

A first order polynomial was too simple for the data and resulted in underfitting (high bias), so a 2° order polynomial was used. The regularization parameter λ can significantly affect the results of the polynomial regression. In particular, a model without regularization ($\lambda = 0$) fits the training set well, but does not generalize. Conversely, a model with too much regularization ($\lambda = 100$) does not fit the training set and testing set well. A good choice of λ can provide a good fit to the data.

We used the Matlab[®] *fminunc* optimization solver to optimize the cost function $J_{train}(\theta)$ with parameters θ on the training dataset. Concretely we passed to *fminunc* function the following inputs:

- The initial values of the parameters to be optimized
- A function that, when given the training set and a particular θ , computes the logistic regression cost and gradient with respect to θ for the dataset (x, y). This allows *fminunc* to use the gradient when minimizing the function.

For the regularized logistic regression, the Eq. (2) of the cost function becomes

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} \left[-y^{(i)} log\left(h_{\theta}\left(x^{(i)}\right)\right) - \left(1 - y^{(i)}\right) log\left(1 - h_{\theta}\left(x^{(i)}\right)\right) \right] + \frac{\lambda}{2m} \sum_{j=1}^{n} \theta_{j}^{2}$$
(5)

Correspondingly, the partial derivative of regularized logistic regression cost for θ_i is defined as

$$\frac{\partial J(\theta)}{\partial \theta_0} = \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)} \qquad \text{for } j = 0$$
$$\frac{\partial J(\theta)}{\partial \theta_j} = \left(\frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}\right) + \frac{\lambda}{m} \theta_j \quad \text{for } j \ge 1$$

After that the optimal values of θ were found, the model was then validated on the cross-validation dataset computing the cost function $J_{CV}(\theta)$ for different values of λ . We found that, for the dataset considered, $\lambda=8$ is the value that works best in terms of having a small cross-validation and test set error (Figure 5).



Figure 5. Selecting λ using a cross-validation set

Finally the model's performance has been evaluated on the test set, since it was not used in any part of training (that is, it was neither used to select the λ parameters, nor to learn the model parameters θ). The test error for $\lambda = 8$ was $J_{test}(\theta) = 0.64e-04$ with 100% accuracy, that is the percentage of examples that the classifier got correct.

After learning the parameters θ , to help visualize the model learned by the classifier, we have plotted the non-linear decision boundary that separates the positive and negative examples in a 3-dimensional space.



Figure 6. Class 1 classifier decision boundaries



Figure 7. Class 2 classifier decision boundaries



Figure 8. Class 3 classifier decision boundaries



Figure 9. Class 4 classifier decision boundaries

In Figure 6 to Figure 9, the decision boundary for each of the 4 assigned classes is shown in green. The red dots are the positive example, while the yellows ones are the negative examples.

4.2. NEURAL NETWORK TRAINING AND VALIDATION

The same dataset of section 4.1 was used to build a neural network based classifier. The architecture selected for the network is the feed-forward with sigmoid transfer functions in both hidden and output layers. The network has four output neurons, because there are four categories associated with each input vector, thus each output neuron represents a category. When an input vector x of the appropriate category is applied to the network, the corresponding neuron should produce a 1 and the other neurons should output 0. The influence of the number of neurons in the hidden layer was evaluated by comparing the response of different ANNs with different numbers of hidden neurons. Ten neurons in the hidden layer were considered an acceptable compromise between ANN accuracy and computational time required for the training. Due to the high number of patterns used for the training, the overfitting phenomenon (when the model learns the training data so well that it loses the ability to generalize) is unlikely to happen.

The Matlab[®] Neural Network Toolbox was used for the training process. The best validation performance was found at iteration 93 with 100% of cases perfectly classified.

5. RESULTS ON REAL WORLD DATASETS

As explained in section 4.1, the training dataset was obtained through an artificial data synthesis method on the observation of some relevant cases. For the validation on real data, time series with a one-minute sampling rate are used. Datasets prepared have duration of about one week before and after the event for positive cases and total length of 5 months for negative cases.

Starting from combustion labeled cases stored in the RM&D issue database and other past events notified to customers, 5 datasets, one for each class, have been identified (25 fault-free cases, 25 cases of anomalies, 25 sensor failures/out of range, 25 cold spots and 4 hot spots). The hot spots cases are less numerous because they have a lower probability of occurrence. An additional class has been added to those seen previously in this paper, this new class contains out of range anomalies, which in most cases are broken probes with unreliable or full scale values. These cases are filtered by the algorithm without passing through classifier and must be correctly detected by the diagnostic system.

A criterion to evaluate performance of classification problem is the *contingency table* that contains information about the outcome of the classifier compared with the target, giving information about the true or false positives and true or false negatives. The True Positive is a Target correctly identified whereas the True Negative is a Target correctly rejected. The False Positive, also known as *Type I error*, is a test result that is read as positive when it is really negative, whereas the False Negative, also known as *Type II error*, is a test result read as negative when it is really positive.

Table 1: Sensor Failure Continge	ency Table
----------------------------------	------------

Sensor Failure		Target (Gold Standard)		
		Positive	Negative	
Test Outcome	Positive	True Positive	False Positive	
		23	0	
	Negative	False Negative	True Negative	
		0	25	

Anomaly		Target (Gold Standard)		
		Positive	Negative	
Test Outcome	Docitivo	True Positive	False Positive	
	rostive	24	0	
	Negative	False Negative	True Negative	
		1	25	

Table 3:	Cold	Spot	Contingency	y Table
----------	------	------	-------------	---------

Cold Spot		Target (Gold Standard)		
		Positive	Negative	
	Docitivo	True Positive	False Positive	
Test Outcome	Fositive	25	0	
	Negative	False Negative	True Negative	
		0	25	

ruble 1. Hot Spot Contingency ruble				
Hot Spot		Target (Gold Standard)		
		Positive	Negative	
Test Outcome	Positive	True Positive	False Positive	
		4	0	
	Negative	False Negative	True Negative	
		0	25	

Table 4: Hot Spot Contingency Table

The contingency tables from Table 1 to

Table 4 summarize the results obtained with the classifier based on logistic regression for each class. It's evident that the performance of the classifier is very satisfactory, since it fails to predict only one case from the anomaly test set, whereas the other predictions are correct. These results are also summarized in the confusion matrix in Table 5.

A benchmarking with other two algorithms has been done using the same labeled cases. In particular we considered the Artificial Neural Network classifier described before and a Physics-Based (P-B) approach. The latter is a proprietary algorithm based on the monitoring of the EGT spread and is reinforced with the adjacency check between the coldest/hottest thermocouple and the second coldest/hottest thermocouple for the detection of cold and hot spot anomalies.

Table 5: Confusion Matrix

		Target Class					
		Sensor Failure	Normal	Anomaly	Cold Spot	Hot Spot	
SS	Sensor Failure	25	0	0	0	0	100%
t Cla	Normal	0	25	1	0	0	96.2 %
tpu	Anomaly	0	0	24	0	0	100%
Ou	Cold Spot	0	0	0	25	0	100%
	Hot Spot	0	0	0	0	4	100%
		100 %	100 %	96 %	100 %	100 %	99%

In order to compare the three different algorithms, it is necessary to define some appropriate metrics. Starting from the contingency table explained above, it is possible to derive various indicators like *precision* and *recall*.

In binary classification, precision is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved, while recall is the ratio of the number of relevant records retrieved to the total number of relevant records in the database (Labatut, Cherifi, 2011).

So, precision and recall are defined as:

$$precision = \frac{true \ positive}{true \ positive + false \ positive}$$

$recall = \frac{true \ positive}{true \ positive + false \ negative}$

From the definition above it turns out that a good classifier must have high precision and high recall. In fact, a low precision classifier produces high number of false alarms, whereas a low recall classifier gets a high number of missing alarms.

Analyzing the results obtained in Table 6 and Table 7, the logistic regression classifier shows better performance in terms of precision and recall compared to the other two algorithms used for the benchmark.

T 11 (**D**

Class	Precision LR	Precision ANN	Precision P-B Rule	
Sensor Failure	100%	100%	100%	
Anomaly	100%	100%	88.88%	
Cold Spot	100%	100%	100%	
Hot Spot	100%	100%	100%	
TOTAL	100%	100%	96.96%	

Table 7: Recall				
Class	Recall LR	Recall ANN	Recall P-B Rule	
Sensor Failure	100%	100%	96%	
Anomaly	96%	80 %	64%	
Cold Spot	100%	100%	80%	
Hot Spot	100%	75 %	100%	
TOTAL	98.73%	92.40%	81.01%	

The ANN based classifier generates 6 false negative, failing to predict 5 test cases from the Anomaly dataset and one case from the Hot Spot dataset, without generating any false positive prediction. This result decreases the recall relative to the two classes with the false negative without impacting the precision metrics.

The P-B rule have a very low recall metric due to 5 false negatives in Cold Spot dataset, one in Sensor Failure dataset and 9 in Anomaly dataset. This rule also produces 2 false positives in Anomaly dataset affecting also the precision of the rule.

Another useful metric to compare the three algorithms is the F1-Score. This score weights recall and precision equally, and a good retrieval algorithm will maximize both precision and recall simultaneously. Thus moderately good performance on both will be favored over extremely good performance on one and poor performance on the other. F1-score is defined as:

$$F1 = 2 \frac{precision \cdot recall}{precision + recall}$$

Table 8 confirms the performance results previously found. Despite the high accuracy of the ANN obtained in the training phase, the logistic regression showed a greater ability to place the unseen data in the right classes. This result can be probably explained by the fact that, given the strategy used for the training set generation, the logistic regression has a greater ability to fit the nature of the problem thanks to the analytical definition of its decision boundaries.

Table 8: F1-Score

Class	F1-score	F1-score	F1-score P-B Rule	
Clubb	LR	ANN		
Sensor Failure	1	1	0.9795	
Anomaly	0.9795	0.8888	0.7441	
Cold Spot	1	1	0.8888	
Hot Spot	1	0.8571	1	
TOTAL	0.9936	0.9605	0.8827	

6. CONCLUSIONS

The diagnosis of any malfunction of the combustion system of a gas turbine is critical in preventing costly unplanned maintenance and in reducing life-cycle costs of power plant operations. Monitoring the exhaust temperature spread is a good means of detecting combustion problems. However conventional monitoring systems do not allow robust discrimination between instrumental failures and real combustion issues; furthermore weak diagnostic methods can be source of numerous false alarms.

In this research, a Machine Learning technique, based on classification technology, is proposed to efficiently recognize anomaly patterns of common combustion problems. These specific signatures not only can alert the operator to a possible problem, but they also identify its severity and can guide in understanding the possible root cause. Two multiclass classification algorithms, one based on logistic regression, the other on artificial neural networks, have been trained on labeled patterns extracted from real cases of normal behavior, sensor anomaly, cold spot and hot spot collected in the RM&D center of Florence. An artificial data synthesis method has been used to amplify the original dataset, since only small labeled training set is available. After training process, the developed classification models and an additional physics-based algorithm have been tested on real combustion cases.

The final performance metrics pointed out better results for both data-driven methods compared to the physics-based model. The best performance, both in accuracy and recall, was achieved by the logistic regression algorithm. The ANN based classifier, despite having excellent accuracy, generated 6 false negative resulting in a lower recall.

Future research could investigate how to enhance the insight into the complex combustion system behavior relying not only on EGT profiles. For instance, multi-sensor fusion may provide robust and complete description of the combustion process combining information coming from additional sensors, such as combustion dynamic pressures and pressure ratio across the combustion fuel nozzles.

REFERENCES

- Vachtsevanos, G., Lewis, F., Roemer, M., Hess, A., & WU, B., (2006). *Intelligent fault diagnosis and prognosis for engineering systems*. Hoboken, NJ: John Wiley & Sons, Inc.
- James, G., Witten, D., Hastie, T., & Tibshirani, R., (2013). An Introduction to Statistical Learning. NY, USA: Springer Science + Business Media.
- Hastie, T., Tibshirani, R., & Friedman, J., (2001). *The Elements of Statistical Learning*. NY, USA: Springer Science + Business Media.
- Jlang, X., & Foster, C., (2013). Remote thermal performance monitoring and diagnostics – Turning data into knowledge. *Proceedings of the ASME 2013 Power Conference*, July 29 – August 1, Boston, Massachusetts, USA.
- Hannes, L., Deneve, M., Vanderhaegen, E., Museur, T., (2009). Combustion dynamics data mining techniques: a way to gain enhanced insight in the combustion process of fielded gas turbines. *Proceedings of ASME Turbo Expo 2009: Power for Land, Sea and Air, June 8-12, 2009, Orlando, Florida, USA.*
- Namburu, S. M., Azam, M. S., Luo, J., Choi, K., & Pattipati, K. R. (2007). Data-driven modeling, fault diagnosis, and optimal sensor selection for HVAC chillers. *IEEE transactions on automation science and engineering*, vol. 4, no. 3. doi: 10.1109/TASE.2006.888053.
- Yan, W., Yu, L., Sherbahn, J., and Brahmakshatriya, U., (2013). On Optimizing Anomaly Detection Rules for Gas Turbine Health Monitoring. *Proceedings of the Annual Conference of the Prognostics and Health Management Society 2013*, October 14-17, New Orleans, LA.
- Haykin, S., (1999), Neural Networks A Comprehensive Foundation, 2nd Ed., NJ, USA: Prentice Hall International.
- Breeze, P., (2005), *Power Generation Technologies*, Oxford: Elsevier.
- Labatut, V., Cherifi, H., (2011). Accuracy Measures for the Comparison of Classifiers. *The 5th International Conference on Information Technology*, arXiv : 1207.3790
- Beale, M., Hagan, M., Demuth, H., (2011). *Neural Network Toolbox™ User's Guide*. Natick, MA, USA: The MathWorks, Inc.
- Ghoreyshi, M., Singh, R., (2004). Using neural network for diagnostics of an industrial gas turbine. *Proceedings of* ASME Turbo Expo 2004: Power for Land, Sea and Air, June 14-17, 2004, Vienna, Austria.
- Landgrebe, T.C.W., Paclik, P., Duin, R.P.W., Bradley, A.P., (2006). Precision-recall operating characteristic (P-ROC) curves in imprecise environments (123-127), Hong Kong. doi: 10.1109/ICPR.2006.941.
- Dreiseitl S., Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: a methodology review. *Journal of Biomedical Informatics*, Oct-Dec, 2000; 35(5-6):352-9.

BIOGRAPHIES



Carmine Allegorico is senior engineer at the GE Oil&Gas in Florence, Italy. He received his Master Degree in Mechanical Engineering from the University of Napoli Federico II. He currently works in the Remote Monitoring & Diagnostic Center and is involved in the development and

implementation of complex analytics for on-line diagnostics and predictive maintenance; furthermore he is technical leader of projects for advanced remote system monitoring, prognostic and asset health management, leading collaborations with Universities and GRC. As expert of Gas Turbines and data analysis, Carmine also provides support for performance studies, operability of turbomachineries and development of machine learning algorithms. Before joining the RM&D Center, Carmine has worked for 5 years in the design engineering team doing a variety of tasks ranging from the design of new products, performance testing and troubleshooting, dynamic model simulations and design of GT control philosophies.



Valerio Mantini is a Systems and Analytics Engineer at GE Oil&Gas in Florence, Italy. He received his Master Degree in Control System Engineering from University of Rome Tor Vergata.

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developing and implementing diagnostic algorithms and techniques for early warning sensor fault detection; furthermore he has to follow test campaigns on pilot projects to install advanced instrumentation and analyze data acquired. Before joining the RM&D Center, Valerio has worked more than 3 years in space sector developing the thrust vector control system for VEGA launcher, 6dof simulator and post-flight analysis on official launcher telemetry.

Statistical Approach to Diagnostic Rules for Various Malfunctions of Journal Bearing System Using Fisher Discriminant Analysis

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ABSTRACT

This research is focused on developing an efficient fault diagnosis procedure for a journal bearing system. Vibration data of journal bearing rotor simulator under four conditions (i.e. a normal condition and three anomaly conditions including unbalance, rubbing and misalignment) was used to develop the algorithm. In order to improve diagnostic performance, cycle based time-domain features and frequency-domain features were extracted after resampling process being applied to the raw vibration data. Then, the optimal feature selection was accomplished by mixture of random combination performance test and Fisher Discriminant Ratio (FDR) criteria. After selecting optimal features, Fisher Discriminant Analysis (FDA) algorithm classified each abnormal conditions mentioned above. To end with, the result of classification is evaluated and verified.

1. INTRODUCTION

The modern machineries widely deployed in manufacturing sectors and power plant facilities have rotors as a core part. Naturally, bearings supporting the rotors frequently fail to perform their designed responsibility due to various reasons. Failure in bearings may affect the entire system to deteriorate or cause stopover of the system since it incorporates high energy. This also can generate casualties or damages when the counter measures are not held in suitable time (Yaguo Lei, He, & Zi, 2008). To maintain performance of the rotating machineries and to prevent the catastrophe of having casualties and economic loss, numerous attempts have been made to diagnose the faults in their initial states.

Vibration data is one of the reliable parameters that efficiently represents the performance of machineries, and it is widely used to define the health status of systems (Gupta, 1997; Yaguo Lei, He, Zi, & Chen, 2008; Ocak, Loparo, & Discenzo, 2007). However, without proper signal processing techniques and knowledge on vibration, the data itself does not denote any information of health status. Though sometimes even when processing has been done properly, lack of knowledge hinders the successful diagnosis. Therefore, the need for setting up a reliable diagnose algorithm without any help from experts has been steadily increasing (Jardine, Lin, & Banjevic, 2006; Y. Lei, He, Zi, & Hu, 2007; Wong, Jack, & Nandi, 2006).

In response to the request, an automatic diagnosis algorithm implementing Artificial Neural Network (ANN) was developed (Chen & Mo, 2004; Li, Chow, Tipsuwan, & Hung, 2000; Samanta & Al-Balushi, 2003). Vibration data were acquired from both the normal and abnormal bearing system, and from the data time-domain features or frequency-domain features were extracted, which were used as an input for ANN. ANN diagnosed the system as normal or abnormal upon those features. In addition, features from wavelet analysis in time-frequency domain facilitated constructing ANN based diagnosis (Al-Raheem & Abdul-Karem, 2010; Han, Yang, Choi, & Kim, 2006; Sanz, Perera, & Huerta, 2007; Yang, Han, & An, 2004). Rather than piling more features, study on selecting effective features such as genetic algorithm took a part in this process (Han et al., 2006). Many fault diagnosis algorithms based on ANN have been introduced. However the limited use of ANN, which require certain amount of data, had led a way to other machine learning (Ahmadi, Moosavian, & Khazaee, 2012).

In order to overcome the limitation in ANN, Support Vector Machine (SVM) based algorithms were suggested. Since SVM is a linear classifier for two-class problems, its use has

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been limited to linearly separable data sets. However, with the invention of the kernels and other techniques as well, SVM has gained popularity among researchers (Huo-Ching & Yann-Chang, 2012; Yang, Han, & Hwang, 2005). Often, ANN and SVM were used individually to compare performance of each algorithm, whereas others tried to combine these two method to generate more reliable diagnosis algorithm (Salahshoor, Kordestani, & Khoshro, 2010; Samanta, Al-Balushi, & Al-Araimi, 2003).

Fisher Discriminant Analysis (FDA) is another widely used machine learning technique. The basic principle of FDA is similar to that of SVM, but then FDA utilizes the scatter of data rather than the data itself. The advantage of using scatter over data lies in computational efficiency. Specifically, for large multi-class data set, FDA can save its resources while SVM wastes resources finding the optimal vector. The performance difference of FDA and SVM depends on the data set, which does not show much difference in this research. Thus, FDA was chosen as the main classifying algorithm.

In this research, advanced fault diagnosis algorithm for journal bearing system has been developed. Advanced algorithm can be attributed to the features extracted from vibration per cycle while other researches have extracted features for certain amount of time. 'A cycle' method allows to identify the fault characteristics of the vibration signal more thoroughly. To achieve features per cycle, data were resampled before being extracted. Then, extracted features numbered more than 50, which needed dimensional reduction. In addition, not only the features incorporating cycle characteristics of vibration but also average and standard deviation of multiple cycles can represent the faults clearly. Features selection method by Fisher Discriminant Ratio (FDR) and random combination of features has been applied.

Through the paper, the following section will cover the type of features extracted from the test-bed. Then, in section three feature extraction procedures will be clearly stated, and in section four, feature selection method will be revealed. Finally, the result of the classification will be discussed.

2. EXPERIMENTAL SETUP AND DATA ACQUISITION

2.1. Experimental Setup

The RK4 rotor kit of GE Bently Nevada was used as a journal bearing rotor system for implementing anomaly conditions. This experimental apparatus is shown in Figure 1. Rotor shaft with a disc of 800g supported by two journal bearings were tested. Two shafts were connected by a flexible coupling to acquire more reliable data. The vibration data was acquired from the middle of the test-bed, close to the point where the abnormal conditions were induced. Among several anomaly conditions of rotor

systems, three kinds of abnormal conditions, unbalance, rubbing, misalignment, were induced to the test-bed.

For unbalance test, a small amount of weight has been injected in the disc. Rubbing test was done by a rubbing screw to make partial rub on shaft. Additional misalignment device with ball bearing shifted the shaft up & downward to produce misaligned shaft data. In addition to those conditions, normal data was set as a reference.



Figure 1. RK4 test-bed

2.2. Vibration Data Acquisition

To achieve consistent and reliable data sets, weight balancing procedure preceded the actual experiment. Unlike a ball bearing system or a roller bearing system, a journal bearing system shows relatively simple sinusoidal wave. Even the slightest alteration of the settings result in a big change of the waves. For example, improper disc joining practice will cause differences in the signal. Therefore, among various candidates, vibration amplitude and phase have been selected to represent the initial state of the system. So as to have consistent amplitude and phase throughout the whole data sets, balancing procedure preceded every experiment to make the system fit into the same amplitude and phase. This preceded action gives reliability to compare with the other data sets.

After the balancing procedure is done, vibration data for four conditions can be achieved from the proximity probe installed between the journal bearings. Two points on the shaft, just beside the bearings have been chosen, and at each point, two probes are mounted at a right angle to receive voltage signal. Both the relative and absolute displacement between the sensor and the shaft can be measured. In addition to the time-based vibration signals of each sensor, shaft centerline orbit could be tracked via vibration signals of two probes mounted in a right angle. The phase information can be obtained through the keyphasor signal which prints once-per-revolution pulse to provide a precise timing measurement. This keyphasor signal enables us to dissect the signal into a cycle unit, which will be discussed in section 4. Vibration signals of proximity sensor were acquired by the rate of 4,000 samples/s via NI DAQ 4432. Each normal and abnormal state has been repeated three times, and for each case, data was obtained for 60 second long at 3600 rpm.

3. FEATURE TYPES

The vibration data itself may show the difference among abnormal conditions graphically. Specifically, for journal bearing systems, modified sinusoidal wave of vibration undeniably proves that the system is not in a normal state. However, all data cannot be analyzed manually due to its large size. It will take tremendous amount of resources if all the data is processed by humans, while losing the reliability due to human factors. It is no doubt that quantified indicator is required to precisely diagnose malfunctions and to utilize the automatic system which can process big data in a short period of time.

Statistical parameters were defined for features of vibration data, the quantified indicator of vibration. Some features were extracted for every cycle, while others were extracted for number of cycles. Whether a cycle or few cycles, unit for features must be defined considering the statistical definition and implication.

3.1. Time-domain Features

Time-domain indicates statistical features from the predefined period of vibration data. Maximum, root-meansquare, kurtosis and more features are extracted from every rotation. Also, mean and deviation for every rotation in 60 cycles at 3600 rpm, are defined as each features.

The first three features in Table 1 represents the vibration amplitude. In other words, they can be indicator of kinetic energy of the system. The next five features form skewness to entropy can be interpreted as indicators of shape of the wave. Upper/lower bound and AR coefficient represents distribution characteristics and signal changes over time. Especially, the information of orbit can be gathered via proximity probe mounted at a right angle. The mean and variance of each time-domain feature for 60 cycles are also adopted as features for anomaly diagnostics. Table 1 lists the features of time-domain.

3.2. Frequency-domain Features

Features in frequency-domain also implies important characteristics of vibration signals as much as time-domain features. All the frequency features are based on the power spectrum for one-second long data. Power spectrum itself shows distribution of the frequency elements, but needs to be quantified just like the vibration data.

Five features were defined in this paper. The definition of frequency center (FC), root mean square frequency (RMSF), and root variance frequency (RVF) are stated in Table 2. (Wei, Guo, Jia, Liu, & Yuan, 2013; Yang & Widodo, 2009).

s(f) denotes the power spectrum of signal, so that according to the definition FC and RMSF show alteration in position change of main frequencies, RVF describes the convergence of the spectrum power. Additionally, two more

Table 1.	Time-do	omain	features
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Features	Description
Maximum	$Max(X_i)$
Mean absolute	$Mean(X_i)$
RMS	$\sqrt{\frac{\sum X_i^2}{N}}$
Skewness	$\frac{\sum (X_i - \bar{X})^3}{(N-1)s^3}$
Kurtosis	$\frac{\sum (X_i - \bar{X})^4}{(N-1)s^4}$
Crest factor	$\frac{X_{peak}}{X_{rms}}$
Shape factor	$\frac{X_{rms}}{\text{Mean}(X_i)}$
Impulse factor	$\frac{\operatorname{Max}(X_i)}{\operatorname{Mean}(X_i)}$
Entropy	$-\sum p_i imes \log p_i$
Upper bound	$Max(X_i) + \frac{Max(X_i) - Min(X_i)}{2(N-1)}$
Lower bound	$\operatorname{Min}(X_i) - \frac{\operatorname{Max}(X_i) - \operatorname{Min}(X_i)}{2(N-1)}$
AR Coefficient	Auto regressive coefficient(1st to 8th)
Effective orbit radius(1x, total)	$\frac{\sum(X_i^2+Y_i^2)}{N}$
Aspect ratio of 1x orbit	Minor Axis Major Axis

Table 2. Frequency-domain features

Features	Description
FC	$\frac{\int f \times s(f)df}{\int s(f)df}$
RMSF	$\left[\frac{\int f^2 \times s(f)df}{\int s(f)df}\right]^{1/2}$
RVF	$\left[\frac{\int (f - FC)^2 \times s(f)df}{\int s(f)df}\right]^{1/2}$
2X / 1X	$\sqrt{\frac{s(f_{2X})}{s(f_{1X})}}$
(Total-1X) / 1X	$\frac{\left[\int \sqrt{s(f)} df - \sqrt{s(f_{1X})}\right]}{\sqrt{s(f_{1X})}}$

features regarding the ratio between the main and other frequency components are introduced as in the last two rows in Table 2. $\sqrt{s(f_{1x})}$ and $\sqrt{s(f_{2x})}$ indicates the magnitude of 1X and 2X component of vibration signal, respectively.

4. STATISTICAL ANOMALY DETECTION METHODS

4.1. Feature Extraction

In this research, 47 features have been set as the candidate parameters for anomaly diagnosis of above mentioned conditions. Both time-domain and frequency-domain features are extracted for one rotation or/and one second. As stated in previous section, the raw vibration data should be segmented to maintain consistency of the features.

4.1.1. Preprocessing for Feature Extraction

The fundamental frequency of journal bearing systems dominates other frequencies. Naturally, the sub-harmonic frequencies as well as super-harmonic frequencies were often utilized in traditional diagnosis algorithm (Randall & Antoni, 2011). In this study, the test-bed used here shows typical journal bearing characteristics, so that features are extracted based on cycles. Feature extraction unit differs according to feature types, some use one rotation while others use multiple rotations. For either of the case, keyphasor signal must be implemented to segment the signal into exact cycles. The sampling rate, 4,000 samples per second, creates unevenly distributed sample points per cycle at target speed of 3,600 rpm, as in the Figure 2(b). And even if the sampling rate has altered to multiples of speed, the rotating speed cannot be controlled at exactly 3,600 rpm, which makes resampling process inevitable.

Resampling process enables the signal to have same number of data points per cycle. For example, in Figure 2(c), resampled signal shows eight points per cycle. With the given sampling rate and the target speed, signal was resamp-



Figure 2. Resampling procedure (a) Keyphasor signal (b) raw Signal (c) resampled Signal

led to have 64 points per cycle starting from the keyphasor signal to the next keyphasor signal. Intervals between data points were set by equivalent rotation angle difference, so as to have same data points even when the rpm changes. The resampled signal can now be used to extract features in accordance with the same criteria.

4.1.2. Cycle based Feature Extraction

As stated in section 3, time-domain features are extracted based on a cycle or several cycles. Features from certain period of time are universally used in developing fault diagnosis. However, considering the fact that fundamental frequency dominates in the journal bearing system, and the sensitivity that journal bearing sinusoidal waveforms have, one rotation of a signal would regard significant amount of information. If features are extracted one second without applying resampling process, for example, the particular information on a sinusoidal wave fades away as it is averaged with other non-particular information. This is the reason we are focusing on the cycle based features for journal bearing. Simultaneously, features related to valuable information such as the trend being shifted to other states are extracted from 60 cycle data. Widely scattered features of a cycle will grant a large variation, which itself can be an independent feature. Therefore, time-domain features are statistically described by the mean and variance terms of time-domain features.

On the other hand, for frequency-domain features, it is desirable to extract 60 cycle based features. The longer the signal is acquired, the higher resolution of FFT result can be achieved. Since the target speed is 60 rev/sec, extreme high frequency components are not required. Rather subharmonic frequencies or super-harmonic frequencies are required.

So far, from raw vibration data 47 features are extracted. Among the 47 extracted ones, a few features have been chosen to check whether they are able to separate the malfunctions clearly. As presented in Figure 3, health classes can be unclearly or clearly separated depending on selection of a key feature set. In other words, it is sufficient to classify all health states if a key feature set is properly selected.



Figure 3. Graphical expression of features in (a) timedomain (b) frequency-domain

4.2. Feature Selection

Accuracy and computational efficiency are the two main factors that define the performance of the diagnosis algorithm. In view of those two points, the best feature sets are minimum number of features that produce good result. Minimizing the number of features would greatly contribute to reducing computational demands. Reducing the time and effort for computation may be very critical to some realtime diagnosis systems. Although real-time is not required, some features might hinder the characteristics of the data group which deteriorates algorithm performance. Therefore, many researches had been conducted solely on feature selection.

In this research, feature selection was accomplished by mixture of Fisher Discriminant Ratio ranking and random combination performance test.

4.2.1. FDR & Correlation Coefficient Ranking

FDR is a criterion that indicates separable ability for twoclass data. In this research each abnormal conditions can be regarded as a class, as of universal terms. So high FDR value means that it can distinguish an abnormal condition from another condition. Its definition is in equation (1). The numerator shows that difference between mean of each class. In the denominator variance for each class data are summed to represent how well class data is congested. Specifically, two class data, whose mean difference is large, and which has small variance, FDR value for the feature will grant a high value (S. Theodoridis & Koutroumbas, 2008).



Figure 4. Feature selection using FDR

$$FDR = \frac{(\mu_i - \mu_j)^2}{\sigma_i^2 + \sigma_i^2}$$
(1)

The explained FDR values will be derived for every feature, and also for every abnormal combination sets of two. In this research 47 features are extracted for four classes, so total of 47 x $_4C_2$ FDR values will be calculated.

However, FDR criteria does not take any consideration in reducing number of features. It only gives separable ability of individual features. Hence correlation coefficients between features are deliberated to obtain a cost function in equation (2). This cost function will sort out the features in a new ranking. The feature that used to have higher FDR value might be ranked very low in a new cost function ranking, and vice versa. The cost function can be used as a criteria for reducing the number of features.

$$i_{k} = \arg \max_{j} \left\{ a_{1}C_{j} - \frac{a_{2}}{k-1} \sum_{r=1}^{k-1} \left| \rho_{i_{r},j} \right| \right\}$$
(2)

Yet, the combined FDR and correlation ranking is still based on two-class problems, which does not guarantee decent performance features for multi-class problems as well. To utilize in multi-class, random combination method is used.

4.2.2. Random Combination Test

To apply the feature rankings to multiple class problem, random combination of features are selected and evaluated by the performance of classification of training data set. First, the cost function value of feature rankings in section 4.2.1. is examined. Though its absolute values do not hold crucial meaning, they can be used as a rough measure for separable ability in each two-class sets. As shown Figure 4, for each two class combination set, features that have less than half of the maximum value of cost function are discarded as they have bad separable ability. Selected high



Figure 5. Random combination testing process

separable features represented in right bottom of Figure 4(the orange colored values). To find priorities among the selected high separable features, random combination test was applied. The brief process is shown Figure 5.

Random combination of features have tested 5000 times in this study. The occurrence of individual feature is accumulated when the prediction accuracy is above the threshold. The priority is ranked by the accumulated occurrence descending. The result in details will be described in section 5.1.

4.3. Classification – Fishier Discriminant Analysis

FDA (Fisher Discriminant Analysis) was used for a classification scheme. FDA classification algorithm is to find a hyper-plane, where projected data on to this plane maximizes the cost function, FDR(Welling, 2005).

In the two-class problem, hyper-plane becomes a single line, represented by **w**. Assuming that the data are projected, high FDR corresponds to the difference of mean value being far away and the variance of each class being as small. Finding the line **w** manually might be computationally demanding, but the maximum eigenvalue of $S_w^{-1}S_B$ matrix is proven to be the vector **w**, where S_B means covariance between classes, and S_w means covariance within the class.



Figure 6. Fisher Discriminant Analysis for two class problem

For the multi-class problem, FDA criteria is substituted to other cost function J_3 , and the rest are the same as the two-class problem(Sergios Theodoridis & Theodoridis, 2010).

$$J_{3} = trace\{S_{w}^{-1}S_{B}\}$$
(3)

The overall procedure of developing classification starts with acquiring data sets. Other researches have used a part of one set for training, and the rest for testing. Conversely, this research acquired two sets of data, one for training and the other for testing. After both data sets were resampled and normalized, the defined features were extracted. Then, the features from training data set was used in feature selection process since there will be no testing data in real systems. Selected features of the training data were utilized to develop the classification model by FDA, and the three \mathbf{w} vectors were derived. The selected features of testing data are classified with the \mathbf{w} vectors.

5. RESULTS

This section can be divided into two parts. The first one will discuss the optimal selected features accomplished by feature selection process. The latter part will discuss the result of class prediction of testing data sets. The training set and testing set is listed in the Table 3.

Table 3. Training and testing data sets

Training Data		Testing Data					
Conditions		Data #	Features	Conditions		Data #	Features
Condition	IS	N	d	Conditions		N	d
Normal 2	1	3600	47	Normal	1	3600	47
	2	3600	47		2	3600	47
	3	3600	47		3	3600	47
Unbalance $\frac{1}{2}$	1	3600	47	Unbalance	1	3600	47
	2	3600	47		2	3600	47
	3	3600	47		3	3600	47
Rubbing 1 3	1	3600	47	Rubbing	1	3600	47
	2	3600	47		2	3600	47
	3	3600	47		3	3600	47
Misalign- ment	1	3600	47	Misalign- ment	1	3600	47
	2	3600	47		2	3600	47
	3	3600	47		3	3600	47

Before stating the result, data sets must be organized clearly. For feature selection and training the classifier, only training data sets were used. At classifier evaluation step, the testing data set was predicted using the classifier developed by training data sets.

5.1. Feature Selection Results

The main function of feature selection is to reduce the dimension to increase the efficiency of diagnosis algorithm. The test-bed vibration data had been transformed to timedomain and frequency-domain features. Total 47 candidate features were extracted to be used as an input in classification. However, 47 seemed heavy even for the simplest classification algorithm, because the number of data, or cycles, was quite large. At the same time, applying too much features in poor separability for anomaly diagnosis may lowering the efficiency of the classifier. When all 47 features are used, the class prediction for the training set leaves only 74.7% accuracy, because not all the features were capable of classifying the conditions. So, feature selection by mixed FDR and correlation coefficient criteria was performed. Features that had higher value than the half of the maximum cost function value had been selected. Through this mixed feature selection method, 16 features, almost one third of all 47 features, were recognized as valid parameters. These selected 16 parameter are same as the number listed in the x-axis of Figure 7.





Among these 16 remaining features, three features were selected randomly for 5000 times to evaluate the performance of the combinations. Three was selected as the least number of parameters for classifying the four-class problem. Each feature combination of training data set in Table 3 were trained and tested. In order to acquire the optimal features, the threshold of prediction accuracy was used as 80%. The 80% criteria above is supposed to be reasonable in a sense that prediction accuracy using all 47 features yielding 74.7%, but further research needs to be done. Then, only the eligible feature combination scores the individual features as shown in Figure 5. The result produces a ranking list of 16 features, which are used in section 5.2 to predict the testing set classes. Through these selection process, optimal feature sets could be picked.

5.2. Classification Results

Before referring the classification result, the proposed feature extraction method in section 4.1. enhanced the consistency in features. Compared to the features from the previous studies, based on certain period of time, the proposed features showed separable ability more than twice as well as the previous ones.

With the improved features, FDR feature selection method was performed to find the optimal features for classification. The first step was to obtain the FDR & correlation ranking list which is based on only training sets. Then, feature combinations according to the list rankings were formed and classified the testing data set. Starting from the top three feature combinations, a next ranking feature was added each time after classification result was attained. The result is shown in Figure 8.

As it is displayed in the chart, all 16 feature combination does not yield good prediction result. Rather smaller number, from three to eleven features, gave 100% accurate prediction. In addition to the improved accuracy, computation time was saved greatly. The result more than



Figure 8. Classification accuracy by number of features

16 features have been achieved by adding left features after feature selection process. This chart insists that feature selection process was successful.

6. CONCLUSION

In this research, diagnose algorithm for four conditions of journal bearing systems has been developed. Two separate data sets were grouped as training set and testing set, respectively. Each of the condition was repeated three times and each test preceded the balancing procedure to enhance the reliability of the data sets. The initial vibration amplitude, indeed, had crucial effect in consistency. Considering the characteristics of a journal bearing system, features have been extracted based on a cycle or cycles after the proximitor signal was resampled. Keyphasor signal has made the resampling procedure possible, and that cycle segmentation became possible. Total of 47 Cycle based features are defined in time-domain and frequency-domain. Among those features 16 of them had been chosen to be effective parameter by FDR criteria and random combination performance test. This feature selection played key role in developing competent diagnosis algorithm with only three to eleven features being used. However, when choosing the features via random combination method, the accuracy threshold, which has not been studied deeply, plays key role. Further research must be conducted on this subject.

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REFERENCES

- Ahmadi, H., Moosavian, A., & Khazaee, M. (2012). An appropriate approach for misalignment fault diagnosis based on feature selection and least square support vector machine.
- Al-Raheem, K.F., & Abdul-Karem, W. (2010). Rolling bearing fault diagnostics using artificial neural networks based on laplace wavelet analysis. *International Journal of Engineering, Science and Technology*, 2(6).
- Chen, C., & Mo, C. (2004). A method for intelligent fault diagnosis of rotating machinery. *Digital Signal Processing*, 14(3), 203-217.
- Gupta, K. (1997). Vibration—a tool for machine diagnostics and condition monitoring. *Sadhana*, 22(3), 393-410.
- Han, T., Yang, B.-S., Choi, W.-H., & Kim, J.-S. (2006). Fault diagnosis system of induction motors based on neural network and genetic algorithm using stator current signals. *International Journal of Rotating Machinery*, 2006.
- Huo-Ching, S., & Yann-Chang, H. (2012, 4-6 June 2012). Fault diagnosis of steam turbine-generator sets using evolutionary based support vector machine. Paper presented at the Computer, Consumer and Control (IS3C), 2012 International Symposium on.
- Jardine, A.K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, 20(7), 1483-1510. doi: DOI 10.1016/j.ymssp.2005.09.012
- Lei, Y., He, Z., & Zi, Y. (2008). A new approach to intelligent fault diagnosis of rotating machinery. *Expert Systems with Applications*, 35(4), 1593-1600.
- Lei, Y., He, Z., Zi, Y., & Chen, X. (2008). New clustering algorithm-based fault diagnosis using compensation distance evaluation technique. *Mechanical Systems and Signal Processing*, 22(2), 419-435.
- Lei, Y., He, Z., Zi, Y., & Hu, Q. (2007). Fault diagnosis of rotating machinery based on multiple anfis combination with gas. *Mechanical Systems and Signal Processing*, 21(5), 2280-2294. doi: DOI 10.1016/j.ymssp.2006.11.003
- Li, B., Chow, M.-Y., Tipsuwan, Y., & Hung, J.C. (2000). Neural-network-based motor rolling bearing fault diagnosis. *Industrial Electronics, IEEE Transactions on, 47*(5), 1060-1069.
- Ocak, H., Loparo, K.A., & Discenzo, F.M. (2007). Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: A method for bearing prognostics. *Journal of sound and vibration*, *302*(4), 951-961.

- Randall, R.B., & Antoni, J. (2011). Rolling element bearing diagnostics—a tutorial. *Mechanical Systems and Signal Processing*, 25(2), 485-520.
- Salahshoor, K., Kordestani, M., & Khoshro, M.S. (2010). Fault detection and diagnosis of an industrial steam turbine using fusion of svm (support vector machine) and anfis (adaptive neuro-fuzzy inference system) classifiers. *Energy*, 35(12), 5472-5482.
- Samanta, B., & Al-Balushi, K. (2003). Artificial neural network based fault diagnostics of rolling element bearings using time-domain features. *Mechanical* systems and signal processing, 17(2), 317-328.
- Samanta, B., Al-Balushi, K., & Al-Araimi, S. (2003). Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection. *Engineering Applications of Artificial Intelligence*, 16(7), 657-665.
- Sanz, J., Perera, R., & Huerta, C. (2007). Fault diagnosis of rotating machinery based on auto-associative neural networks and wavelet transforms. *Journal of Sound and Vibration*, 302(4), 981-999.
- Theodoridis, S., & Koutroumbas, K. (2008). *Pattern recognition*: Elsevier Science.
- Theodoridis, S., & Theodoridis, S. (2010). *Introduction to pattern recognition : A matlab approach*. Burlington, MA: Academic Press.
- Wei, X., Guo, K., Jia, L., Liu, G., & Yuan, M. (2013). Fault isolation of light rail vehicle suspension system based on ds evidence theory and improvement application case. *Journal of Intelligent Learning Systems & Applications*, 5(4).
- Welling, M. (2005). Fisher linear discriminant analysis. Department of Computer Science, University of Toronto.
- Wong, M., Jack, L., & Nandi, A. (2006). Modified selforganising map for automated novelty detection applied to vibration signal monitoring. *Mechanical Systems and Signal Processing*, 20(3), 593-610.
- Yang, B.-S., Han, T., & An, J.L. (2004). Art–kohonen neural network for fault diagnosis of rotating machinery. *Mechanical Systems and Signal Processing*, 18(3), 645-657.
- Yang, B.-S., Han, T., & Hwang, W.-W. (2005). Fault diagnosis of rotating machinery based on multiclass support vector machines. *Journal of Mechanical Science and Technology*, 19(3), 846-859.
- Yang, B.-S., & Widodo, A. (2009). Introduction of intelligent machine fault diagnosis and prognosis: Nova Science Publishers.

BIOGRAPHIES

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Anomaly Detection Using Self-Organizing Maps-Based K-Nearest Neighbor Algorithm

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ABSTRACT

Self-organizing maps have been used extensively for condition-based maintenance, where quantization errors of test data referring to the self-organizing maps of healthy training data have been used as features. Researchers have used minimum quantization error as a health indicator, which is sensitive to noise in the training data. Some other researchers have used the average of the quantization errors as a health indicator, where the best matching units of the trained self-organizing maps are required to be convex. These requirements are not always satisfied. This paper introduces a method that improves self-organizing maps for anomaly detection by addressing these issues. Noise dominated best matching units extracted from the map trained by the healthy training data are removed, and the rest are used as healthy references. For a given test data observation, the k-nearest neighbor algorithm is applied to identify neighbors of the observation that occur in the references. Then the Euclidean distance between the test data observation and the centroid of the neighbors is calculated as a health indicator. Compared with the minimum quantization error, the health indicator extracted by this method is less sensitive to noise, and compared with the average of quantization errors, it does not put limitations on the convexity or distribution of the best matching units. The result was validated using data from experiments on cooling fan bearings.

1. INTRODUCTION

Anomalies are patterns in data that do not conform to a defined notion of normal behavior (Chandola, Banerjee, & Kumar, 2009). Anomaly detection is used in the prognostics and health management (PHM) of mechanical and electronic systems to detect the existence of a fault before failure happens. The performance of currently available

anomaly detection methods leaves room for improvement because some systems are still failing without warning. For example, even though maintained regularly, bearings remain the top contributor to failures of systems like computer cooling fans (Tian, 2006) and induction motors (Bianchini, Immovilli, Cocconcelli, Rubini, & Bellini, 2011).

The data used in anomaly detection for mechanical and electronic systems are signals that are sensitive to faults. For example, in rotating machinery, time series like vibration signals and motor current signals have been used because they are sensitive to faults, widely available, and nonintrusive. Some other signals like acoustic emission signals were found to be sensitivity to a fault at an early stage (Oh, Azarian, & Pecht, 2011), and they have been used as precursor parameters in the health monitoring of cooling fan bearings (Oh & Shibutani, 2012).

Sensor signals may not be adequate for users to identify an anomaly of the system so fault features have been extracted from the sensor signals to increase separation of the normal and abnormal behavior of the system. For time series signals, commonly used features include peak-to-peak, rms, and kurtosis of the signal's amplitude in the time domain, characteristic frequency components, wavelet coefficients, and empirical mode decomposition energy in frequency and time-frequency domains. Some researchers have introduced more sophisticated features (Tian, Morillo, & Pecht, 2013).

The extracted features need to be transformed to understandable information to determine if a test observation is an anomaly or not. There are two approaches to perform this task. One is the physics-of-failure (PoF) approach. Variables of PoF models are monitored and compared to the calculated value from the model. When deviation of the monitored value from the model value exceeds a predetermined threshold, an anomaly is identified. Another is data-driven approach, where data mining techniques are applied to explore the structure of the data of the extracted features. Based on the structure, deviation of the system from a normal state is estimated. The PoF

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approach requires physical models of the system failure mechanisms, which are not available in many applications. The data-driven approach does not have this requirement, but it needs more data than the PoF approach. With the rapid development of data acquisition techniques, the obstacle to obtain data is weakened, and therefore datadriven approaches are preferred in many applications.

The data-driven approach is usually realized by machine learning techniques. Based on the use of the data, machine learning techniques can be classified as supervised machine learning techniques and unsupervised machine learning techniques (Pecht, 2008). To detect a fault, supervised machine learning techniques require healthy training data and faulty training data to construct regions of healthy conditions and faulty conditions, and then a test data observation is classified to be healthy or faulty depending on which region it falls into. In anomaly detection, representative supervised machine learning techniques include support vector machine (SVM) (Sotiris, Tse, & Pecht, 2010) and *k*-nearest neighbor (KNN) algorithms (He, Li, & Zhu, 2013). Application of these techniques is limited by the availability of training data of anomalies.

Unsupervised machine learning techniques do not need training data. They group observations into different clusters according to their mutual similarity. For example, during clustering, normal data and anomalies have different performance. Normal data may form large and dense clusters, and anomalies may form small and sparse clusters. Popular unsupervised machine learning techniques for anomaly detection in mechanical and electronic systems include self-organizing maps (SOM) (Huang, Xi, Li, Liu, Qiu & Lee, 2007) and *k*-means clustering (Wang, Liu, & Cui, 2012). Success of these techniques depends on the assumed relationship between the characteristics of the clusters and the anomalies.

In many cases, normal data are abundant and the anomalies that can be used for training are scarce. Semi-supervised learning techniques are preferred in these cases. Some researchers identify the class for normal data and use these data as references to calculate the Mahalanobis distance (MD) of the test data (Jin, Ma, Cheng, & Pecht, 2012). The test data are classified as anomalies if their MD values are above a certain threshold. When the normal data are distributed in several clusters, current applications of MD cannot reflect the degree of deviation of the test data from being normal. Some researchers have used self-organizing maps (SOM) to cluster the data in terms of best matching units (BMUs) (Huang et al. 2007). The smallest distance of a test data observation to the BMUs, which is called the minimum quantization error (MQE) is used as an indicator for anomaly detection. In the presence of noise, which is introduced into the signals via sources like other interfering signals and errors of measurements, MQE can be the

distance of the test data observation to a noise-dominated BMU, resulting in false detection.

In this study, the semi-supervised application of SOM in anomaly detection is improved. After the maps are trained by normal training data, some BMUs are removed to reduce the influence of noise, and the neighbors in the BMUs of a given test data observation are identified by the *k*-nearest neighbor algorithm. Then the Euclidean distance between the test data observation and the centroid of the neighbors is calculated as an anomaly indicator.

The rest of the paper is organized as follows: in section 2, the theoretical background of SOM and its application in system health monitoring are introduced. The SOM-based KNN algorithm developed in this study is introduced in section 3, and the algorithm is validated with an experimental study in section 4. In section 5, conclusions from this study are presented.

2. SELF-ORGANIZING MAPS

Self-Organizing Maps (SOM), also called Kohonen neural network, is a type of unsupervised machine learning technique based on competitive learning (Kohonen, 1990). It creates a network that maintains information on the topological relationships within the training data.

2.1. Theoretical Background of SOM

An SOM consists of a number of neurons. Each neuron is represented by a weight vector that has the same dimension of the training data. The neurons are organized according to their similarity where the neurons with the similar weight vectors are grouped as neighbors. This neighborhood relationship describes the structure of the map, which reflects the relationship in the training data.

To create an SOM, at first the input data is normalized per variable by calculating the z-score of each observation. The size of the map is then determined by calculating the number of neurons from the number of observations in the training data using Eq. (1).

$$M \approx 5\sqrt{N} \tag{1}$$

where M is the number of neurons, which is an integer close to the result of the right hand side of the equation, and N is the number of observations.

The neurons are organized in a 2-dimensional map. The ratio of the side lengths of the map is approximately the ratio of the two largest eigenvalues of the training data's covariance matrix.

Elements of the weight vector of each neuron are initialized randomly. A training data observation is then picked as an input vector to calculate its Euclidean distance between all the neurons. For each input observation, the neuron that has the minimum distance is found. This neuron is called the best matching unit (BMU) of that input observation. Neighbors of the BMU are selected, and their weight vectors are updated using a neighborhood function in described Eq. (2).

$$h_{ai}(t) = a(t)e^{(-\frac{\|r_c - r_i\|^2}{2\sigma^2(t)})}$$
(2)

where h_{ci} is the neighborhood function between the BMU *c* and a neuron *i*. *t* is the index of iterations of training. *a* is the learning rate. r_c is the vector of the BMU *c*, and r_i is the vector of neuron *i*. σ is the radius around *c*.

The neighborhood function is a non-increasing function of t and the distance between neuron i and the BMU c so that the neurons close to the BMU c are moving closer to c and the rate of moving is decreasing over the iterations of training.

The neurons are updated according to Eq. (3).

$$W_i(t+1) = W_i(t) + h_{ci}(t)[x(t) - W_i(t)]$$
(3)

where $W_i(t)$ is the weight vector of neuron *i* at t^{th} iteration of training. h_{ci} is the neighborhood function, and x(t) is the input observation of the BMU *c*.

The SOM is trained iteratively until all the weight vectors of the map are grouped into clusters according to their distance. When the learning process finished, the SOM is created. The procedure is summarized in Figure 1. Details of SOM can be found in (Kohonen, 1990).

2.2. Application of SOM in Mechanical and Electronic System Health Monitoring

Researchers have explored the performance of SOM in health monitoring of mechanical and electronic systems where minimum quantization error (MQE) of a test data observation to the SOM has been used as a indicator to evaluate the health of the system (Qiu, Lee, Jin, & Yu, 2003).

Quantization error describes the distance between the input data observation and the BMU of the SOM. MQE is calculated as in Eq. (4):

$$Q = \min_{k} \left\| D - B_{k} \right\| \tag{4}$$

where Q is the MQE, D is a test data observation, and B_k is the weight vector of the k^{th} BMU.

To monitor health conditions, at first the SOM is trained by the healthy training data, and then the MQE of a test data observation to the SOM is obtained. Large MQE indicates that the test data observation belongs to a space which is not covered by the training data. Based on the assumption that any deviation from the space covered by the normal training data is regarded as a deviation of the system from being normal, MQE can be used to indicate the severity of the system's deviation from normal. This assumption is evaluated in the studies of (Kang & Birtwhistle, 2003). When MQE values are calculated for different stages in the life cycle of the system, the trend of the system's health condition is obtained.



Figure 1. Flow chart of the training process of SOM

In practical situations, the normal training data are inevitably contaminated by noise. It is likely that during the training process, noise may have dominant influence on some BMUs in the map. During the testing process, when a test data observation is close to one of the noise dominated BMUs, its value of MQE is small, and it would be classified as normal. As a result, false detection may occur.

One method to reduce the influence of noise dominated BMUs is to use the average of all the quantization errors as an indicator. This is equal to the Euclidean distance between the test observation and the centroid of all the BMUs. However, if the BMUs are distributed in different clusters, or if they are non-convex, the centroid of the BMUs may fail to represent the collective information of the BMUs. Therefore, a method is needed to improve the application of SOM in anomaly detection under noisy conditions.

3. SELF-ORGANIZING MAPS-BASED K-NEAREST NEIGHBOR ALGORITHM

As discussed in section 2, MQE is subject to the influence of noise in the training data, and the average of quantization errors fails to work for the training data that are non-convex or have isolated clusters. These shortcomings can be overcome by selecting a subset of the BMUs and calculating their average quantization errors as an anomaly indicator.

At first, a threshold is applied to the BMUs to remove the noise dominated BMUs. The normal training data contains information of both the dynamics of the system and noise. The dynamics of the system are stable and the data should concentrate on certain neurons in the SOM. As a result, some neurons become BMUs multiple times. The noise is random and the data from the noise do not concentrate on any neuron. As a result, even if some neurons become BMUs because of the noise, these neurons do not become BMUs very often. By removing the BMUs with relatively few hits, the influence of noise can be reduced.

A subset of the BMUs is then selected. The average quantization error of a test observation to the BMUs in the subset is calculated as an anomaly indicator. Using the subset of BMUs has two benefits. First, by calculating the average of the quantization errors of the subset, the influence of noise is further reduced. Second, for a certain size of the subset in a local region, the data of the subset can be confined to the same cluster and be approximately convex, and therefore, the centroid of the subset is representative of the health condition of this subset.

A main task is to select the BMUs that form the subset as the normal reference. In this study, the BMUs in the subset are selected as the nearest neighbors of the test data observation. If one nearest neighbor is selected, the health indicator is the MQE. If *k* nearest neighbors are selected, the health indicator is calculated as the average of the MQE, the second minimum quantization error, and up to the k^{th} minimum quantization error. By including multiple nearest neighbors, the influence of noise is reduced.

Identification of the nearest neighbors is performed by the *k*nearest neighbor (KNN) algorithm. In most cases, KNN is used as a classification technique, where a test data observation is classified to a class if it is closer to the nearest neighbors in that class. In this study, KNN is used as a semi-supervised learning technique, where KNN is only used to identify the nearest neighbors in the reference BMUs. The distance of the test data observation to the centroid of the identified neighbors is calculated. In this study this distance is called KNN distance. It is used as the health indicator. The use of KNN in this study is illustrated in Figure 2.



Figure 2. KNN distance of a test data observation when k=3





Figure 3. Flow chart of the SOM-based KNN Algorithm

In anomaly detection, the method is first applied to the healthy training data to get the sample of the value from the health indicator of the healthy system. A percentile of the sample is then selected as the anomaly threshold.

4. EXPERIMENTAL STUDY

The data from a cooling fan accelerated life test was used to validate the method developed in this study. The data have a tendency to form several clusters and they contain noise, which can present difficulties when used with conventional methods. The SOM approaches which involve either directly using the MQE or taking the distance to the centroid of multiple BMUs as the healthy reference produce erroneous detection results when used with this type of data or with non-convex data. The method developed in this paper was designed to address these two issues, which is demonstrated using data collected from the cooling fan bearing in the experiment.

4.1. Setup of the Experiment

A new cooling fan with ball bearings was tested. The ball bearings were designed to be lubricated by grease and oil. To accelerate the degradation, the bearings were only lubricated by oil. After an initial measurement, the cooling fan was run at its rated speed of 4,800 rpm in a chamber at the fan's maximum rated temperature of 70 °C. The cooling fan under test is shown in Figure 4.



Figure 4. The cooling fan under test

4.2. Data Acquisition

The vibration acceleration signal and the motor current signal have been identified as sensitive to bearing faults (Immovilli, Bellini, Rubini, & Tassoni, 2010). The two signals were monitored in this study. The measurements were collected while the cooling fan was run at room temperature for a brief time between stressing periods. Signals collected at each measurement have a time span of 10 seconds and consist of 1,024,000 observations, where the sampling rate is 102,400 Hz. Before the accelerated life test, three measurements of signals were collected as training data, which form a 3,072,000 by 2 matrix. Each row is an observation, and each column is a signal. Test data were collected after 0 hours, 8 hours, 16 hours, 24 hours, 48 hours, and 72 hours of accelerated life testing, which form 6 stages of the test. At each stage there was one measurement of the signals, which form a 1,024,000 by 2 matrix. The 0 hour signal was one of the three measurements from the training data.

The data were cut into segments sequentially. Each segment has 0.2 seconds of data, each containing 20,480 observations. For one measurement, there are 50 segments. Features were extracted from these segments. The structure of a measurement is shown in Table 1.

Segment index	Observation index	Vibration	Current
	1	0.06	-6.84
1	2	0.12	-6.66
	20480	0.11	5.66
2	20481	0.15	5.75
	40960	0.26	6.34
•••			
	921601	-0.23	5.84
50			
	1024000	0.29	-6.98

Table 1. Structure of a measurement

4.3. Feature Extraction

Some commonly used fault features were extracted from the segments of the data for both the vibration signal and the current signal. These features include peak-to-peak, rms, standard deviation, skewness, and kurtosis of the amplitude. For each signal, there are 5 features, and for both the vibration and current signals, together there are 10 features. After feature extraction, the data of each measurement is a 50 by 10 matrix, where the row is an observation of the features, and the column is a feature.

4.4. Analysis Result

All the data were normalized by calculating z-scores referring to the mean and standard deviation of the training data. The size of the SOM was determined according to Eq. (1). The training data have three measurements, each of which has 50 observations, so there are 150 observations for training. According to Eq. (1), the map size was determined as 9 by 7 with 63 neurons. Each neuron is a vector with 10 elements, corresponding to the number of features.

After training, BMUs were identified in the map, as shown in Figure 5. Each lattice cell represents a neuron, and the number in a cell is the number of times the neuron has become a BMU, or the number of hits. The map shows the data tend to form several clusters.

To determine the threshold to remove noise dominated neurons, hits of the neurons were sorted in a descending manner. The percentage of the cumulative sum of hits was plotted in Figure 6.

The x axis is the index denoting the neurons with the same number of hits. For example, 3 denotes the neurons that have 3 hits. There are 9 such neurons, and altogether they account for 45 hits in the map. The y axis is the cumulative fraction of hits for the neurons referring to the total sum of hits.



Figure 5. Hits of BMUs in the trained SOM



Figure 6. Cumulative fraction of hits

Among the 63 neurons, 52 neurons have become BMUs at least once. The sum of hits from neurons with more than 1 hit account for 91.3% of the total hits. If we accept that 90% of the BMU neurons are not dominated by the noise, the neurons that have 1 hit should be removed. The remaining BMU neurons were used as reference data for KNN analysis.

For each observation from the features of the test data, KNN found k nearest neighbors in the reference data, which are the BMUs. A larger k reduces influence of noise better, but it makes the algorithm more sensitive to the convexity of the data. Also, an odd value of k can help the algorithm to avoid tied votes. In this study, k was set to 3, considering that one neighbor is too sensitive to noise, and the next odd number is 3. The Euclidean distance of the test observation to the centroid of the BMUs neighbors was calculated as a health indicator. Values of the health indicator for the training data were calculated to establish a baseline for healthy condition. Distribution fitting of the health indicator value for the training data is shown in Figure 7. The Kolmogorov–

Smirnov goodness-of-fit test verified that the data could be fitted with a lognormal distribution. Using the 99.7 percentile as the threshold to separate healthy data and anomalies, the anomaly threshold on the health indicator was found to be 3.6. If the value of the health indicator of a test observation is higher than this value, the observation is classified as an anomaly.

The algorithm was applied to the data at all six stages of the test. Results are shown in Figure 8.



Figure 7. Distribution fitting of the health indicator of the healthy training data



Figure 8. Health indicator for the test data

The health indicator values of the test data at each stage are shown in box plots. For each box, the central mark is the median, the edges are the 25th and 75th percentiles, and the whiskers extend to the most extreme data observations not considered outliers. Outliers are observations which are outside 2.7 standard deviations from the mean value of the data and are marked as crosses. The circles are the means. Means at different time intervals are linked by straight lines.

According to the health indicator value at each stage, the cooling fan bearings began to have anomalies after 8 hours

of test. The health indicator indicates that the bearing degraded monotonically until the end of the test after 72 hours of test, where the bearing failed with audible sound emitted. The results are consistent with the observations in the experiment. The increase of the health indicator, which is the distance between the test data to their nearest neighbors in the reference BMUs, occurred because the reference BMUs established a region representing healthy conditions of the bearings. Larger distances to this region indicate a larger deviation from the healthy conditions of the bearings degraded, their condition deviates from being healthy, so the distance to the healthy region, which is the health indicator, increased.

Besides the mean value, the standard deviation of the health indicator value is also increasing with the degradation of the bearings. This observation can be directly seen in Figure 8. The standard deviation of the health indicator value at each stage of the test is shown in Figure 9.

The increase of the standard deviation can be explained as occurring because, as bearings degrade, random fluctuations become more frequent and intense in the vibration signal and the current signal. Values of the fault features extracted from the signals are distributed in a wider range due to these fluctuations, and as a result, the health indicator has a larger standard deviation as it combines the information of the features.



Figure 9. Standard deviation of the health indicator

In summary, although the data tended to form clusters, and contained noise, the method monitored the degradation of the bearing, and successfully detected the anomalies. The unsupervised learning method employed in this study has the benefit of reduced sensitivity to noise in the data and the ability to accommodate data non-convex distributions including data with multiple clusters. The requirements of this method are that training data are needed that sample the full range of healthy behavior (i.e., represent all the possible healthy clusters and the complexity of their distribution). This can impose practical limitations on the use of this method, since it can be costly or time consuming to collect this type of data for some systems. Furthermore, this method needs to be combined with other algorithms for diagnostic or prognostic functions, since it is limited to anomaly detection.

5. CONCLUSIONS

This paper presents a self-organizing maps-based k-nearest neighbor algorithm for anomaly detection, which is applied in the health monitoring of mechanical and electronic systems. BMUs of the SOM trained by the healthy training data are extracted as healthy references. BMUs with small hits are removed from the references to reduce the influence of noise. For a test data observation, its Euclidean distance to the nearest neighbors in the reference BMUs is calculated as its health indicator value.

The algorithm provides a measure of health monitoring and anomaly detection of bearings where the influence of the noise from the monitoring signals is reduced by removing noise dominated BMUs and by averaging neighboring reference BMUs. The influence of the distribution of the healthy training data is reduced by using KNN to take a subset of BMUs in a local region as references. Outputs of the algorithm include a health indicator that monotonically increases with the degradation of the system, and an anomaly detection threshold on the value of the health indicator. Moreover, the standard deviation of the health indicator can also be used as a measure of degradation for the system.

The algorithm can be implemented in applications where the healthy training data are non-convex, for example, the data have several clusters. The algorithm can also reduce the influence of noise.

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REFERENCES

- Bianchini, C., Immovilli, F., Cocconcelli, M., Rubini, R., & Bellini, A. (2011). Fault detection of linear bearings in brushless AC linear motors by vibration analysis. *IEEE Transactions on Industrial Electronics*, vol. 58, no. 5, pp. 1684-1694.
- Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. ACM Computing Surveys (CSUR), vol. 41, no. 3, pp. 15:1-15:58.
- He, D., Li, R., & Zhu, J. (2013). Plastic bearing fault diagnosis based on a two-step data mining approach. *IEEE Transactions on Industrial Electronics*, vol. 60, no. 8, pp. 3429-3440.
- Huang, R., Xi, L., Li, X., Richard Liu, C., Qiu, H., & Lee, J. (2007). Residual life predictions for ball bearings based

on self-organizing map and back propagation neural network methods. *Mechanical Systems and Signal Processing*, vol. 21, no.1, pp. 193-207.

- Immovilli, F., Bellini, A., Rubini, R., & Tassoni, C. (2010). Diagnosis of bearing faults in induction machines by vibration or current signals: A critical comparison. *IEEE Transactions on Industry Applications*, vol. 46, no. 4, pp. 1350-1359.
- Jin, X., Ma, E. W., Cheng, L. L., & Pecht, M. (2012). Health monitoring of cooling fans based on Mahalanobis distance with mRMR feature selection. *Instrumentation and Measurement, IEEE Transactions* on, vol. 61, no.8, pp. 2222-2229.
- Kang, P., & Birtwhistle, D. (2003). Condition assessment of power transformer onload tap changers using wavelet analysis and self-organizing map: field evaluation. *IEEE Transactions on Power Delivery*, vol. 18, no.1, pp. 78-84.
- Kohonen, T. (1990), The self organizing map. *Proceedings* of the IEEE, vol. 78, no. 9, pp. 1464-1480.
- Lau, E. C., & Ngan, H. W. (2010). Detection of motor bearing outer raceway defect by wavelet packet transformed motor current signature analysis. *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 10, pp. 2683-2690.
- Oh, H., Azarian, M. H., & Pecht, M. (2011). Estimation of fan bearing degradation using acoustic emission analysis and Mahalanobis distance. *Proceedings of the Applied Systems Health Management Conference* (pp. 1-12), May 10-12, Virginia Beach, VA, U.S.A.
- Oh, H., Shibutani, T., & Pecht, M. (2012). Precursor monitoring approach for reliability assessment of cooling fans. *Journal of Intelligent Manufacturing*, Vol. 23, no. 2, pp. 173-178.
- Pecht, M. (2008). *Prognostics and Health Management of Electronics*. New York: Wiley-Interscience, New York.
- Qiu, H., Lee, J., Lin, J., & Yu, G. (2003). Robust performance degradation assessment methods for enhanced rolling element bearing prognostics. *Advanced Engineering Informatics*, vol. 17, no. 3, pp. 127-140.
- Sotiris, V. A., Tse, P. W., & Pecht, M. G. (2010). Anomaly detection through a Bayesian support vector machine. , *IEEE Transactions on Reliability*, vol. 59, no. 2, pp. 277-286.
- Tian, J., Morillo, C., & Pecht, M. G. (2013). Rolling element bearing fault diagnosis using simulated annealing optimized spectral kurtosis. *IEEE Conference* on Prognostics and Health Management (PHM), (pp. 1-5), June 24-27, Gaithersburg, MD, U.S.A.
- Tian, X. (2006), Cooling fan reliability: failure criteria, accelerated life testing, modeling and qualification. *Proceedings of 2006 Reliability and Maintainability Symposium* (pp. 380-384), Jan 23-26, Newport Beach, CA, U.S.A.

Wang, G., Liu, C., & Cui, Y. (2012). Clustering diagnosis of rolling element bearing fault based on integrated Autoregressive/Autoregressive Conditional Heteroscedasticity model. *Journal of Sound and Vibration*, vol. 331, no. 19, pp. 4379-4387.

BIOGRAPHIES

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Refining Envelope Analysis Methods using Wavelet De-Noising to Identify Bearing Faults

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ABSTRACT

In the field of machine health monitoring, vibration analysis is a proven method for detecting and diagnosing bearing faults in rotating machines. One popular method for interpreting vibration signals is envelope-demodulation, which allows the maintainer to clearly identify an impulsive fault source and its severity. In some cases, in-band noise can make impulses associated with incipient faults difficult to detect and interpret. In this paper, we use Wavelet De-Noising (WDN) after envelope-demodulation to improve the accuracy of bearing fault diagnostics. This contrasts the typical approach of de-noising raw vibration signals prior to demodulation. We find that WDN removes low amplitude harmonics and spurious reflections which may interfere with FFT techniques to identify low-frequency peaks in the signal spectrum. When measuring impact frequencies in the time-domain using a peakthresholding method, the proposed algorithm exhibits increasingly confident periodicity at bearing fault frequencies.

1. INTRODUCTION

1.1. Bearing Fault Diagnosis

A faulty bearing will typically create periodic, impulsive vibrations, which are proportional to rotational speed. These vibrations may be recorded and analyzed to reveal the nature of a given fault. Systems with multiple bearings and gear reduction systems will exhibit unique fault frequencies due to varying component dimensions and operating speeds. This simple observation may be exploited to determine exactly which component is failing (Qui, Lee, Lin, & Yu, 2006). In more sophisticated systems, multiple sensors are often used to indicate fault locations based on local vibration power levels (Waters & Beaujean, 2013).

1.2. Envelope Analysis

Within a given structure, fault-induced impulses will amplitudemodulate mechanical resonances (McFadden & Smith, 1984). Research on which this paper is based (Waters & Beaujean, 2013) utilizes envelope analysis to extract impulses from the modulated signal, which allows for quick diagnosis of apparent mechanical problems.

However, incipient faults are rather difficult to detect using this method, due to lower signal-to-noise ratio (SNR). Extraneous noise sources such as nearby modal resonances, vibrational reflections, and vibrational harmonics corrupt the envelope signal. We find that low SNR degrades early-detection abilities and in turn deteriorates estimates of Remaining Useful Life (RUL). These noise sources are in-band and nonwhite, so their removal is less than trivial.

To combat a low SNR in the demodulated signal, we require a "de-noising" technique. This research focuses on wavelet de-noising and its use in vibration analysis, particularly as a post-processing scheme for envelope analysis. A secondary objective is to reduce user-interaction with the algorithm's parameters to obtain beneficial results.

1.3. Wavelet De-Noising

Many techniques have been devised for noise removal via signal processing. For our purposes, the algorithm must process non-stationary signals with good time-resolution. Vibration statistics will be in constant flux, given changes in bearing wear, speed, and operating environment. More importantly, it must perform without *a priori* knowledge of the noise.

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As far as the aforementioned requirements specify, Wavelet De-Noising (WDN) is a proven candidate. The wavelet transform outperforms the Short-Time Fourier Transform (STFT) in terms of temporal resolution, allowing it greater flexibility in analyzing non-stationary signals (Rioul & Vetterli, 1991). It has also been demonstrated that WDN requires no knowl-edge of the noise level in order to optimally remove it (Donoho, 1995).

1.4. Paper Structure

Section 2 provides a brief overview of wavelet de-noising and its function, and reviews previous literature pertaining to PHM applications. Section 3 explains the proposed methodology, then sections 4 and 5 contain results supporting the use of WDN to help interpret demodulated vibration signals, and Section 6 contains a few concluding remarks.

2. BACKGROUND

2.1. Discrete Wavelet Transform

A more in-depth discussion of wavelet techniques can be found in (Daubechies, 1992). The wavelet transform, given as the operator W, is easily visualized in the continuous domain:

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt$$
(1)

where f is an arbitrary function of the independent variable t, and $\psi_{a,b}$ is a family of wavelet functions defined by scaling and shifting – respectively a and b,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

where ψ is a prototype function, or wavelet kernel.

In order to utilize this transform for sampled data, we discretize the scaling and shifting parameters in the following manner:

$$a_m = a_0^m \tag{3}$$

$$b_{m,n} = nb_0 a_0^m \tag{4}$$

where m and n are the discrete analogues of frequency and time, respectively.

Notably, the shifting parameter b is a function of scale a. This illustrates a crucial advantage of the Discrete Wavelet Transform (DWT); the distribution of information in frequency is dyadic, or octave-band. For analyzing natural signals, this is highly useful (Rioul & Vetterli, 1991).

The DWT results in a set of wavelet coefficients d, which are given by the inner product

$$d_{m,n} = \langle f(t), \psi_{m,n}(t) \rangle \tag{5}$$

which, when the proper wavelet family is chosen, represents

a frequency-orthogonal decomposition of the original signal into subbands which are logarithmically spaced in frequency, as shown in Figures 1 and 2. In Figure 1, the wavelet inner product is functionally equivalent to BPF and LPF, or bandpass and lowpass filtering.



Figure 1. Octave subband tree structure with three levels of decomposition. Each filtering results in a set of coefficients, typically referred to as detail (high frequency, cD) and approximation (low frequency, cA) coefficients. If this pattern is repeated until cD_6 and cA_6 , the 6-level decomposition shown in Figure 2 will result.



Figure 2. Filter magnitude responses of a six level wavelet decomposition, using the db6 wavelet. Note the logarithmic frequency scale.

2.2. Coefficient Thresholding

As originally proposed in (Donoho & Johnstone, 1994), the linear soft thresholding function is given by

$$\tau(x) = \begin{cases} x - \lambda \operatorname{sgn}(x), & |x| \ge \lambda \\ 0, & |x| < \lambda \end{cases}$$
(6)

where x are the values being thresholded, sgn(x) is the sign of x, and λ is the threshold below which values are set to zero. Donoho and Johnstone (1994) prove that the threshold λ for near-optimality (in the minimax sense) is calculated as

$$\lambda = \sigma_x \sqrt{2\log(N)} \tag{7}$$

where N is the number of samples in the time series and σ_x is the noise deviation. Exact noise statistics are difficult to estimate without *a priori* characteristics or reference measurements. A simplifying assumption is to consider Gaussian noise as the dominant source in an incipient fault situation, as suggested in Bozchalooi and Liang (2007). Therefore, the noise deviation $sigma_x$ is just the unbiased estimate of the standard deviation of the input signal.

$$\sigma_x \approx \sqrt{\frac{1}{N-1} \sum_{k=1}^N (x_k - \mu_x)^2} \tag{8}$$

where x_k are sample values and μ_x is the arithmetic mean of the time series.

When the thresholding function is applied to orthogonally derived wavelet coefficients, the result is a de-noised version of the original signal.

2.3. Existing Literature

Qui et al. (2006) discussed wavelet domain techniques for vibration analysis applications. The authors use the same method described in Section 2, but they criticize the use of WDN for vibration signals due to tuning difficulties:

[...] there are other factors influencing the effectiveness of [wavelet] de-noising, such as the wavelet decomposition level and threshold rescaling method selection, which make the de-noising problem even more intricate. Since there are no explicit guidelines for how to tune the existing parameters, most of the time de-noising becomes a trial-and-error process. (Qui et al., 2006, pg. 1080)

There is much truth to these statements, and using WDN on raw vibrational signals generally gives unpredictable results. However, this paper concludes that WDN is quite functional in the context of envelope-demodulated vibration signals.

3. SIGNAL FLOW & METHODOLOGY

Typically, de-noising algorithms are used as a pre-processing step to improve the effectiveness of subsequent signal processing. However we find that when used prior to envelope demodulation, WDN removes low-amplitude modal resonances that allow the Hilbert Transform to work well. If the denoising is performed after demodulation, the impulse signal is more effectively de-noised.

The full signal processing procedure is as follows:

- 1. The raw vibration signal is Hilbert filtered at a chosen modal vibration frequency, resulting in a bandpass signal.
- 2. A Hilbert transform is performed, bringing the signal into the baseband.

- 3. WDN is used to attenuate lower amplitude harmonics and vibrational reflections.
- 4. The signal is searched for faults using peak detection in both time and frequency.

This report mainly focuses on the third step of this process.

3.1. Time-Domain Detection

For time-domain peak detection, the MATLAB ^(R) function findpeaks is used to find local maxima. These peaks are thresholded at thr_e , which is a function of the average signal power,

$$thr_e = \alpha \frac{1}{N_e} \sum_{i=0}^{N_e-1} e_i^2.$$
 (9)

where N_e is the number of samples in the envelope signal e. The constant α allows for adjustment to this threshold. This function will remove smaller peaks that are not associated with larger impacts.

The times between all successive peaks in the envelope signal are measured, resulting in a vector of impulse periods. The inverse of this vector is a set of impulse frequencies. A histogram will reveal higher concentrations on fault frequencies.

3.2. Frequency-Domain Detection

We use a Welch PSD estimate to visualize the distribution of energy in the frequency domain. This allows for smaller time windows and reduces spurious peaks in the FFT via averaging.

4. SYNTHETIC SIGNAL TESTING

4.1. Setup

A synthetic vibration signal was constructed to test WDN effectiveness on a controlled envelope signal.

$$d[n] = e^{-\gamma\tau} sin(\omega\tau) \tag{10}$$

$$\tau = \frac{n}{f_s} \tag{11}$$

n is the sample number, f_s is the sampling frequency, τ is time relative to n = 0, and ω is the simulated modal resonance frequency (rad/sec). γ is the exponential decay constant. This damped sine function is windowed and repeated in time to simulate a periodic impact, much like a bearing fault may produce in rotating machinery.

Modeled after real fault signals from the Case Western Reserve University bearing data set (*Bearing Data Center*, 2013), these values are inferred by observing real signals:

$$\gamma \approx 1000 \qquad \omega \approx 5000 \pi \frac{rad}{sec} \qquad f_s = 48 \text{kHz}$$

White noise is added to the signal at $\text{SNR}_T \approx 0$ dB, where SNR_T is the time-domain signal-to-noise ratio. This is calculated within a window of one time-constant of the exponentially decaying signal. This prevents inclusion of zeros between pulses, which would artificially reduce the SNR measure.

4.2. Discussion of Parameter Selection

Sensible parameter choices are derived from this experiment, which help to effectively de-noise the envelope signal.

The first parameter is n_d , or the number of decomposition levels. Selection of this value essentially determines the bandwidth of the lowest two subbands. If the desired signal is placed between subbands, then undesired attenuation may occur during thresholding.

For baseband envelopes, the number of decompositions depends on the highest possible fault frequency. In the case of a rolling element bearing, this is usually BPFI (Ball Pass Frequency of Inner raceway) (McFadden & Smith, 1984). Therefore, to determine the maximum number of decompositions allowable, we find n_d such that

$$f_s \frac{\pi/2^{n_d}}{2\pi} > \text{BPFI.} \tag{12}$$

This will ensure that the frequencies of interest are not lost between subbands.

The other important parameter is the wavelet, ϕ , which will determine the amount of energy leakage between subbands. Higher-order wavelets decrease subband leakage, but require more computational power. In the time-domain, baseband envelopes simply correspond to a lowpass-filtered impulse train. In the frequency domain, this corresponds to high energy concentrations near DC. Higher order wavelets will more accurately de-noise and reconstruct the low frequency band, which contains frequencies of interest. Throughout these experiments, the Daubechies 20-tap wavelet (db20) is sufficient.

4.3. Results

The synthesized signal is Hilbert-filtered (bandpass) at ω , Hilbert transformed (demodulated), and WDN is applied. The waveforms in Figure 3 show all stages of the algorithm.

To de-noise the envelope signal, we choose to use 10 levels of decomposition. The reasoning, using Equation 12, is that 10 levels of decomposition will give a lowpass (scaling filter) cutoff at ≈ 24 Hz. This cutoff needs to be set above the synthesized fault frequency, which is 20Hz.

4.3.1. Frequency-Domain Detection

Figure 4 shows a low-frequency Welch PSD of the signal before and after WDN, with the expected fault frequencies



Figure 3. WGN added to damped sine pulses. The fourth and fifth plots show an increase in SNR_T by $\approx +1$ dB from applying WDN. The benefits of this procedure are not immediately obvious in the time-domain. Wavelet decomposition using db20 wavelet at a depth of 10 levels.

in grey. WDN removes higher harmonics that dominate the PSD, which increases the likelihood of proper fault identification using frequency-domain techniques.

4.3.2. Time-Domain Detection

To identify the fault in the time-domain, the signal is run through a peak detector and thresholded. The confidence interval plot in Figure 5 shows the improvement in detection ability for a wider range of α . The bands around the estimate denote 95% confidence intervals. The histograms in Figures 6 and 7 demonstrate what happens as α becomes too high, and the time-domain plot in Figure 8 shows the location of the threshold for $\alpha = 46$.

4.4. Remarks

The WDN algorithm successfully attenuates non-fault related envelopes in the signal, increasing the probability of proper fault identification using both frequency-domain (PSD) and time-domain (peak thresholding) methods. The confidence



Figure 4. Welch PSD of signals shown in Figure 3 before (top) and after (bottom) WDN. Gray area shows $\pm 10\%$ of possible fault frequencies



Figure 8. A high threshold causes peaks to be discarded from the first plot, whereas the WDN version of the signal still contains these peaks.

interval plot in Figure 5 shows a "compression" in confidence with variation in threshold scaling α . In the sections that follow, this technique is tested on real-world signals to verify results.

5. REAL SIGNAL TEST RESULTS

5.1. Setup

The Case Western Reserve University bearing data were tested with the WDN algorithm. The precisely seeded faults were created with electro-discharge machining, with the smallest faults at 0.007". A short time-domain waveform is shown of the signal at all stages of the algorithm in Figure 9. The fault frequency is at BPFO (Ball Pass Frequency of Outer raceway).

The db20 wavelet is used to de-noise at 7 levels of decomposi-

tion. The resulting lowpass (scaling filter) cutoff is ≈ 187 Hz. With a rotational speed of around 1796 RPM (30Hz), the theoretical maximum fault frequency (BPFI) for the SKF 6205-2RS bearing is approximately 107Hz.

5.2. Frequency-Domain Results

The 0.007" outer raceway fault is distinguishable by the large spectral peak in Figure 10. One small, but noticeable improvement is the BPFO harmonic at ≈ 210 Hz, marked with an arrow in the figure, which is removed by WDN.

5.3. Time-Domain Results

The removal of harmonics has implications when attempting to identify faults in the time-domain. Figure 11 shows that the threshold method may pick up harmonics as the domi-



Figure 10. Low frequency PSD of the vibration signal shown in Figure 9. The fault frequency BPFO is approximately 107Hz.



Figure 5. Estimated fault frequency vs. threshold level for the noisy pulse signal shown in 3, periodic at 20Hz. By thresholding the peaks of this envelope at a variable level α , the de-noised envelope signal is shown to more accurately reflect periodicity at the fault frequency.

nant envelope peak frequency. This issue arises when dealing with the BPFO and BSF (Ball Spin Frequency), since their harmonics may be near BPFI. In this case, low α makes estimation inaccurate for the non de-noised signal. With WDN applied, this method works well for low thresholds. At large negative values of α , the algorithm is simply measuring the distance between local maxima.

5.4. Remarks

WDN successfully improved the time-domain fault identification method by reducing its dependence on α . Other data from the Case Western bearing dataset was tested, with similar results.



Figure 6. Histogram of impulse frequencies, before WDN. These values are derived from the threshold shown in Figure 8. Low frequency content is a result of the threshold missing lower-amplitude peaks.

6. CONCLUSION

In this paper, we have presented a method to improve detection confidence in fault identification using wavelet denoising. The method deals with the myriad of in-band noise sources in narrowband vibration signals without *a priori* noise statistics.

Decomposition techniques are more suitable to detecting smooth signals, therefore, WDN is applied after envelope demodulation. This yields better results than attempting to de-noise a broadband vibration signal, as in (Qui et al., 2006).

For general purpose signal conditioning, wavelet de-noising is a low-risk, widely applicable technique. Donoho (1995) proves that the gains in noise reduction outweigh the costs of removing low-energy details from the signal. Therefore, unless computational limitations are critical, there is little reason



Figure 7. Histogram of impulse frequencies, after WDN. With the same threshold as Figure 6, more peaks are included in the measure, at the proper fault frequency (around 20Hz).

not to utilize such an algorithm.

While this paper demonstrates the function of WDN in the context of demodulated vibration signals, it also serves as a guide for parameter choice. The number of parameters that control this algorithm can be unwieldy, but some sensible decisions and simplifying assumptions allow for ease of use:

- φ wavelet type In this paper, we decide upon the Daubechies wavelet for its flat passband characteristics. This choice allows for accurate representation of signal proportions in the scale-space domain. In our experiments, the db20 wavelet is sufficient. We choose a high order wavelet, so that the passband cutoff is sharp. This allows for a high number of decompositions without compromising the amplitudes of coefficients in the lower passbands.
- λ soft threshold level This value was derived by Donoho (Donoho, 1995) to be a function of noise variance, which is unknown. We simplify this choice by assuming the inband noise is white, so that the resulting threshold is a function of signal variance, which is known.
- n_d decomposition level For our applications, we are searching for energy in the baseband (a demodulated AM-signal). The maximum frequency of a bearing fault is the inner raceway fault frequency (BPFI). Therefore, the decomposition level must not be so high as to place the lowest subband cutoff below this frequency.



Figure 9. The time-domain waveform of a seeded fault with 0.007" diameter in the outer-raceway at all stages of the algorithm.



Figure 11. Estimated fault frequency 95% confidence intervals vs. threshold level for the vibration signal shown in 9. This figure demonstrates the importance of removing vibrational harmonics from envelope signals when using a peak thresholding method.

7. FUTURE WORK

To carry this research one step further, it is recommended that power levels be trended over long timescales. The improvements provided by WDN have yet to be tested for evaluation of RUL. It may be hypothesized that, due to the earlydetection and confidence improvements demonstrated in this paper, any RUL measure will benefit from earlier, more accurate fault specifics.

With reference to those algorithms tested by Qui et al. (Qui et al., 2006), a direct comparison between wavelet filtering and WDN was never performed, but may be warranted. The WDN algorithm as presented in this paper requires minimal interaction to improve results, where wavelet filtering requires some recursion to tune parameters. Their relative speeds and effectiveness may be a worthwhile measurement.

REFERENCES

- Bearing data center. (2013). Case Western Reserve University. Retrieved Jan 2014, from http://csegroups .case.edu/bearingdatacenter/
- Bozchalooi, I. S., & Liang, M. (2007, July). A combined spectral subtraction and wavelet de-noising method for bearing fault diagnosis. *IEEE Proceedings of the 2007 American Control Conference*, 2533-2538.
- Daubechies, I. (1992). *Ten lectures on wavelets*. Philadelphia, PA: Society for Industrial and Applied Mathematics.
- Donoho, D. L. (1995). De-noising by soft-thresholding. *IEEE Transactions on Information Theory*, 41(3), 613-627.
- Donoho, D. L., & Johnstone, I. M. (1994). Ideal spatial adaptation via wavelet shrinkage. *Biometrika*, 81, 425-455.
- McFadden, P., & Smith, J. (1984). Model for the vibration produced by a single point defect in a rolling element bearing. *Journal of Sound and Vibration*, *96*, 69-82.
- Qui, H., Lee, J., Lin, J., & Yu, G. (2006). Wavelet filter-based weak signature detection method and its application on roller element bearing prognostics. *Journal of Sound and Vibration*, 289, 1066-1090.
- Rioul, O., & Vetterli, M. (1991, October). Wavelets and signal processing. *IEEE Signal Processing Magazine*,

8(4), 14-38.

Waters, N., & Beaujean, P. (2013). Targeting faulty bearings for an ocean turbine dynamometer. *International Jour*nal of Prognostics and Health Monitoring, 4, 1-15.

BIOGRAPHIES



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Towards an Integrated COTS Toolset for IVHM Design

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ABSTRACT

This paper describes an end-to-end Integrated Vehicle Health Management (IVHM) development process with a strong emphasis on the automation in creating functional models from 3D Computer Aided Design (CAD) system's representation, throughout the implementation of this process. It has been demonstrated that functional analysis enhances the design and development of IVHM but this approach is not widely adopted by industry and the research community as it carries a significant amount of subjectivism. This paper is meant to be a guideline that supports the correctness through construction of a functional representation for a complex mechatronic system. The knowledge encapsulated in the 3D CATIA[™] System Design environment was linked with the Maintenance Aware Design environment (MADeTM) with the scope of automatically creating functional models of the geometry of a system. The entire process is documented step by step and it is demonstrated on a laboratory fuel system test rig. The paper is part of a larger effort towards an integrated COTS toolset for IVHM design. Another objective of the study is to identify the relations between the different types of knowledge supporting the health management development process when used together with the spatial and functional dimensions of an asset. The conclusion of this work is that a 3D CAD model containing the topological representation of a complex system can automate the development of the functional model of such a system.

1. INTRODUCTION

Functional Modeling is a System Engineering discipline typically carried out in the conceptual design phase of an asset. The main goal of the functional modelling is to capture, as early as possible, the overall main function of the system as well as the function of each individual component of this system. Complex systems from aerospace, off-shore, mining and maritime industry sectors change their role over the life time, and in these cases they have to meet new requirements related safety, to cost, reliability, maintainability and availability (Stecki et al., 2014). The first three types of requirements are typically specified upfront and they have been embedded into best design practices for nearly six decades. The last two types of requirements are often derived from the initial three sets of requirements as the hardware and software limitation force the designers to think of the design using one or a mix of the following three approaches:

- 1. Design alterations
- 2. Redundancy
- 3. Adoption of IVHM technologies

The last approach can be successfully used when the system's risks are identified in a systematic manner. Functional decomposition of a complex system. identification of critical components, Functional Failure Mode Effect and Criticality Analysis (FFMECA) are developed of the same time in order to construct a complete picture at the effects of failure models on the overall system's function. FFMECA can also act as foundation for assessment of failure mode propagation throughout system, identification and optimization of sensor set solutions, and construction of expert systems capable of detecting and isolating a given failure mode universe. Functional dimension of a system has to be backed up by the engineering knowledge expressed typically through physicsbased models. An IVHM development process based on a mix of physical-functional analysis proved to offer a systematic approach in designing IVHM solutions of small scale real systems (e.g. an UAV fuel system) (Niculita, 2012). This process was instantiated using strictly COTS software tools (Niculita, 2013). One of main challenges throughout this instantiation was the construction of the functional model of the fuel system from scratch. Also, the significant amount of engineering knowledge related to the

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system itself that has to be readily available to the IVHM analyst when constructing its functional representation (so that this model is indeed a true representation of the real system) is another explanation for this approach not being used at a wide scale. Functional analysis was previously described in the literature as a tool to support the overall engineering design process of large-scale cyber-physical systems (Stone & Wood, 2000; Hirtz et al, 2002, Kurtoglu et al., 2008; Uckun, 2011; Komoto & Tomiyama, 2012). All these references focused on the use of functional analysis in supporting various engineering tasks throughout the design of complex systems from a healthy perspective. Although the references mentioned above point to the functionbehavior-structure (FBS) triad when shaping a new design, this triad only captures the healthy state of a system. Stecki (2013) introduced MADeTM as the one of the COTS software tools capable of employing functional reasoning approach to support development of IVHM capability by taking into account the healthy and faulty states of a system. The goal of the current paper was to automate the IVHM design phase within the health management development process when using this particular tool. The main purpose of this effort was to be able to reuse the existent information regarding the structure of a system, information which is already available at different design stages of a given asset. For this purpose, we used a laboratory test rig to identify the steps of the process that allows an IVHM analyst to automatically generate the functional model from the 3D representation of such a system, representation which is typically constructed by a fuel system designer using a bespoke CAD tool. This paper employs CATIA[™] to emulate the fuel system designer activity of capturing the structural layer of a system.

Compared to the previous work in functional modelling, the novel contribution of this paper can be summarized as follows:

- A practical guide in identifying the steps an IVHM analyst has to go through to automatically generate functional models from structural models (previously created by system designers) using strictly COTS tools (CATIATM and MADeTM).
- 2. Enhancements required to be carried out on the functional models in order to be a truly representative qualitative dimension of the behavior quantitative models of the same system.
- 3. A use-case of an UAV fuel system application that highlights the main benefits of this approach in designing IVHM solutions for complex systems.

The paper is organized as follows. Section 2 describes the IVHM development process. Section 3 summarizes the CATIATM 3D representation of the test bed as part of the system design and also of the steps of the process that automatically generates the MADeTM functional model out

of 3D structural representation. The enhancements made to the functional model to be an accurate representation of the physics-based behavior model are described in Section 4. Section 5 collates the concluding remarks and a summary of the future direction of this research.

2. IVHM DEVELOPMENT PROCESS

The IVHM development process has been previously described in (Niculita, 2013). In this, a functional analysis is used (Figure 1) for the modelling of the effects of failure modes throughout the system (downstream effects but also upstream effects). The existent process will be enhanced by using the information gathered within CAD models to reduce the time and work required to create from scratch a functional representation of a given asset. Very often, physics-based models (depicted as an output of the System Design activity - first stage of the IVHM development process) do not necessarily describe the exact structure of a system. For example, if a pipe doesn't introduce a significant pressure drop, it will be easily discarded by the system modeler when constructing a physics-based model of a fuel system or of an environmental control system. In this context, construction of functional models based on design schematics of physics-based models is difficult. For this reason, we attempted to link the development of functional models to 3D CAD models as such representations capture every single component within a complex system.



Figure 1. Health management development process.

Although the IVHM development process is mapped against the generic engineering cycle (Design, Safety and Reliability analysis, Integration, Service and Maintenance) the modelling activities supporting the IVHM Design do not necessarily take place sequentially as depicted in the above cycle. Over the last two decades, industry and academia attempted to integrate the IVHM Design into System Design, although a clear methodology is still not available. Three dimensions in modelling a system have been identified as being capable of supporting the integration of two processes (Design and IVHM) into a common thread:

- 1. Functional modelling
- 2. Behavior modelling
- 3. Structure modelling

These three dimensions are complemented by the physical embodiment of a system as per Figure 2. The current paper will address the Function-Structure link and will offer a method to execute this link using COTS tools.



Figure 2. FBS and Physical embodiment relations

(Canedo, 2013) described the generation of multi-domain simulation models capturing both the behavior-structural dimensions of a system from the functional representation of a system that is constructed using basic elementary functions to simulation components available in Modelica (Modelica Association). This study constructs the Functional-Behavior-Structure framework from a Design perspective without introducing IVHM related concepts. Our attempt is to instantiate a generic FBS triad with the information related to system risk identification, effects of failure modes throughout the system, criticality figures in order to support Design for Availability of cyber-physical system.

3. SYSTEM DESIGN - STRUCTURE MODEL

A CAD model encapsulates a 3D representation of a given system capable of offering a digital product view.

MADe has the capability of importing CAD models to automatically create functional models from a 3D representation of an asset; this was exercised on a laboratory test-bench fuel system example and the overall step-by-step process is thoroughly described in this paper. Within this section, several findings are marked with label Fx in order to support future implementation of this process.

The CAD model has to be represented at the part level (F1); Figure 3 highlights the CAD model and its decomposition at the part level for a fuel filter component. The fuel filter selected for this fuel system (ASSY-Filter FESTO VAF-PK-3 535883) is composed of five internal parts/elements: indicator, filter head, o-ring seal, filter element, filter housing.

All these part have to be represented in CATIA in order to allow MADe to correctly import this particular component. The same level of detail has been employed for the representation of the entire fuel system test rig. At the end of the design process, after modelling and assembling components, a final assembly emerges. Figure 4 shows the CATIA Final ASSY of the fuel system test bed subject to study.



Figure 3. CAD model of the fuel filter.



Figure 4. CAD model of the fuel system.

In order to exchange this information to business partners, supply chain or contractors, it is necessary to generate a file in a neutral computer interpretable representation of system data. The International Organization for Standardization generated the ISO 10303 standard that can support this task. (SCRA Advanced Technology Institute, 2006) discusses in their publication STEP Application Handbook the current state of art in generating STEP files and their usability in the industry by CAD, CAM and CAE systems. Also, they highlight the importance of maintaining and updating the when information exchanged among different users/departments of large organization. The main advantage of the STEP file format is the fact that it can be used by other software platforms to exchange information. CATIA software automatically generates this *.stp file from a CAD model using the ISO-10303-21 standard.

Figure 5 highlights a part of the STEP code that was generated from the CAD model for this particular system.

4. SYSTEM DESIGN - FUNCTIONAL MODEL

The STEP file was then imported into the MADeTM CAD interface in order to extract information contained inside the CAD solid models. This interface identifies and selects information located in the Product definition section of the STEP file. Within the next step, this information is translated it into a *.mcdx file, which is a transition format before the data characterizing a component/system is finally imported into MADeTM. Figure 6 illustrates the extracted information from the CAD file that is translated into a *.mcdx file. Pairs between components can be also created by this interface. The pairs constitute the relationships among the different parts that directly interact within a component. Assembly components are structured in a hierarchical list. This arrangement highlights the level of each component and their hierarchical position within the system under investigation.

Within this intermediate step, the MADe FMEA Interface will validate imported files against those currently available in the MADe library (a standard library or a customized library by the IVHM Team). The CAD model should use the same taxonomy as the one available within the MADe built-in component library (*F2*). If a functional model of a filter manufactured by FESTO has been previously created and saved as part of a MADe library under the name "ASSY-Filter FESTO VAF- PK-3 535883", the CAD model of the fuel system will have to carry exactly this label when this specific type of filter is used as part of the fuel system design (*F3*).

During the import process, the hierarchy of the system and all the connections between sub-systems, components, parts have to be carefully mapped by the IVHM analyst as no automated technique is currently available in MADe (F4).

Figure 7 depicts a flow diagram containing specific tasks that are required to be carried out in order to use the MADe CAD interface.



Figure 5. STEP File associated to the fuel system CAD Design.

ENDSEC,	
/* file written by CATIA V5R20 */	
DATA;	Breduct Definition
#5=PRODUCT('Product1','','',(#2));	Product Demnition
#56=PRODUCT('Base','','',(#2));	<pre></pre>
<pre>#110808=PRODUCT('Part1','','',(#2));</pre>	<pre><pre>cpart DEVELOP name="Part1" EMEA Critical="0" EMEA component</pre></pre>
#111125=PRODUCT('bracket 1-Base','','',(#2))	(part DEVELOP pare "pace (F Motor)" FMEA Critical "O" FMEA
#112266=PRODUCT('Bracket TOP','','',(#2));	<pre><pre>cpart bevelop_name= base (e-motor) FMEA_critical= 0 FMEA</pre></pre>
#112767=PRODUCT('Base (E-Motor)','','',(#2))	<pre><pre></pre></pre>
#112942=PRODUCT('Electric Motor','','',(#2))	<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>
#123852=PRODUCT('ASSY-SELENOID VALVE', ', ',	<pre>chart DEVELOP name="bracket 1_Base" EMEA Critical="0" EME4</pre>
#123860=PRODUCT('Connector- Joint 6mm Double	ant DEVELOP name "Inacket TOD" [Michael [10] [10] [10]
#124308=PRODUCT('Selenoid valve','','',(#2))	<pre><pre> <pre> <</pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre></pre>
#126543=PRODUCT('ASSY-PUMP','','',(#2));	<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>
#126566=PRODUCT('Pump 3 MM','','',(#2));	<pre>><assembly critical<="" develop="" fmea="" name="ASSY-SELENOID VALVE" pre=""></assembly></pre>
#130195=PRODUCT('Pump1MM','','',(#2));	<pre>chart DEVELOB name="Connector_ loipt 6mm Double" f</pre>
#135034=PRODUCT('ASSY-INJECTOR','','',(#2))	spart bevelor_name= connector = borne form bouble r
#135042=PRODUCT('nozzle - fuel injector','',	<pre><pre>connector- Joint 6mm Double F</pre></pre>
#136242=PRODUCT('Holder Injector','','',(#2)	<pre><pre><pre><pre>content</pre> <pre><pre>part DEVELOP_name="Selenoid Valve" FMEA_Critical=</pre></pre></pre></pre></pre>
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Figure 6. Component selection from product structure contained by the MCDX file.





Following the steps described in the previous flow diagram, the functional model of each individual component of the fuel system has been created (at the part level). As an example, the figure below describes the links between the parts of the filter component which match the physical links of this particular component (e.g. the filter element is coupled to the filter head and the filter housing, each of these two couplings forming two pairs). The translation of a CAD model into a functional model using the MADe dedicated FMEA Step tool is carried out at the component level.

The MADe CAD Interface is capable of creating pairs between parts, but this process is manually done through the CAD Interface tool (F5).



Figure 8. Translation of physical connections internal parts of a filter into the functional pairs.



Figure 9. The fuel system functional model automatically created by the MADe CAD Interface from a CAD 3D model (hydraulic view).

Presently, there is no automatic technique for determining pairs in the MADe CAD Interface, as it is considered very difficult to determine accurately the connections between parts based primarily off the geometry of the CAD (for example, if a part was really close to another but had no actual interaction between another it would potentially make an erroneous pairing) (F6). Figure 9 describes the hydraulic engineer view as the CAD 3D model addressed only the hydraulic representation of the fuel system (it included the pump motor and shut-off valve solenoid). The rest of the components forming the fuel system electrics and controls have to be integrated with the CAD 3D hydraulic model in order to be automatically linked (as part of the automated process) with functional models characterizing such components. If the representations of such systems (e.g. electrical system, control system) are not available for the IVHM analyst, functional models of representative components can be used and they are manually added to the model in order to obtain a complete picture of the fuel system functional model. Figure 9 depicts a multidimensional view of the fuel system. Different engineering disciplines are nowadays integrated as part of the same system. The representation of this fuel system schematic in MADe software (containing the information from three

different worlds - hydraulic, electrical, and controls) and it was obtained by linking the input and output flows of the components from Figure 8 and by manually adding the functional representation of power unit, control unit and different wires used to connect these units to the fuel system.

The output flows were connected with the input flows of the downstream component and an initial functional representation of the fuel system was achieved. The output of this operation is depicted in the Figure 11 as it captures the collection of functional models for all components of the fuel system test rig.



Figure 10. Multi-dimensional view of the fuel system.



Figure 11. Fuel system MADe functional model.

5. SYSTEM DESIGN – BEHAVIOR AND RISK IDENTIFICATION MODEL

The components models in Figures 8 and 10 contain the function of each individual component, the input and output flow(s) and the causal relationship between them. The causal relationship maps out the physical behavior of a component. For a normally closed valve, the function is depicted in Figure 12. The functions of this component will be to channel the flow and also to regulate the amount of volumetric flow rate in the system. The bigger the pressure at the inlet of this valve, the larger amount of volumetric flow channel through the outlet as hydraulic energy. Increasing the linear velocity input flow will allow more volumetric flow rate through the outlet, therefore a positive causal relation between these two parameters. In the case of a normally open valve, by increasing the linear velocity

input flow less flow will be allowed to pass through the valve. This is actually captured within the component functional model in Figure 13 as a negative causal relationship between these two particular flows. Similar functional models are used to automatically generate the hydraulic dimension of the fuel system (Figure 9) that was sequentially updated with the electrical and control dimension (Figure 11). Input and output flows were connected in order to allow flows to be exchanged between components. The model in Figure 10 represents the healthy state of the fuel system – as it captures the way this system was intended to operate.

The functional dimension of each component (created by linking a 3D CAD component to a functional model of the respective component from the MADe library) contains failure modes associated to various parts that are forming the respective component. The failure modes are described as failure diagrams and they can support safety and reliability analysis by injecting failure diagram in this model. Failure diagram can also support the identification of the most critical components that will have to be monitored in order to support health management function.







Figure 13. Functional model of a shut-off valve (normally open).

Failure diagrams are documented in MADe by using four different types of concepts (causes - mechanisms - faults symptoms). They all get connected into a tree architecture and they will document automatically a model-based FMECA analysis. The advantages of a model-based FMECA versus traditional FMECA spreadsheets are highlighted by Stecki (2014). The failure diagrams can be as simple as the one depicted in Figure 14. Typically, this sort information is captured by the system integrators who are dealing most of the times at component level or line replaceable unit (LRU). Component manufacturers might want to define FMECAs at the part level and failure diagrams of a gear could shape as complex as the one depicted in Figure 14. The elements of the failure diagram are ultimately linked to the functional failure of a given component. This translates into a deviation from normality of one or several of the output functional flows of that component. For example: the function of the gear pump of this fuel system is to supply volumetric flow rate as hydraulic energy down the line. When this component is affected by one of the faults captured within the failure diagram from Figure 15, the volumetric flow rate generated by this pump will drop. This should be explicitly captured by the IVHM analyst as part of the functional model a pump (Figure 16). Engineering judgment should be encapsulated in the modelling activity when such models are created in

the first place as part of a new MADe library. If available, this information will be retrieved as part of a functional model created following the automated process described in the previous sections.



Figure 14. Failure diagram of a shut-off valve.



Figure 15. A fraction of gear pump failure diagram (failure diagram of the idle gear)

The correct selection of *High* or *Low* for the deviation of output flows for components affected by failure modes will enable the propagation of flows through the functional layer throughout the system (downstream). In order to capture the upstream propagation of faults within a complex system several enhancements have to be carried out on the functional model. For example, a clogged nozzle will automatically determine the output flow (volumetric flow rate - as hydraulic energy) to decrease, but there will also be some increase of the input flow to increase (pressure -ashydraulic energy). In order to describe this particular type of behavior feedback loops have to be manually added to the model (Figure 17). Assuming there are no leaks in this system, if less flow is coming out from the nozzle component, more flow will be pumped in the inlet pipe (Pipe-4 component) as input flow. The positive causal relationship between input and output flow of the pipe component determines the output flow to increase, which is an accurate representation of the behavior of this part of the fuel system when clogging phenomena is occurring. This representation was achieved using a negative feedback loop (F-). This approach was repeated throughout the entire system, for each individual component in order to fully capture the effects of faults on the overall system. This correlation has to be made by using expert knowledge or by using physics-based models that are capable of describing the behavior of the system under faulty scenarios.

Enable Fault Injection

Flow	Response	Activation
🖃 📲 Supply		
🖃 🛑 Hydraulic		
🖃 🔴 Flow rate		
High (+1)	High	
🕒 Low (-1)	Low	\checkmark

Figure 16. Engineering rational related to the effects of failure modes on the output functional flow of a component.



Figure 17. Functional feedback loops.

Complexity of the failure diagrams might not always be positively received by the IVHM analysts. A way to overcome this issue is to establish criticality figures for the elements of a failure diagram, calculate the risk priority numbers (RPN) of each individual components (RPN=Occurrence x Severity x Detectability) and tackle top x most critical components of the system in order to meet specific budget and time targets for the development of IVHM capability. This approach is not new, but the entire health management development process can be automated by using COTS software tools that allow execution of functional models automatically from the 3D representation of a complex asset.

This automated approach enables the identification of system-level risks and it can be applied for new or legacy systems. Selection of the test points (incl. the sensor identification and optimization analysis) for the fuel system is directly derived from the functional model developed in MADe. Sensor locations are highlighted in Figure 18.



Figure 18. Test points selection fuel system

6. CONCLUDING REMARKS

The overall aim of this work is to enhance the health management development process and to support the execution of this process using COTS software tools. Since the CAD models tend to reside these days in the center of the overall engineering process, this paper describes step by step the workflow of creating functional models automatically from CAD models that were previously developed by the system designers. The functional models can be further enhanced by capturing failure diagrams to support safety, reliability and IVHM analysis. Using a laboratory fuel system design use-case, we demonstrated which steps are fully automated and which require manual manipulation in order to construct the functional model of the system being study. The functional model was previously constructed as part of a different project (by a different IVHM analyst) and the overall task took 3-6 months. Using the CAD import feature in MADe, the CAD model and a predefined Fuel System MADe functional library, the same system was functionally modelled in less than 1 month (this included the time to construct the CAD model of the fuel system at the part level). Once developed, the functional model captures system's behavior under healthy conditions. A fair amount of information has to be manually added to this functional model to reflect system behavior under faulty conditions and to ensure it captures the overall effects of the failure mode universe throughout the system. The effects of failure modes throughout the system (downstream and upstream) have to be mapped out manually within this process. In MADe, this was carried out using the feedback loop mechanism. The workflow presented in this paper supports the consistency through construction of models ultimately used for Asset Design and IVHM Design, and the existent health management development process was enhanced by adding a feature that allows passing the geometry between the Asset Design and IVHM Design in an automated manner. The automation in construction of context-sensitive functional models for complex systems forms part of the future work. This will be achieved by linking the functional layer to the physics-based models (that should encapsulate system's behavior for both healthy and faulty scenarios) of these systems.

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REFERENCES

Canedo A., Schwarzenbach E, Faruque M.A.A. (2013). Context-sensitive Synthesis of Executable Functional Models of Cyber-Physical Systems. *ACM/IEEE 4th International Conference on Cyber-Physical Systems* (ICCPS'13), pp. 99–108.

- CATIATM, Dassault Systems, <u>http://www.3ds.com/products-</u> services/catia - Accessed 2014.
- Hirtz, J., Stone, R.B., Szykman, S., McAdams, D.A. & Wood, K.L. (2002). A functional basis for engineering design: Reconciling and evolving previous efforts. *Technical report* NIST.
- Komoto, H., & Tomiyama T. (2012). A framework for computer aided conceptual design and its application to system architecting of mechatronics *products*, *Computer Aided Design*, 44(10), pp. 931-946.
- Kurtoglu, T., & Campbell, M.I. (2008). Automated synthesis of electromechanical design configurations from empirical analysis of function to form mapping. *Journal of Engineering Design*, 19.

MADe[™], PHM Technology, <u>http://www.phmtechnology.com</u> – Accessed 2014.

- Modelica Association, Modelica Standard Library, http://modelica.org/library/Modelica/.
- Niculita O., Jennions I.K., Irving P. (2013). Design for Diagnostics and Prognostics: A Physical-Functional Approach, *Proceedings of the IEEE Aerospace Conference*, BigSky Montana, paper # 2393.
- Niculita O., Irving P., Jennions I.K. (2012). Use of COTS functional analysis software as an IVHM Design Tool for Detection and Isolation of UAV Fuel System Faults, *Proceedings of the Conference of the Prognostics and Health Management Society*, Minneapolis, paper #105.
- Stecki, J., & Stecki, C. (2013). Computer Aided Design in Condition Based Maintenance, Proceedings of The British Institute of Non-Destructive Testing (BINDT) Conference, Kraków, Poland.
- Stecki, J., Rudov-Clark, S., & Stecki, C. (2014). The Rise and Fall of CBM (Condition Based Maintenance). *Key Engineering Materials*, vol. 588, pp. 290-301.
- Stone, R.B., & Wood, K.L. (2000). Development of a functional basis for design. *Journal of Mechanical Design*, 122(4), pp. 359-370.

Uckun, S. (2011). Meta ii: Formal co-verification of correctness of large-scale cyber-physical systems during design, *Technical report*, Palo Alto Research Centre.

BIOGRAPHIES



Octavian Niculita gained his BSc in Automation Control and Computer Science (Technical University of Iasi, Romania). He undertook his PhD research at TUIASI, Romania and at the University of Ferrara, Italy as part of the European Doctorate of Sound and Vibration Studies. Since 2009 he has been actively involved

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Practical PHM for Medium to Large Aerospace Grade Li-Ion Battery Systems

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ABSTRACT

In this paper we will discuss some practical aspects of health management for a rechargeable Li-ion battery system for aerospace applications. Industry working groups have developed guidance for the flight certification of this type of battery system, and we will show how this guidance is used in the design. We will also discuss safety features embedded in the battery system related to industry guidance; including cell energy balancing, internal temperature monitoring and emergency fuses. The keys to battery prognostics and health management (PHM) are analytic State of Charge (SoC) and State of Health (SoH) algorithms implemented in these battery systems. We show how these are developed and how we have tested them before deployment. These battery systems also collect data that is made available to the aircraft processing systems, e.g., Aircraft Health Management System, On-board Maintenance System, etc.. This allows for near real-time confirmation of proper operation of these battery systems as well as adherence to MSG-3 maintenance standards. We close with a brief discussion of the practical limitations in our implementation and a discussion of our ongoing and future development in this area.

1. INTRODUCTION

Lightweight, high capacity, rechargeable batteries, primarily based on compounds of lithium, are becoming widely available due in part to increased demand for electric vehicle energy storage. The cost of individual battery cells continues to drop, making these battery systems more affordable for consumer products, where they are replacing mature technologies such as NiCd (Nickel Cadmium) and NiMH (Nickel Metal Hydride) (Economist (2008), Electropaedia).

This trend has impacted the aerospace industry as well, where lithium based batteries are starting to replace mature technologies for aircraft energy storage.

Aerospace batteries are required to deliver power reliably, have a reasonably long life, have a consistent output over their lifetime, and be certifiably safe. In addition, with a high premium on weight, in order to replace the older technology, they should be lightweight when compared to the traditional technologies.

While lithium based products still require more electronics than the NiCd and SLA (sealed lead acid) products, lithium chemistries are of considerably greater energy density than traditional technologies. Further, costs are trending downward. For example, a 2012 report in the McKinsey Quarterly (Hensley et al. 2012) shows that the price, around \$500/kWh then, could fall to \$200/kWh by 2020 and to about \$160/kWh by 2025. Though the numbers are approximations which do not deal with variations in lithium based chemistries, etc., they do illustrate the potential for lithium based energy storage as an advantageous alternative.

Lithium chemistries, being of considerably greater energy density than the traditional technologies, are also more volatile. This volatility has resulted in the need for development of battery management and safety monitoring subsystems for lithium-based battery systems. Despite many well publicized thermal issues with Li-ion batteries in recent times (see e.g., Chang et al., 2010, George, 2010, FAA, 2011, and NTSB, 2014), these systems are certifiably safe and reliable.

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Our battery systems have integrated battery PHM in the form of cell energy balancing, SoH as a measure for remaining useful life estimation, internal fault detection, and system status monitoring. These subsystems are supported by the integration of data collection, processing, storage and reporting; thus integrating high density energy storage and battery management into a single embedded package.

By additionally integrating the ability to send monitored data to the aircraft data systems, which can then be offboarded for immediate processing, these battery systems enable redundant and sophisticated processing for both remaining useful life predictions as well as near real-time stress level assessments.

2. BATTERY SYSTEMS DESIGNED TO ENHANCE SAFETY

When any technology is developed or modified for use in a civil aviation application, a critical step in the deployment process is system certification. This is the process by which regulatory authorities are assured of the safety of the system with respect to itself and the environment. The civil aviation authorities work to ensure the safety of all concerned by levying the need to demonstrate that all risks have been reduced to an acceptable level prior to certifying the system for flight. Some of the standards, guidelines, and recommended practices published by organizations such as SAE and RTCA that are applicable to the certification of aviation batteries and battery systems are:

- ARP4754: Guidelines for Development of Civil Aircraft and Systems
- ARP4761: Guidelines and Methods for Conducting the Safety Assessment Process on Civil Airborne Systems and Equipment
- DO-160: Environmental Conditions and Test Procedures for Airborne Equipment
- DO-178: Software Considerations in Airborne Systems and Equipment Certification
- DO-227: Minimum Operational Performance Standards for Lithium Batteries
- DO-254: Design Assurance Guidance for Airborne Electronic Hardware
- DO-311: Minimum Operational Performance Standards for Rechargeable Lithium Battery Systems; see also FAA memorandum recommending the use of DO-311 (FAA, 2010)
- DO-347: Certification Test Guidance for Small and Medium Sized Rechargeable Lithium Batteries and Battery Systems

The number and types of tests required to certify a system for flight is determined by the impact on flight safety as determined by the safety analysis of that system, which, as may be inferred by the number of industry specifications listed above, may be considerable. There are generally five design assurance levels (DAL) of safety assessment in the collective guidance. With the introduction of lithium based chemistries for aviation applications in recent years, regulatory "Special Conditions" are being levied on a caseby-case basis to supplement the number and types of tests required to certify traditional chemistries.

The additional monitoring and controlled levied by the "Special Conditions" drive the need for more electronic circuit based protection sub-systems. There is also need for high reliability/redundancy of the protection circuitry in order to satisfy the means of compliance associated with rechargeable lithium batteries.

There are some applications wherein an indication of battery status prior to dispatch is required for the flight crew. The status message for such an application may be a "Clear to Dispatch" indication, and may be annunciated to the crew on the flight deck, with the minimum criteria for the indication being SoH and/or SoC above required levels.

A common practice for measuring battery capacity is based on the voltage of a battery or the charge current of the battery, with the capacity of the battery being checked periodically via off-wing testing. These capacity tests are performed by removing the battery from the aircraft, fully charging it in a specialty shop, then determining the capacity stored by measuring the energy extracted through a complete discharge. This gives the new capacity of the battery (reflecting its SoH). The battery is then returned to the aircraft or serviced, if needed. This labor intensive method is meant to give confidence that the capacity (SoH) of the battery is not less than the required minimum level; allowing for an assurance of safety until the next battery offwing test takes place.

With SoH data supported via "off-wing" tests, the crew reviews the SoC estimated data in real-time (i.e. via battery voltage) prior to flight. This provides the crew a go/no-go determination method.

2.1. Advancement in Battery PHM

The focus of battery PHM has been its application to automobiles (electrical vehicles (EV) and hybrid electrical vehicles (HEV)) but the techniques are similar when applied to civil aviation applications. The need for increased system certification and qualification testing brings additional constraints which need to be thoroughly dealt with before the product can be deployed. See the proceedings of the recent workshop (PHM Society, 2011) for an overview of the current state of the art in PHM research.

Typically, large rechargeable battery stacks consist of smaller cells that are connected in series and parallel to get the requisite voltage range and current capacity. Most of our Li-ion batteries contain eight modules in series that generate the requisite voltage, and the number of cells within each module connected in parallel as needed to supply the necessary current. Consequently, the desired output for a given application can be adjusted in a modular fashion by adding or removing individual module packs and cells to meet the application requirements.

Charging and discharging the module cell stacks is a critical function because over-charging or over-discharging may prematurely degrade the cells within them. When all cells in a module are not identical, as is almost surely the case in practice, there is a danger of overcharging or excessively discharging any given cell if mechanisms are not emplaced to prevent it. The management of these functions is essential to maximize the life of the battery cells. This is fairly well known but see, e.g. the Battery University on the web for a lay exposition of this fact (batteryuniversity.com).

Our battery management system has a dedicated Battery Management Unit (BMU); circuitry to implement fault detection, safety assessment, fault diagnostics, SoH, SoC and communications via industry standard ARINC 429 to the central Aircraft Health Management System (AHMS).

The BMU combined with the battery chargers, allow the battery modules to be charged independently so as to prevent charging at higher than allowed voltages as may occur if one were charging modules in series. Further, the modules are discharged in a balanced fashion; meaning that the system is continuously working to balance the voltage in each module to better utilize the energy in the modules and to prevent any single module from prematurely terminating a discharge.

The independent charging system ensures that the cells are charged at the cell voltage level, the very act of which eliminates the need for independent balancing techniques during charge. Moreover, during the discharge cycle, cell energy is redistributed to ensure more energy can be removed from the system before low voltage cut-off.

Cell temperature has a critical role in the management of lithium based battery systems. We have incorporated a multi-stage power-down process by which the BMU ensures the control of the operation temperature of the battery system. There are multiple monitoring points for the temperature, including at the battery cell level and the internal ambient temperature of the entire battery system. Additional safety mechanisms in the battery system include physical fuses for over current protection.

3. SOC AND SOH FUNCTIONS

The topic of battery management is of considerable interest presently. As a result, there are numerous discussions in the literature covering a wide array of methods for SoC and SoH calculations. SoC, usually in a percentage, is a measure of the charge stored in a battery relative to its maximum charge storage capacity. Some aircraft batteries are essential for continuous safe flight and landing. In such case, the FAA Special Conditions require an indication of the SoC for the flight crew. The dispatch ready requirement for the SoC may vary per application however a common value chosen is when the SoC is greater than 90%. When this condition is met, the dispatch criteria are declared to be satisfied.

SoH, expressed as a percentage, is a measure of actual capacity with respect to the declared battery capacity. We express the SoH as the ratio of the estimated battery capacity (in Ah) to the battery capacity when new, i.e., $SoH = \frac{SoH_t}{SoH_{new}}$. In this sense, the SoH can be additionally used as an advance indication of the future usefulness of a battery.

Our lithium batteries provide a signal to the flight crew indicating that the battery can perform the required mission in the form of a "Clear to Dispatch" signal. For battery systems whose mission involves starting aircraft engines, there may be an additional 'Clear to Start' indicator. Both of these indicators may be generalized as an indication that the battery has sufficient available capacity, given the present environmental conditions and age, needed to perform a task. We began this work with these criteria in mind and with an economically beneficial intention of eliminating the need for removing the battery for SoH testing.

3.1. Estimation of SoC and SoH

There are several practical constraints to consider for an embedded SoC estimator; not the least is the need to include present environmental conditions in the state model (not a trivial matter as these state parameters are, themselves, dynamic and must be estimated) as well as available computational throughput. There are numerous methods for measuring SoC and SoH in current literature. For example, Di Domenico et al. (2010) use a model of the transport phenomenon in their approach and Lin et al. (2013) use thermal conduction models in theirs. The approach that we initially settled on was to employ the Unscented Kalman filter (UKF). A good description of the UKF is available in Kim et al. (2009) or Terajanu (2011). We used the UKF to develop an estimator used to build the SoC algorithm.

During validation and under certain conditions, the results were promising but not consistent. The testing clearly exposed the sensitivity of the filter, which relies on a system state, or battery model. Even slight variations in the battery model caused divergence in the filter such that, in the end, the results required further refinement prior to being directly implemented as targeted.

The sensitivity of the system parameters led us to conclude that an adaptive model, necessary to accurately reflect the physical changes in the battery due to aging, was not likely to prove sufficient for our needs at this time. Such an adaptive model is impractical given our computational constraints and the need for a much larger set of data to fully characterize the different environmental effects. This is not to say that the UKF is a bad observer for this problem in general. Other researchers have been very successful in its application. See for example, Daigle et al. (2012), and we may reconsider it at a future time. Our current program constraints drove us to look further.

3.2. State of charge (SoC)

While refinements with the UKF carried forward, in a parallel fashion, we set about exploring alternate methods for tracking the SoC. An alternate method for calculating the SoC relies on coulomb counting (CC). This method maintains an accurate audit of charge moving in and out of the system over time. The basic requirements for this method are to have accurate measuring of the magnitude and direction of the current flow. There are a variety of physical effects to overcome, hardware related and chemically based obstacles, which make even such a seemingly simple approach quite involved. There are nonlinear effects stemming from environmental conditions, battery life, power losses, and measurement accuracy due to hardware limitations, which need to considered. The ability to provide this estimate within the required accuracy depends critically on sensor accuracy and knowing the SoH of the battery. As SoC tracking via CC requires knowing how much total charge can be held by the battery, the two cannot be separated. The type of application facing the SoC algorithm is a strong determining factor in the suitability of the CC method, along with the accuracy requirements on the SoH and current sensor. Tracking the SoC of an automobile's battery is very different when compared to tracking the SoC of an airborne vehicle. This is due in part to the different charge and discharge scenarios experienced in those two examples. If relatively frequent full charge cycles are experienced, as in the case of civil aviation, calibration of the SoC estimate can take place with the completion of each charge cycle. This mitigates drift due to current sensing inaccuracies.

Voltage-based SoC estimation is another method for tracking SoC, and used in lead-acid batteries. However, because in Li-ion cells, the voltage decreases non-linearly with the SoC, this method requires precise measurement of the system voltage, accurate predefined knowledge of the voltage decay profile under a myriad of conditions and accurate knowledge of ambient conditions as well as knowledge of operational history to be effective in estimating SoC for these chemistries. These requirements make voltage-based SoC less appealing than the CC method, which, as noted, relies most heavily on the current sensor and SoH accuracy. The exact voltage discharge curve, depends on the specific chemistry of the Li-Ion cell used. In our case, lithium iron phosphate (LiFePO₄) is used. Unfortunately (at least for the purpose of voltage based SoC tracking), this chemistry has a very large section of the voltage curve that is nearly constant during discharge. In fact, approximately 80% of the charge might be stored within 130 mV of the voltage profile, making it very difficult to use the relationship between the voltage and the state of charge in this region.

Other methodologies have been proposed in the literature, including physics and empirical model-based techniques. Like any analytical model, a physics-based model trades off complexity for accuracy. There are various approaches taken in the literature; such as Di Domenico et al. (2010), that incorporates a model of the transport mechanism of Li ions in the electrolyte to estimate charge. See also Malinowski (2011).

One can also identify critical parameters for an empirical model, conduct experiments and use the experimental data to identify correlations. Figure 1, taken from Electropaedia, shows the result of a series of experiments that has established usable capacity as a function of discharge rate and temperature. This data can be turned into lookup tables or more sophisticated regression models to form the basis of an empirical SoC model. This has shown success both in the laboratory and in practical applications, though it also illustrates the need for a very large set of data solely to characterize one aspect of the SoC.



Figure 1: Experimental data to support a model

For our battery system, the design goal was to implement a SoC (and SoH) algorithm for aerospace applications that gives an estimate within a given error band when compared to the actual SoC and to do so in real-time. The end goal is to eliminate the need for periodic removal of the battery system from the host aircraft for SoH testing.

3.2.1. The implemented algorithm

Our early empirically based SoC algorithms were not successful in reaching our targets. Validation testing exposed weaknesses in correlating the slower time constants of the model with the rapid dynamic responses resulting from changing load conditions. As a result, a new approach was formulated which combined a voltage based method and the CC tracking method. The SoC is determined by using a weighing factor to change the amount of reliance on SoC calculated based on CC vs. the open circuit voltage (OCV) vs. SoC data on the cells (this data is collected during assembly and stored on the battery). The weighting scheme will be described further below.

A charge cycle is completed when the upper cut off voltage is reached in constant current mode followed by a constant voltage charge. Most often in civil aviation, the battery will complete a charge cycle on a regular frequency. By definition when fully charged the actual SoC is at 100%. We calibrate the SoC estimate by setting it to 100% whenever the unit completes a charge. This is done during the testing phase.

The OCV charge/discharge curve for lithium iron phosphate has a large, nearly constant voltage region, e.g., a 15% SoC range may be represented by an approximately 3 mV voltage change. Voltage readings in nearly constant regions are not sufficiently reliable due to the necessary accuracy of the measurement in such a region. For this reason, our algorithm incorporates a disparity weighting technique for the final SoC estimate. When not charging or discharging, the SOC_{OCV} is combined with the most recent SOC_{CC} by weighting the contribution from each method as a function of the OCV.

The weighting curve is given through incremental or differential capacity analysis as a scaling factor.

$$Q_{diff} = \frac{1}{Q} \frac{d(Ah)}{dV},\tag{1}$$

Where Q_{diff} is the differential capacity, Q is the total capacity in coulombs, and d(Ah)/dV is the derivative of the amount of charge added or removed with respect to the cell voltage change.

The method relies on the fact that in regions where a large amount of charge (d(Ah)) is stored with a very small change in voltage (dV), the SOC_{CC} is likely to be more accurate than the SOC_{v} , and is thus amplified.

With this real-time algorithm in place several tests were run in our actual battery system, at a variety of currents and temperatures. The test set included "ping-pong" testing; where we ran charge and discharge cycles for a variety of fixed time periods to quantify the effect of drift in the SoC estimate over time, drift being a known weakness of the CC method. In the long run, the drift is overcome by the battery charge cycle. When the battery charges to full capacity during normal operation, the SoC is known to be 100%. When reset to the known value, the drift resulting from the CC accumulation measurement error is eliminate and the cycle restarts. The results, which meet our expectation, are discussed in the results section.

3.3. State of Health (SoH)

As in the case of SoC, there are several methods for measuring SoH. Model-based, as well as empirical, methods

are popular for determining SoH Williard et al. (2011) give a brief survey of some of these techniques. Hu et al. (2011) develop a multi-scale model for determining SoC and SoH based on an Extended Kalman Filtering technique. He et al. (2011) demonstrated an empirical model based on simple regression equations and optimal updating techniques. Le et al. (2011) show some very promising results using empirical techniques for the determination of SoH. A comprehensive presentation from Salman, et al. (2011) discusses what GM Research has been doing in all BPHM fields. Similarly, Klein (2011) gives a good overall perspective of BPHM.

Typically, aviation batteries have an end of life defined as when the measured capacity is at 80% of the declared capacity. Capacity for this definition is determined at a rate of discharge that would result in the rated capacity of a new battery (1C) at room temperature. In most existing batteries, the capacity can only be measured in the lab. This requires the battery to be removed prior to testing and replaced which testing is completed. The goal of a SoH calculation is to determine the battery degradation without removing the battery from the installation.

To mitigate uncertainty we intentionally load stress the battery to compare the impedance of the cells at the present time against the impedance of those same cells when they were new.

The basis for our SoH estimation is a multi-stage load test built into the battery. When the assembly of a battery unit is complete, an initial impedance test is conducted. This initial impedance is saved in the BMU and used as the baseline for the SoH calculations for the life of the battery unit.

SoH tests are initiated automatically by the BMU at regular time intervals or at an end-of-charge event. The accuracy of the SoH results is increased when the battery SoC is at a known level; therefore the SoH test is run after every completed battery charge.

The BMU initializes the module level impedance calculation by loading modules at a discharge rate designed to completely deplete the battery within 1 hour, or a 1C discharge rate. The individual module voltages and currents are logged. The BMU then initializes a high rate discharge for all modules. Again the module voltages and currents are logged. The voltage and current deltas are calculated and compared to determine the modules impedances.

Cell impedance can be influenced greatly by temperature therefore the cell impedances must be scaled by a temperature scaling factor so the measured impedance can be correlated to the initial impedance measurement. This temperature factor polynomial was experimentally derived and is of the form:

$$T_{f} = \frac{(a+T*(b+T*c))}{(1.0+T*(d+T*(e+T*f)))}$$
(2)

Where T_f is the temperature scaling factor, T is the measured temperature and a, b, c, d, e and f are experimentally determined coefficients.

A ratio of the temperature scaled module impedances to the initial module impedances, Z_{dc_ratio} , is calculated and used as an input into another polynomial that was also experimentally derived.

The SoH polynomial is shown in (3).

$$SoH = \frac{(g + Z_{dc_ratio}*h)}{\left(1.0 + Z_{dc_ratio}*(i + Z_{dc_ratio}*j)\right)}$$
(3)

Where Z_{dc_ratio} is the ratio of temperature scaled impedance to initial impedance and g, h, i and j are experimentally determined coefficients.

Combined with boundary conditions and weighted data such as temperature historical measurements, the results have correlated well to the actual SoH of the battery modules.

4. RESULTS

Before discussing the results, the legends in the following figures will be described. The BMU has an on board embedded system which logs and reports the SoC, as measured by the Securaplane system, over time. This corresponds to the "BMU Reported SoC" seen in the graph legends. A precision external data logging system was connected to the BMU to measure the voltage across and current into a given module. These voltages and currents were used to calculate the "Measured SoC" seen in the graph legends. The % error from the graph legends corresponds to the absolute value of the percent error between the "BMU Reported SoC" and "Measured SoC" as seen in equation 4.

$$\% Error = \left| \frac{"BMU \text{ Reported SoC}" - "Measured SoC"}{"BMU \text{ Reported SoC"}} \right|$$
(4)

The two figures (Figure 2: Module A - SoC and Percent Error and Figure 3: Module B - SoC and Percent Error) show how our SoC algorithm tracks the measured SoC for two individual modules, A and B. The algorithm is generalized for all modules and as such the percent error does vary between modules; this accounts for the error discrepancy between module A and module B when comparing Figures 2 and 3.

Also of note is the jump in the BMU reported SoC data at the end of the data sets. This is the aforementioned algorithm calibration when the end-of-charge is detected. The error between the final SoC value and 100% arises when a 0% SoC is assumed when the module is not actually at a 0% SoC value. This calibration can be seen in the Figure 2 and 3 for both modules A and B.



Figure 2: Module A - SoC and Percent Error



Figure 3: Module B - SoC and Percent Error

Also included in the figures is the absolute value of the percent error for modules A and B. For both modules this error is under 2% for the majority of the charge cycle. The rise in percent error near the end of the graphs occurs as all modules transition to the constant voltage portion of the charging cycle and the charge current decreases. Due to the dynamic range of current required to be measured, our BMU inaccurately measures very low current values. This is the source of the error during the constant voltage charge mode.

The "ping-pong" test results for module A are shown in Figure 4: Module A - "Ping Pong" Test Results. This figure shows the robustness of the algorithm over time with varying levels of current charge or draw. A divergence between the measured SoC and the BMU reported SoC can most easily be observed at 1:15, 2:15 and 3:15 on the figure. The BMU is required to measure a large current range; ones of amps to hundreds of amps. The divergence in Figure 4 is due to the BMU's inaccuracy measuring currents on the lower end of the measurement spectrum. To verify the accuracy of the algorithm an additional dataset was created and plotted which compensates for the incorrect current readings of the BMU.



Figure 4: Module A - "Ping Pong" Test Results

SoH testing on substantially depleted battery modules has not yet been completed. However initial test results shown in Figure 5: Module B SoH show relatively stable readings that establish a downward trend. The SoH progressing lower as the battery is aged is congruent with the expectation. Earlier results (prior to test number 26) show inaccuracies in the temperature scaling coefficients that are shown to be resolved from test 26 onwards. These initial results are promising; however more exhaustive testing is required to validate our SoH algorithm.



Figure 5: Module B SoH

5. FUTURE WORK

The practical implementation of high accuracy SoC and SoH algorithms in embedded real-time battery systems has proven quite challenging. Such implementations require both measurement accuracy and robustness to environmental effects. The most significant challenge has proven to be developing accurate scaling factor calculations for consistent SoH results and having all necessary parameters accurately measured by the BMU for precise SoC results. Improvement to the algorithm's accuracy and robustness can be attained through further refinement of these parameters and increased hardware sensitivity and characterization.

6. References

- Batteryuniversity, How to Prolong Lithium-based Batteries, <u>http://batteryuniversity.com/index.php/learn/article/</u> <u>how to prolong</u>
- Chang, V.W., Waggoner, S.B. & Gallman, J.W. (2010). System Integration of a Safe, High Power, Lithium Ion Main Battery into a Civil Aviation Aircraft. *SAE Int. J. Aerospace*. 3(1). 149-158. doi: 10.4271/2010-01-1770
- Daigle, M., Saxena A, & Goebel, K (2012), An Efficient Deterministic Approach to Model-based Prediction Uncertainty Estimation, Annual conference of the PHM Society 2012, Minneapolis, MN.
- Di Domenico, D., Stefanopoulou, A., & Fiengo, G. (2010). Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter. Journal of Dynamic Systems, Measurement, and Control, 132(6), 061302.
- Economist. (2008), In search of the perfect battery. *The Economist.* 386 (8570) 22– 24Mar 6th. <u>http://www.</u> <u>economist.com/node/10789409</u>Electropaedia. The Encylopaedia of Battery and Energy Technologies. *Woodbank Communications*, http://www.electropaedia.com.
- FAA (2010). Part 25 policy statement on rechargeable lithium batteries and rechargeable lithium-battery systems permanently installed on aircraft. FAA Memorandum, ANM-113-10-004.
- FAA (2001) Airworthiness Directive 2011-21-51, Affecting Cessna Aircraft Company Model 525C airplanes. October 2011.
- George, F. (2010), Analysis: Citation CJ4. Aviation Week Business & Commercial Aviation.
- He, W., Williard, N., Osterman, M., & Pecht, M. (2011). Remaining useful performance analysis of batteries. In Prognostics and Health Management (PHM), 2011 IEEE Conference on (pp. 1-6).
- Hensley, R., Newman, J., & Rogers, M. (2012), Battery technology charges ahead. *McKinsey Quarterly* 07.. https://www.mckinseyquarterly.com/Battery_techno logy_charges_ahead_2997.
- Hu, C., Youn, B. D., Kim, T., & Chung, J. (2011). Online Estimation of Lithium-Ion Battery State-of-Charge and Capacity with a Multiscale Filtering Technique. *Transition.* 1, 1.
- Kim, J., Lee, S., & Cho, B. (2009). The state of charge estimation employing empirical parameters measurements for various temperatures. *Power*

Electronics and Motion Control Conference 2009. IPEMC'09. IEEE 6th International. 939-944.

- Klein, M. (2011), Viewing the Battery Management System Through Many Lenses. Battery Management Systems Workshop, Annual Conference of the PHM Society. September, Montreal, Canada.
- Le, D. & Xidong Tang, X. (2011) Data-driven methods for State of Health estimation in Li-Ion batteries, Battery Management Systems Workshop, Annual Conference of the PHM Society, September, Montreal, Canada..
- Lin, X., Perez, H.E., Siegel, J.B., Stefanopoulou, A.G., Yonghua Li, Anderson, R.D., Yi Ding & Castanier, M. P. (2013). Online parameterization of lumped thermal dynamics in cylindrical lithium ion batteries for core temperature estimation and health monitoring. *IEEE Transactions on Control Systems Technology*, 21(5), 1745-1755. DOI: 10.1109/ TCST.2012.2217143
- Malinowski, K. D. (2011). State of Charge Estimation for Advanced Batteries: Reduced Order Electrochemical Modeling with Error Compensation Doctoral dissertation, Auburn University. <u>https://etd.</u> <u>auburn.edu/handle/10415/2858</u>
- NTSB (2014), Safety recommendation to the FAA <u>http://www.ntsb.gov/doclib/recletters/2014/A-14-032-036.pdf</u>, May 2014.
- PHM Society (2011), "Battery Management Systems Workshop," Annual Conference of the PHM Society, Montreal, Canada, Sept 2011 <u>https://www.phmsociety.org/documents/BMS-Work</u> <u>shop-2011-Notes</u>
- Salman, M., Tang, X., & Mao, X. (2011). Li-ion Battery State Estimation and Prognosis. Battery Management Systems Workshop, Annual Conference of the PHM Society. September 26. Montreal, Canada.
- Terejanu, G. A. (2011). Unscented Kalman filter tutorial. Department of Computer Science and Engineering, University of Buffalo, Buffalo, NY14260.
- Williard, N., He, W., Osterman, M., & Pecht, M. (2011). Improved SOH Estimation through Coulomb Counting Battery Management Systems Workshop, Annual Conference of the PHM Society. September 26. Montreal, Canada.

BIOGRAPHIES

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Kyle Hamblin obtained his B.S. in Electrical Engineering from the University of Akron, Akron, Ohio, USA. From 2008 to 2010 he worked on wireless power transfer and charging systems for NiMH and lithium battery technologies in the consumer electronics industry. In 2011 he transferred to Meggitt Aircraft Braking Systems and ultimately to Meggitt USA in 2012. His research interests include power management, wireless power transfer, embedded systems, health management of Li-ion battery systems as well as robotics.

John Jackson was born in Columbus, Georgia. He received the BS CmpE degree (with highest honors) from the Georgia Institute of Technology, Atlanta, Georgia, USA, and the ME EE degree from the University of Arizona, Tucson, Arizona, USA, in 2003 and 2007, respectively. From 2004 to 2005, he worked for the University of Arizona, as a Graduate Teaching Assistant for an introductory circuit analysis course. From 2005 to 2006, he worked for Securaplane, a Meggitt company., as an Electrical Engineering Intern in the Sustaining Engineering Group. In 2007, he was promoted to a full-time Electrical Engineer and has since worked on several projects that utilize Li-ion battery technology. His research interests include analog behavioral modeling of Li-ion batteries for SPICE simulation, battery management system design, and low-power circuit design techniques for battery applications.

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Dr. Ravi Rajamani joined Meggitt in 2011 as an Engineering Director, after spending nearly 11 years with United Technologies Corporation, first at the Research Center, and then with its Pratt & Whitney division. Before this he was with the General Electric Company for 10 years, most closely associated with its Research Center and the Power Generation business, but working with all other businesses as well. While his interests have changed over the years, his primary focus has been the area of controls and diagnostics of gas turbines for aerospace and industrial applications. He has published four book chapters, numerous papers in refereed journals and conference proceedings, has been invited to speak at conferences and institutions around the world, and has 24 patents to his name. He is active within SAE's Engine Health Management (E-32) and Integrated Vehicle Health Management (HM-1) committees, currently serving as the chair of HM-1. He is also active in the PHM Society and is serving as the general chair of the 2014 European PHM conference in Nantes.

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Prognostics and Energy Efficiency: Survey and Investigations

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ABSTRACT

The paper presents firstly an overview of various definitions/concepts of energy efficiency and their related applications in different contexts, especially in industrial sectors. Each definition/concept is analyzed and recommended for different decision-making levels. Then a multi-level approach is described in detail for evaluating energy efficiency index of an industrial process. In addition, the paper discusses potential prognostic approaches in order to forecast energy efficiency index by underlining difficulties and opportunities to implement such approaches. Finally, a specific example based on an air-fan system is introduced to illustrate energy efficiency concepts and the added value of the prognostics to predict energy efficiency evolution.

1. INTRODUCTION

Today, energy is the most concerned issue in economic growth (Jollands et al., 2010; Steuwer, 2013; Andrea Trianni, Cagno, Thollander, & Backlund, 2013). Energy resources are nonetheless limited and become more and more costly while manufacturing activities or operation of complex products (Lambert, Hall, Balogh, Gupta, & Arnold, 2014; Urban & Ščasný, 2012) may involve significant energy consumption. Energy optimization of plants/centers and mobile systems (for example, industrial processes, manufacturing, computer data centers, transport, weapons systems and vehicles) is therefore an important issue to be solved in order to keep economic competitiveness and to reduce environmental impacts (Al-mofleh, 2009). This should be primarily reflected on by improving energy efficiency (EE), i.e. reducing the amount of energy required to provide products and services. Indeed, energy efficiency is considered as a key to sustainability (Oikonomou, Becchis, Steg, & Russolillo, 2009), industrial ecology (Boardman, 2004), and circular economy (Dixon, McGowan, Onysko, & Scheer, 2010; Wiel, Egan, & delta

Cava, 2006).

To support these sustainability issues, Europe has set ambitious goals to promote the development of new methodologies, new technologies or disruptive technologies that can improve the energy efficiency and reduce energy costs by up to 20% in the most energy-intensive industrial sectors (European Commission, 2013).

To face with this challenge, one of powerful solutions is to implement the energy efficiency as an important indicator for various decision-makings related to monitoring, operation management, modernization and maintenance plans, etc. It is important to note that the decision-makings are essentially based on age or/and reliability/remaining useful life of components/system (Do Van, Voisin, Levrat, & Iung, 2013; Nicolai & Dekker, 1997; Wang, 2002). To be able to implement energy efficiency in decision-makings, the evaluation of energy efficiency is essential. This is the first objective of the present paper.

Moreover, it is shown that Energy Efficiency Performance (EEP) is an upheaval during process-lifetime (Hasan & Arif, 2014; Zhou & Ang, 2008). Predicting the degradation behavior of energy efficiency of components/systems is therefore crucial. It is however not very well founded. In fact, prognostics approaches have been basically used for predicting the remaining useful life (RUL) of components/systems (Byington, Roemer, Kacprzynski & Drive, 2002; Saha, Goebel, Poll, & Christophersen, 2007; Sankararaman, Daigle, Saxena, & Goebel, 2013; Saxena, Celaya, Saha, Saha, & Goebel, 2010). Enlarging this scope of prediction, several variants have been proposed to predict some other kinds of system features such as health or performance of components/systems (Cocheteux, Voisin, Levrat, & Iung, 2010). In that way, the second objective of the paper is to propose a new concept for the EE prediction.

Thus, with regards to this global EE optimization and forecasting context, an overview of energy efficiency is presented in Section 2. The assessment of EE indicators in the case of industrial applications is also investigated. Then Section 3 focuses on describing potential prognostic approaches for EE prediction. An air-fan system is

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introduced in Section 4 as an example to illustrate not only the proposed EE concepts but also the added value of prognostics implementation. Finally, Section 5 concludes the paper and prospects to prognostic-based energy efficiency in future works.

2. CONCEPTS OF ENERGY EFFICIENCY

2.1. General concepts

Over the past decades, many governments and industrialists have focused on energy efficiency (EE) assessment which can be used for decision-making on strategy and priority actions in order to reduce energy consumption, energy demand and environmental problems.

For this assessment, EE is expressed as using less energy to produce the same amount of services or useful outputs. In that way, EE equation is formulated as: *Useful work of a process*

Energy input into a process (Patterson, 1996). It means

that a smaller amount of energy input is needed for the same useful produced output, or that a higher output is provided with the same energy input. In this way, energy efficiency can be used in a very wide range of applications and for different levels of features (Hilke & Lisa, 2012) in terms of energy demand sectors (buildings, appliances, transports, industries, services, etc.), sizes (on a local, national, international or global scopes), stake-holders (decisionmakers, energy providers, end-users, energy services companies, energy audit services companies, or particular equipment). For example, EE has already been investigated in several sectors such as industries (Boyd, 2014; Fleiter, Fehrenbach, Worrell, & Eichhammer, 2012), transport (Parry, Evans, & Oates, 2013; Zou, Elke, Hansen, & Kafle, 2014), and buildings (Centre, Cddex, & April, 1992; Chirarattananon, Chaiwiwatworakul, Hien, Rakkwamsuk, & Kubaha, 2010). Nevertheless, for each sector (Darabnia & Demichela, 2013; Virtanen, Tuomaala, & Pentti, 2013), different visions of EE concept have been introduced.

In fact, there are many ways to quantify energy efficiency level of a typical machine, factory or country. The wellknown concept of "energy efficiency indicators" or "energy efficiency index" (EEI) is often used basically with the evaluation of energy efficiency. Indicators of energy efficiency may provide the connection between the energy consumption and certain relevant economic and physical outputs (Salonitis & Ball, 2013). Four following categories of EEI: thermodynamic, physical-thermodynamic, economic-thermodynamic, and economic indicators have been mentioned by many authors:

Thermodynamic indicators: They are measured as the energy dissipated or consumed by the system compared to

the amount of energy in the resource processed. Both input and output are measured in thermodynamic units (e.g., GJ of delivered energy consumed in the production coke for coking coal). The importance of efficiency comes from the thermodynamic laws, namely the conservation of energy and the irreversible energy conversion to uselessness. By decreasing the energy loss in the processing, the useful energy transformed from energy input is increased. Thus, the thermodynamic definition of energy efficiency can be

expressed as follows: $\frac{Useful \ work \ or \ energy \ output}{Energy \ input}$

(Jørgensen, 2010; Udphzrun, 2001). For example, the energy efficiency of a steam boiler is calculated as the ratio of the energy amount of steam output to the input heat needed to boil the water inside. In the case of motors, it should be the mechanical energy output divided by the input electricity. This type of EE indicators should not be applied to unknown thermodynamic characteristics or to the case in which there is no or poorly-monitored process because of missing information about energy loss. Relatively, thermodynamic indicators are not the best choice at the top level of national and international energy. According to (Tanaka, 2008), thermodynamic energy efficiency can be used only at the device level, end-use technology or energy conversion technology.

Physical-thermodynamic indicators: This kind of indicators has been introduced to avoid the limit of thermodynamic indicators in systems with output units that are uncountable or specific energy format like systems in transport or agriculture. In fact, the output is evaluated in physical units while the input is in energy. In this way, the energy efficiency can be evaluated as follows: *Useful physical work output*

Energy input (Ang, 2006; Bor, 2008;

Giacone & Manco, 2012). It is important to note that the units of physical output have to be expressed in the designed units of the system capacity (tonnes of cement, passengers, kilometers, vehicles, the number of rooms, etc.). Calculated in either aggregated or disaggregated methods, these indicators directly stick to the technical power flow. As a consequence of various physical outputs, multiple forms are used for physical-based indicators such as energy intensities, specific energy consumption, etc. In spite of difficulties in quantifying the higher level of aggregated process, the physical-thermodynamic indicators can be applied to a variety of levels ranging from a very simple component level to a sector level (Farla & Blok, 2000).

Economic-thermodynamic indicators: These indicators are hybrid indicators, in which the energy input is measured in thermodynamic units and the output is measured in market prices (\$). The market prices are measured by the gross domestic product (GDP) or the market value of all final goods and services produced within a country or a

sector (Gavankar & Geyer, 2010; Rosenquist, McNeil, Iyer, Meyers, & McMahon, 2006; Scofield, 2009; Tsvetanov & Segerson, 2013). In this case, any difference in the output or input number can be affiliated to economic, social behaviors or calculation methods. The information of technical process is unnecessary and the energy output number is conveyed through energy price factors. The "Energy:GDP" increments may be misunderstood as the positive result of energy efficiency investment. But economic-thermodynamic indicators can be calculated by multiplying thermodynamic indicators with the economic value of output units. Thus, these indicators can be applied to high levels of economic structures such as the corporate, sub-sector, sector and national levels.

Economic indicators or monetary indicators: These indicators are used to measure changes in energy efficiency purely in terms of market values. They are named as the energy to GDP ratio, energy coefficient or energy elasticity. Economic indicators are given as the ratio of energy consumption in an energy unit to an economic activity in a

monetary unit $\frac{dollarized of output}{dollarized Energy input}$ (Ang & Xu, 2013;

Gvozdenac-Urosevic, 2010; Worrell, Price, Martin, Farla, & Schaeffer, 1997; Wu, Chen, Bor, & Wu, 2007). Sometime, these indicators would be convertible from their physicalthermodynamic indicator counterparts by simply multiplying the energy input with appropriated added energy prices. But, in another way, these economic indicators are just seen as a purely economic efficiency indicator rather than as an EEI because they are fully measured in economic values. This type of indicators should not be used in monitoring EEP systems. The economic indicators are often used when energy efficiency is measured at a high level of aggregation (international, national and sector levels), where it is impossible to characterize the output by a single physical unit.

The EEI concepts previously detailed have been used in a number of studies as the root definition and referred to by various names like thermal energy efficiency (IEA, 2008), economic ratios, techno-economic ratios (Gavankar & Geyer, 2010), energy intensity or energy efficiency intensity (Hsu, 2014), Energy Efficiency Design Index (Lloyd's Register, 2012), or benchmarks for energy efficiency (D. Phylipsen, Blok, Worrell, & Beer, 2002).

From these definitions, it is possible to characterize also EEIs with regards to the abstraction level of decisionmakers mainly in terms of energy consumers and usage functions. In that way, we propose a classification of EEIs based on their potential applications (Figure 1).



Figure 1. Potential applications of energy efficiency indicators depending on levels of decision-makers and aggregation

In Figure 1, it is illustrating that the more the energy consumers, the more chance and benefits energy efficiency investment brings about. Therefore, opportunities and challenges of energy efficiency applications at industrial sectors have to be addressed.

2.2. Concepts of EEIs for industrial sectors

As multiple factors are affecting energy efficiency performance of industrial sectors (process complexity, internal energy transformations various products and production rates, etc.), quantifying movement of energy efficiency needs explicit definitions and energy efficiency measurement.

In industrial sectors, for measurement and management purposes, Specific Energy Consumption(SEC) is the most common EEI ("ODYSSEE database," 2010; G. J. M. Phylipsen, Blok, & Worrell, 1997; Sudhakara Reddy & Kumar Ray, 2011). SEC is the ratio of the energy consumption to the useful physical output of a process or activity. By multiplying the physical unit by its economic value, the monetary unit can be created and the effect of economic factors could be concerned. When the output is measured in common physical units, an estimate of physical energy intensity is obtained (e.g. TJ/tonne). The total energy consumption in an industrial process is the summation of all types of energy such as electricity, gas, coal, and oil. The SEC for industrial processes is expressed as follows:

$$SEC = \frac{E_{Consumed}}{P_{out}}$$
(1)

Where: $E_{Consumed}$ is the used total energy input, P_{out} is the process output in physical units.

When the output of industrial processes is uncountable or invisible (for example, electrical power distribution system or production process are pending but auxiliary system still running and consuming energy), then SEC is the ratio of energy inputs to energy outputs. It will be the inverse formula of thermodynamic energy efficiency. In this case, the difference between the input and the output is the total energy losses during equipment operation or an individual task of processes.

$$SEC = \frac{E_{consumed}}{P_{out}} = \frac{E_{ln}}{E_{out}}$$
(2)

Where: E_{ln} is the necessary energy input used by industrial processes, E_{Out} is the useful energy output delivered for industrial processes.

In a typical industrial process, there are at least several factors affecting the EEI during its life. These factors could be classified into: the structure or function of the process and facility; management, operation methods and maintenance plans; energy categories; raw materials; ages of equipment; and production plans or load profiles. These factors change over time and depend on other parameters. Thus, it is important to discuss methods of EEI evaluation or EEP during its life-time for industrial processes.

2.3. Assessment of EEIs in industrial applications

For focusing on the assessment step, it is necessary to divide the study of energy efficiency into several different abstraction levels. Thus potential applications of EEIs regarding to aggregation/abstraction levels, are the most important factors that affect energy efficiency at each level and the inter-level interactions. They need to be detailed and discussed.

2.3.1. At the component level

According to the evaluation of changes in the efficiency of production equipment or a particular production process, the lower the disaggregation level can be analyzed, the more accurate the measurements of achieved technical energy efficiency improvements can be improved. Applying the component, process unit or sub-system concept offers a way to divide the energy use in an industrial system into smaller parts. A process unit can be considered as the smallest component of an industrial energy system (Schenk & Moll, 2007). A single process/component unit is based on the function of the industrial process, for example, cooling, heating, and packing or air compressors. Input variables of operation conditions are classified into physical indicator (PI) and nonphysical indicator (NPI) categories. Total energy input E_i^t , and total output P_i^t of one component *i* at time t (the time unit could be one hour, one day, one month, etc) can be expressed as:

$$E_i^t = f_i^t (PI_i^E, NPI_i^E)$$
(3)

$$P_i^t = g_i^t (PI_i^P, NPI_i^P)$$
(4)

$$SEC'_{i} = \frac{f'_{i}(PI^{E}_{i}, NPI^{E}_{i})}{g'_{i}(PI^{P}_{i}, NPI^{P}_{i})}$$
(5)

Where:

- PI_i^E is a set of physical indicators affecting energy consumption of component *i* such as energy transformation, working duty cycles, available capacity, deterioration levels of elements, quality of raw materials, etc;
- *NPI*^E is a set of nonphysical indicators affecting energy consumption of component *i* such as ages, production planning, product programs (load profiles or process productivity), human skills, etc;
- *PI_i^P* is a set of physical indicators affecting output of component *i* such as supplier availability, waste products, product types, etc;
- NPI_i^p is a set of nonphysical indicators affecting output of component *i* such as storage, transport stations, etc.

It should be noted that f_i^t and g_i^t are the functions of PIs and NPIs. These functions can be built up based on the data collected from the system or the understanding of the dynamics of the system. Both PIs and NPIs should be specified before applying the aggregation method to calculate energy inputs and useful outputs for each individual component. The PIs and NPIs should be collected. After determining and filtering processes to identify clear trends indicators, the EE threshold can be set from the requirement or field data. In that way, EEP for separated components can be foreseen.

2.3.2. At the function/system level

Together with using EEIs for separated components, the EEP of the global system should be taken into account. It has been shown that each component has its own energy profile depending on its operation modes (stop, on-load, offload, standby, etc.) and operation modes may be modified by system functions. During the operation process, the EEP at the function/system level may not be equal to the total value of all components. Many studies have shown that energy consumption varies with product capacity. Moreover, the system function has a strong impact on EEP and operation sustainability. The biggest challenge is to compute the volume of outputs of largely diverse products produced by industrial processes. For example, it is widely accepted that 'tons of steel' is a well-known measure of capacity and real output in the steel industry. But the output evaluation of a beverage factory by summing liters of beer, alcohol, mineral water, and nutria drink, is inaccurate. The aggregation method to add multiple forms of outputs should be considered. Converting various physical output units into a common unit is commonly applied. In this case, it is needed to consider the weighting factor of separate subsystems or unit processes to produce one output type as Eq. (6).

$$P_{\Sigma}^{t} = \sum \lambda_{i}^{t} . P_{i}^{t} \tag{6}$$

Where: P_{Σ}^{t} is the total system output at time point *t*. λ_{i}^{t} is the output weighting physical factor of the separated disaggregated component *i* at time point *t*.

In comparison with Eq. (4), the value of λ_i^r is a function of total PI_P and NPI_P, which affect the role/duty or position of components in production sequences.

At the component or separated process/sub-system level, the individual activities and processes in the complex process have to be disaggregated. The energy inputs can be simply summed to generate an aggregate energy indicator. But, in a general system, load profile and operation/process functions decide the available productivity, operation mode of equipment and influence production the energy consumption. In this case, in computing energy input, integration of load profile into function factors is highly recommended. The total energy consumption is defined by aggregating the individual energy consumption multiplied by the corresponding weighting energy factor as Eq. (7).

$$E_{\Sigma}^{t} = \sum \omega_{i}^{t} \cdot E_{i}^{t} \tag{7}$$

Where ω_i^t is the energy weighting energy factor of the separated component *i* at time point *t*.

The energy weighting energy factor ω_i^t is based on the energy used within one complete component. At the function/system level, ω_i^t is deeply depended on PI_E and NPI_E of the structure of function/system production sequence. Together with weighting factors of outputs, the impact of weighting factors of each component can be shown clearly in comparison with other components. The higher the values of ω_i^t and λ_i^t , the higher the contribution of component *i*. With the Eq. (6) and (7), formula (1) can be changed to:

$$SEC_{\Sigma}^{t} = \frac{E_{\Sigma}^{t}}{P_{\Sigma}^{t}} = \frac{\sum \omega_{i}^{t} \cdot E_{i}^{t}}{\sum \lambda_{i}^{t} \cdot P_{i}^{t}}$$
(8)

By conducting energy measurement, the total energy input and total system output at the global system level can be evaluated. The dependence of each component on the others ones and function/system process can be shown in Figure 2.



Figure 2. Aggregation approach to calculate EE parameters for the upstream level from separated component levels

Nevertheless, these two types of weighting factors are defined by the share of each component in the total of contribution of the function/system at the upper level of aggregation. They are used to get the weighted aggregate. The function/system factors with characteristics like flexible organizations of process sequence, multi-functional production should be taken into account. The movement of weight factors during time-line depends on the contribution of components to the global system. Thus, weight factors of components will not only influence EEIs and EEP at function/system levels, but also point out the critical components in the archived EEI target.

Based on historical data and measured parameters via conducting energy audit or power management system, EEIs at current time and EEP can be reviewed. Industrial system performances with a variety of system functions, flexible processes and complex equipment are one main target to apply prognostics. Thus predicting the movement of EEIs or EEP is an issue to be supported by prognostics approaches.

3. PROGNOSTIC APPROACHES FOR ENERGY EFFICIENCY

3.1. Prognostics conventional approaches: an overview

With the demand to anticipate the failure of a component/system, prognostics concepts have been introduced and successfully applied for different application fields (Muller, Suhner, & Iung, 2008; Si, Wang, Hu, & Zhou, 2011). The most obvious and widely used prognostic consists in predicting how much time is left before a failure occurs given the current condition, past and future operation profiles. The time left before an occurring failure is usually called remaining useful life (RUL). To support this prediction, various approaches have been developed from experience-based prognostics to model-based prognostics. The required information (depending on the type of prognostics approach) include: engineering model and data, failure history, past operating conditions, current conditions, identified fault patterns, transitional failure trajectories, maintenance history, system degradation and failure modes. The main prognostics approaches that have successfully been applied on different types of problems are:

- Experience-Based Prognostics. Use statistical reliability to predict probability of failure at any time (Dragomir, Gouriveau, Dragomir, Minca, & Zerhouni, 2009; Muller et al., 2008);
- Evolutionary/Statistical Trending Prognostics. Multivariable analysis of system response and error patterns compared to known fault patterns (Muller et al., 2008; Si et al., 2011; Yang, Yu, & Cheng, 2007);
- Data-driven prognostics. These approaches are used to determine the remaining useful life by trending the trajectory of a developing fault and predicting the amount of time before it reaches a predetermined threshold level (Goebel, Saha, & Saxena, 2008; Sankararaman & Goebel, 2014). The strong points of data-driven techniques are their ability to link with recognized system behavior by experience methods and simple in installation and implementation.
- Model-Based (Physics of Failure Based Prognostics). These approaches need fully understanding of system to be expressed by mathematic functions or existing accurate mathematical models (Dai, Das, Ohadi, & Pecht, 2013; Fan, Yung, & Pecht, 2014; Medjaher, Skima, & Zerhouni, 2014). The accuracy of model and also the provided parameters of variables decide the precision of technical approaches. The main advantage of model-based approaches is reusing of model and flexible in configuring input data.

3.2. Prognostic formulation method for energy efficiency: a generic approach

As mentioned above, the existing prognostics concepts concern basically with the prediction of RUL or the failure date. Thus, they seem difficult even no longer to be applied for energy efficiency prediction since the energy efficiency behavior of a machine may be independent with its failure behavior. In this context, prognostic approaches should be used to predict the potential evolution of EEI of a machine, which is directly linked to its energy efficiency behavior, given the current condition, past and future operation profiles. Based on the evolution of EEI of a machine, it is possible to determine the time when EEI reaches its critical value related to the energy efficiency property of the machine. In this way, we propose an extension of RUL, namely REEL, in the framework of prognosis-based EE as follows:

Remaining energy-efficient lifetime (REEL) is defined by the time left before a machine loses its energy efficiency property, which is technically and/or economically fixed in advance, given the current condition, past and future operation profiles. Mathematically, REEL can be expressed as:

$$REEL(t) = \{E[T]: SEC^{t+T} = SEC_{Threshold} \mid SEC^{t} < SEC_{Threshold} \}$$
(9)

Where: T is a random variable; E[T] is mathematic expectation of T and $SEC_{Threshold}$ is an energy efficiency threshold as Figure 3.



Figure 3. EE deterioration behavior and REEL prediction effect on decision-making

It cannot be denied that there are many difficulties to control global EEP because the system environment is changing. EE and system functioning mode are dependent on product flow and component ageing continuously modifies the system characteristics. There is a lack of decision support when it comes to questions of procuring, distributing and accounting for energy in production systems. Decisions in planning and operating production systems are mainly based on traditional metrics such as cost, quality and flexibility and rarely consider energy efficiency (Apostolos, Alexios, Georgios, Panagiotis, & George, 2013; Seow & Rahimifard, 2011; Thiede, Bogdanski, & Herrmann, 2012; Weinert, Chiotellis, & Seliger, 2011). New forecast REEL situations can be seen in the vision deployment of combination the current degradation and EEP deterioration trends.

With prognostic approach for EE, the EEP will be illustrated clearly and REEL can be predicted for various scenarios of actions plan. The predicted development of REEL scenarios will be used as aided-decision-making factor to select most efficient plans. If predicted EE value is not acceptable, various corrective actions such as replacement, update, and maintenance must be conducted at any identified critical level of system. In the other case, the value of EEI value of system is considered as under EE threshold and the remaining efficient life is long enough for securing functions of system, correction action is not necessary taken. The process will be repeated when new monitored data is updated. The outcomes of prognostic analysis combined with a database of traditional commercial operation principal will provide the different references of deciders.

From this definition, it is now needed to discuss on how prognostic approaches can be applied for predicting REEL at component level and function/system one.

3.2.1. REEL at component level

A small number of studies already mentioned about energy aspect with the common issue-energy consumption (Balaban et al., 2013; Chiach, Chiach, Saxena, Rus, & Goebel, 2013) and highlight prognostics as potential tool for prediction of energy demand. But for evaluating the REEL of a component, both the energy consumption and the output for future operation profiles must be estimated. However they depend on several physical and nonphysical indicators, see again Eq. (3) and (4). This means that these physical and nonphysical indicators must be firstly identified and evaluated. Model or experience based techniques (Fleiter et al., 2012; Salta, Polatidis, & Haralambopoulos, 2009) may be secondly used to evaluate the energy consumption at and output from the determined physical and nonphysical indicators.



Figure 4. REEL Prediction process at component level

In general, nonphysical indicators are usually known in advance and physical indicators, which may depend on component characteristics, related environment conditions and nonphysical ones, are often unknown. The deterioration evolution of these physical indicators may be predicted by prognostic approaches mentioned in the previous section (B. lung, M. Veron, M.C. Suhner, 2005; Muller et al., 2008). The proposed generic approach is shown in Figure 4. Only at this level, the EEP of component without the impact of other component or function of system can be evaluated directly. Any correction action at this level can help the component restore the EEI of individual component. Its EEI will be reduced under the EE_{Threshold} or as equal the value of launching time.

3.2.2. REEL at function/system level

As mentioned in Section 2.3, to evaluate the REEL of a function/system, we need not only the information (energy consumption, output, REEL) related to all components but also the information related to function/system such as system structure, dependencies between components, production schedule, support system, operation condition and management, The link between the global energy consumption, the global output and this information are crucial. In fact, as proposed in Section 2.3 these relationships are represented by the weighting energy

factors and the weighting physical factors. In this way, based on the results at component level, to predict the REEL at function/system level, the weighting energy factors and the weighting physical ones must be estimated. Figure 5 illustrates the REEL prediction process for а function/system.

The implementation of the REEL methodology both at the component and function levels need now to be illustrated in order to show its feasibility and added value. At this level, the optimization of operation or function system has strong impact in the energy consumption of each component. An efficient equipment could have a strong weighting factor and have a high opportunities in EE improvement at system level, caused of optimized working chain process, lack of skills of operator or low awareness of manager (A. Trianni & Cagno, 2012).



Figure 5. REEL Prediction process at function/system level

REEL EXPERIMENTATION TO A SPECIFIC 4. **EXAMPLE**

For illustrating the proposed concepts for energy efficiency and related evaluation/prediction approaches, it is chosen an industrial sub-system which is composed of a motor associated to a fan (Figure 6). The electrical motor-drive converts electrical power into mechanical power (via a rotating shaft connect to mechanical load). The electrical motor-drive has a big amount percentage of total power consumption in industrial applications.



Figure 6. Basic components of fan system

The proposed evaluation/prediction is applied at both component and function/system level.

4.1. SEC at component level

For reviewed air-fan system, we are considering the EE effect of three main components which are the control system, the electrical motor and the centrifugal fan. The power and air flows of the system are shown in Figure 7.



Figure 7. Energy flow and Air flow output of fan system

According to the disaggregation method, the detailed mathematic function of EEI at component level have to include both physical and thermal laws in time point t as below:

1. *Centrifugal fan*: Centrifugal fan is used for applications requesting low noise and vibration. It can produce high air pressure, lower noise than axial fan. Fan consumes transformed input energy and converts it to the air-flow power. Fan efficiency is the ratio between the power transferred to the air stream and the mechanical power delivered by the motor. In that way, SEC of centrifugal fan SEC'_{M} is the ratio of electrical input power to air-flow power output:

$$SEC_F^t = \frac{E_{F-in}^t}{E_{F-out}^t} \tag{10}$$

Where: E'_{F-in} is mechanical input of fan and E'_{F-out} is airflow power of drive system.

With the direct connection, an adjustment of fan speed can cause different airflows and pressures or performance levels. According to fan law, power input varies with the cube power while air flow rates vary in direct proportion to the rotational speed of the fan (International Energy agency, 2011). The energy efficiency of the centrifugal fan is shown in Figure 8a.

2. *Electrical motor*: An electric motor converts electricity into mechanical power, usually in the form of a shaft delivering torque at a defined rotational speed to an application machine. SEC of motor SEC'_{M} is the ratio of electrical input power to mechanical output power.

$$SEC'_{M} = \frac{E'_{M-in}}{E'_{M-out}}$$
(11)

Where: E'_{M-in} is electrical input and depends on different physical and nonphysical indicators. However, in this work, it is assumed that E'_{M-in} depends only on the speed of motor. More precisely, by connected in serial with centrifugal fans, that power input E'_{M-in} and power output E'_{M-out} are proportional with the cube power of the operating speed of motor (U.S. Department of Energy Energy Efficiency and Renewable Energy, 1989). This means that SEC of the motor depends on its operating speed. The energy efficiency of the motor in function of its speed is shown in Figure 8b.

It is important to note that the operating speed of the motor may depend on different physical and/or nonphysical factors such as deterioration of the bearing, temperature, control strategy, etc. In this work, only the deterioration of the bearing is considered. Based on the condition/deterioration level, motor speed is set, for example, when the deterioration of bear increases, the speed of motor should be reduced due to a limited noise level constraint. It is assumed also that the motor is considered as failed if the deterioration level of the bearing reaches a limit level, usually called the failure threshold. In this study, this threshold is equal to 200. To predict the deterioration behavior of the bearing, a model-based prognostic is implemented with noise and vibration level as the main indicators of bearing health (Fernández-Francos, Martínez-Rego, Fontenla-Romero, & Alonso-Betanzos, 2013; Satish, Member, Sarma, & Member, 2005). More precisely, stochastic Gamma process is used to model the deterioration behavior of the bearing. The illustration of the bearing deterioration according to physical vibration signal and its corresponding speed are shown in Figure 9.



Figure 9. Illustration of the motor deterioration and its corresponding speed

3. *Control system* is adjusting working-point of fan according to demand of fan or control strategies (noise, positive pressure or negative pressure...). We are considering controller with variable-speed drive (VSD) and limitation of vibrations noise. So that, speed of motor will be reduced when the bearing deterioration level is

increasing. We estimate the SEC of control system SEC_C^t as:

$$SEC_{C}' = \frac{E_{C-in}'}{E_{C-out}'} = \frac{E_{Electrical-in}'}{E_{C-out}'}$$
(12)

Where: E'_{C-in} is electrical input and E'_{C-out} is electrical power output of control system. $E'_{Electrical-in}$ is the electrical input for the air-fan system during at time *t*.

It is show that the energy efficiency of VSD depends principally on the operating speed of the motor (Rooks & Wallace, 2004). The energy efficiency of VSD in function of the speed of the motor is shown in Figure 8c.



Figure 8. Energy efficiency indicator of (a)- fan head, (b)- motor and (c)- flow control with operation conditions (CML Northern Blower Incorporated, 1991; Rooks & Wallace, 2004; U.S. Department of Energy Energy Efficiency and Renewable Energy, 1989)

4.2. SEC and REEL evaluation at function/system level

As discussed above, the energy efficiency performance at function/system level is the most important issue. In fact, it is possible to show the reusability of SEC concept for function/system. For the air-fan system, two cases are considered:

- If we consider that useful output is the air-flow power. EE of fan system is defined by the ratio of power transferred to the airstream to the power input to the fan. the SEC of the air-fan system has to be calculated as:

$$SEC_{System}^{1} = \frac{E_{System-in}^{t}}{E_{System-out}^{t}} = \frac{E_{Electrical-in}^{t}}{E_{F-out}^{t}} = \frac{E_{Electrical-in}^{t}}{\int_{V}^{h} V^{t} \Delta_{p}^{t} \cdot dt}$$
(13)

Where: *h* is operating hours; V^t is air flow (m3/hour) and $\Delta^{t}p$ is pressure difference from the fan inlet to the outlet (Pa)

- If we calculate the useful output as air-flow, in this case, SEC or usually called as "Specific air-fan power (SFP)" is used to estimate the specific power consumption per volume of air delivered and the energy consumption required for transporting air:

$$SEC_{System}^{2} = \frac{E_{System-in}^{t}}{P_{System-out}^{t}} = \frac{E_{Electrical-in}^{t}}{\int_{o}^{h} V^{t} dt}$$
(14)

The Eq. (13) and (14) clearly show that with different types of useful outputs, the final SECs of system may be dramatically different. With complex air-fan systems, in which demanded air-pressure is varied according to the technical process or many types of air distribution existing, the impact of pressure has to be taken into account for EEP. The SFP is a good energy-performance indicator for the whole system, but it does not necessarily indicate the efficiency of the fan. The SFP will be calculated by the real operating conditions, and maximum SFP will be specific by energy standard. So the first one will be used more common in industrial application where air-fan is seen as one component of complex system but the second one will prefer for designing and standalone air-fan system. Thus to be able to evaluate SEC for a function/system, the outputs of the function/system have to be standardized by a unique one.

According to energy flow and air flow shown in Figure 7, the global energy consumption and useful physical output can be calculated as follows:

$$P_{\Sigma}^{t} = 0 + 0 + P_{F}^{t} \tag{15}$$

$$P_{\Sigma}^{t} = 0.P_{C}^{t} + 0.P_{M}^{t} + 1.P_{F}^{t}$$
(16)

$$E_{System}^{t} = E_{C-Consumed}^{t} + E_{M-Consumed}^{t} + E_{F-Consumed}^{t}$$
(17)

$$E_{System}^{\prime} = (1 - \frac{1}{SEC_{C}^{\prime}})E_{C-in}^{\prime} + (1 - \frac{1}{SEC_{M}^{\prime}})E_{M-in}^{\prime} + 1.E_{F-in}^{\prime}$$
(18)

Where:

 P_C^t , P_M^t and P_F^t are useful output produced by control system, motor and centrifugal fan at time *t*.

 $E'_{C-Consumed}$, $E'_{M-Consumed}$ and $E'_{F-Consumed}$ are the energy consumed by at controller, motor and fans, which are considered equal to the total energy losses during component operations at time *t*.

From Eq. (6) and (16) we have the weighting factor for air output of each component as:

$$\boldsymbol{\lambda}^{t} = \begin{bmatrix} \boldsymbol{\lambda}_{C}^{t}, \boldsymbol{\lambda}_{M}^{t}, \boldsymbol{\lambda}_{F}^{t} \end{bmatrix} = \begin{bmatrix} 0, 0, 1 \end{bmatrix}$$
(19)

From Eq. (7) and (18) we have the weighting factor for energy consumption of each component as:

$$\boldsymbol{\omega}^{t} = \left[\boldsymbol{\omega}_{C}^{t}, \boldsymbol{\omega}_{M}^{t}, \boldsymbol{\omega}_{F}^{t}\right] = \left[(1 - 1/SEC_{C}^{t}), (1 - 1/SEC_{M}^{t}), 1\right] \quad (20)$$

At system level, these vectors ω' and λ' are closely related to energy consumption, useful output of control system, motor and centrifugal fan at time *t*. By applying an aggregation method, we can assess the EEP deterioration of the air-fan system in the future. The illustration is shown in Figure 10b.



Figure 10. Integrated generic prognostic approaches for EEP deterioration of fan system

Based on the EEI (SEC) behavior predicted, REEL is evaluated by using Eq. (8). Figure 11a describes the potential evolution of SEC. Given a SEC threshold (herein $SEC_{threshold} = 1.5$) the distribution of REEL is reached, see Figure 11b. The failure distribution of the motor is illustrated in Figure 11c. When compared with the



distribution of REEL, it have a dramatically differences. Air-fan system is seen to reach the energy inefficient zone before it can touch the limit of physical life. This means that air-fan is available to deliver air, but consumed more energy than usual to distribution air and high level of noise and vibration of fan can have bad affections to the convenience of general system. The SEC of any component (motor, controller, etc.) and its EEP evaluation are used to identify the key component to maintain the general EEP of air-fan system. The benefits and complexity of conducting correct actions to maintain EEP with can be consider as a main additional factor for plan-making process. For example, the dust removing of fresh air-filter or air duct should be conducted more often to maintain the EEP than waiting for the next shutdown time of air-system for general inspection period. Thus, various decisions making based RUL may be no longer appropriate when considering the EE performance criterion.

5. SUMMARY AND CONCLUSIONS

In this paper, it is first described an overview on energy efficiency concepts. Different concepts are classified according to the related decision-making levels. Then an EE concept for industrial sector is deeply discussed and developed. It leads to focus on the assessment of the energy efficiency behavior of an industrial component/system. In that way, an energy efficiency indicator (EEI) is introduced. Furthermore, it is proposed a mathematical formulation for calculating the proposed EEI at both component and function/system level. This formulation is illustrated by the implementation of an electrical fan-blower system. In addition, a novel concept related to the remaining efficiency-efficient lifetime, named REEL, of a component/system is proposed. In relation to conventional RUL providing information about failure date, REEL provides the remaining efficient lifetime of a component/system before it loses the energy efficiency property. REEL may be an interesting tool for decision making, for example, in areas such as maintenance, production scheduling, etc. In addition, the paper proposes a prognostic formulation approach which can help to predict the REEL at component and function/system level. This formulation is also tested on the case of electrical fanblower system. To add the human experiences about EE in modeling need extra interesting studies and also analyze the model properties (big data problems, combinatorial explosion, metrics, etc.). These both conceptual and analytical proposals for evaluating the EEI seem powerful. It should be however validated on real industrial system applications to prove its added value and benefits. The later will be our future works.

NOMENCLATURE

- *EE* Energy Efficiency
- *EEI* Energy Efficiency Indicators/Index
- *EEP* Energy Efficiency Performance
- REEL Remaining energy-efficient lifetime
- SEC Specific Energy Consumption
- *VSD* Variable-Speed Drive

REFERENCES

- Al-mofleh, A. (2009). Prospective of Energy Efficiency Practice, Indicator and Power Supplies Efficiency. *Morden applied science*, 3, 158–161.
- Ang, B. W. (2006). Monitoring changes in economy-wide energy efficiency: From energy–GDP ratio to composite efficiency index. *Energy Policy*, 34, 574– 582.
- Ang, B. W., & Xu, X. Y. (2013). Tracking industrial energy efficiency trends using index decomposition analysis. *Energy Economics*, 40, 1014–1021.
- Apostolos, F., Alexios, P., Georgios, P., Panagiotis, S., & George, C. (2013). Energy Efficiency of Manufacturing Processes: A Critical Review. *Procedia CIRP*, 7, 628–633.
- B. lung, M. Veron, M.C. Suhner, A. M. (2005). Integration of Maintenance Strategies into Prognosis Process to Decision-Making Aid on System Operation. *CIRP Annals - Manufacturing Technology*, 54.
- Balaban, E., Narasimhan, S., Daigle, M. J., Roychoudhury, I., Sweet, A., Bond, C., ... Gorospe, G. (2013).
 Development of a Mobile Robot Test Platform and Methods for Validation of Prognostics-Enabled Decision Making Algorithms. *International Journal of Prognostics and Health Management*, 4, 1–19.
- Boardman, B. (2004). Achieving energy efficiency through product policy: the UK experience. *Environmental Science & Policy*, 7, 165–176.
- Bor, Y. J. (2008). Consistent multi-level energy efficiency indicators and their policy implications. *Energy Economics*, *30*, 2401–2419.
- Boyd, G. a. (2014). Estimating the changes in the distribution of energy efficiency in the U.S. automobile assembly industry. *Energy Economics*, 42, 81–87.
- Byington, C. S., Roemer, M. J., Kacprzynski, G. J., & Drive, T. P. (2002). Prognostic Enhancements to Diagnostic Systems for Improved Condition-Based Maintenance 1.
- Centre, R., Cddex, P., & April, R. (1992). Energy signature models for commercial buildings : test with measured data and interpretation. *Energy and Buildings*, 19, 143–154.
- Chiach, J., Chiach, M., Saxena, A., Rus, G., & Goebel, K. (2013). An Energy-Based Prognostic Framework to Predict Fatigue Damage Evolution in Composites. *Annual Conference of the Prognostics and Health Management Society*,, 1–9.
- Chirarattananon, S., Chaiwiwatworakul, P., Hien, V. D., Rakkwamsuk, P., & Kubaha, K. (2010). Assessment of energy savings from the revised building energy code of Thailand. *Energy*, *35*, 1741–1753.
- CML Northern Blower Incorporated. (1991). Fanfacts (p. 11).
- Cocheteux, P., Voisin, A., Levrat, E., & Iung, B. (2010). System performance prognostic : context, issues and requirements. *1st IFAC Workshop on Advanced*

Maintenance Engineering, Services and Technology (AMEST'10).

- Dai, J., Das, D., Ohadi, M., & Pecht, M. (2013). Reliability risk mitigation of free air cooling through prognostics and health management. *Applied Energy*, *111*, 104– 112.
- Darabnia, B., & Demichela, M. (2013). Data Field for Decision Making in Maintenance Optimization : An Opportunity for Energy Saving. *Chemical engineering transactions*, *33*, 367–372.
- Dixon, R. K., McGowan, E., Onysko, G., & Scheer, R. M. (2010). US energy conservation and efficiency policies: Challenges and opportunities. *Energy Policy*, 38, 6398–6408.
- Do Van, P., Voisin, A., Levrat, E., & Iung, B. (2013). Remaining useful life based maintenance decision making for deteriorating systems with both perfect and imperfect maintenance actions. In 2013 IEEE Conference on Prognostics and Health Management (PHM) (pp. 1–9). IEEE.
- Dragomir, O. E., Gouriveau, R., Dragomir, F., Minca, E., & Zerhouni, N. (2009). Review of Prognostic Problem in Condition-Based Maintenance.
- European Commission. (2013). *Energy challenges and policy*.
- Fan, J., Yung, K.-C., & Pecht, M. (2014). Prognostics of lumen maintenance for High power white light emitting diodes using a nonlinear filter-based approach. *Reliability Engineering & System Safety*, 123, 63–72.
- Farla, J. C. ., & Blok, K. (2000). The use of physical indicators for the monitoring of energy intensity developments in the Netherlands, 1980–1995. *Energy*, 25, 609–638.
- Fernández-Francos, D., Martínez-Rego, D., Fontenla-Romero, O., & Alonso-Betanzos, A. (2013). Automatic bearing fault diagnosis based on one-class v-SVM. Computers & Industrial Engineering, 64, 357–365.
- Fleiter, T., Fehrenbach, D., Worrell, E., & Eichhammer, W. (2012). Energy efficiency in the German pulp and paper industry – A model-based assessment of saving potentials. *Energy*, 40, 84–99.
- Gavankar, S., & Geyer, R. (2010). The rebound effect: State of the Debate and Implications for Energy Efficiency Research. *Institute of Energy Efficiency (UCSB)*, 65.
- Giacone, E., & Manco, S. (2012). Energy efficiency measurement in industrial processes. *Energy*, *38*, 331–345.
- Goebel, K., Saha, B., & Saxena, A. (2008). A comparison of three data-driven techniques for prognostics. In 62nd Meeting of the Society for Machinery Failure Prevention Technology (pp. 1–13). Virginia Beach.
- Gvozdenac-Urosevic, B. (2010). Energy efficiency and GDP. *Thermal Science*, *14*, 799–808.

- Hasan, O., & Arif, a. F. M. (2014). Performance and life prediction model for photovoltaic modules: Effect of encapsulant constitutive behavior. *Solar Energy Materials and Solar Cells*, 122, 75–87.
- Hilke, A., & Lisa, R. (2012). Mobilising investment in energy efficiency. © OECD/IEA, 2012.
- Hsu, D. (2014). How much information disclosure of building energy performance is necessary? *Energy Policy*, *64*, 263–272.
- IEA. (2008). Assessing measures of energy efficiency performance and their application in industry. *IEA INFORMATION PAPER*.
- International Energy agency. (2011). Energy-Efficiency Policy Opportunities for Electric Motor-Driven Systems.
- Jollands, N., Waide, P., Ellis, M., Onoda, T., Laustsen, J., Tanaka, K., ... Meier, A. (2010). The 25 IEA energy efficiency policy recommendations to the G8 Gleneagles Plan of Action. *Energy Policy*, *38*, 6409– 6418.
- Jørgensen, S. E. (2010). Ecosystem services, sustainability and thermodynamic indicators. *Ecological Complexity*, 7, 311–313.
- Lambert, J. G., Hall, C. a. S., Balogh, S., Gupta, A., & Arnold, M. (2014). Energy, EROI and quality of life. *Energy Policy*, 64, 153–167.
- Lloyd's Register. (2012). Implementing the Energy Efficiency Design Index (EEDI) Guidance for owners, operators and shipyards. *Lloyd's Register*, *IMO*.
- Medjaher, K., Skima, H., & Zerhouni, N. (2014). Condition assessment and fault prognostics of microelectromechanical systems. *Microelectronics Reliability*, 54, 143–151.
- Muller, A., Suhner, M.-C., & Iung, B. (2008). Formalisation of a new prognosis model for supporting proactive maintenance implementation on industrial system. *Reliability Engineering & System Safety*, 93, 234–253.
- Nicolai, R., & Dekker, R. (1997). A Review of Multi-Component Maintenance Models with Economic Dependence. *Reliability and Societal Safety*, 411–435.
- ODYSSEE database. (2010). ODYSSEE data base.
- Oikonomou, V., Becchis, F., Steg, L., & Russolillo, D. (2009). Energy saving and energy efficiency concepts for policy making. *Energy Policy*, 37, 4787–4796.
- Parry, I. W. H., Evans, D., & Oates, W. E. (2013). Are energy efficiency standards justified? *Journal of Environmental Economics and Management*, 1–22.
- Patterson, M. G. (1996). What is energy efficiency? Concepts, indicators and methodological issues. *Energy Polic*, 24, 377–390.
- Phylipsen, D., Blok, K., Worrell, E., & Beer, J. De. (2002). Benchmarking the energy efficiency of Dutch industry: an assessment of the expected effect on energy consumption and CO2 emissions. *Energy Policy*, 30, 663–679.

- Phylipsen, G. J. M., Blok, K., & Worrell, E. (1997). International comparisons of energy efficiency-Methodologies for the manufacturing industry. *Energy Policy*, 25, 715–725.
- Rooks, J., & Wallace, A. K. (2004). Energy Efficiency Of Variable Speed Drive Systems. *Industry Applications Magazine*, 10, 1–5.
- Rosenquist, G., McNeil, M., Iyer, M., Meyers, S., & McMahon, J. (2006). Energy efficiency standards for equipment: Additional opportunities in the residential and commercial sectors. *Energy Policy*, 34, 3257– 3267.
- Saha, B., Goebel, K., Poll, S., & Christophersen, J. (2007). A Bayesian Framework for Remaining Useful Life Estimation. *Proceedings of AAAI Fall Symposium: AI* for Prognostics (Working Notes), 1–6.
- Salonitis, K., & Ball, P. (2013). Energy Efficient Manufacturing from Machine Tools to Manufacturing Systems. *Procedia CIRP*, 7, 634–639.
- Salta, M., Polatidis, H., & Haralambopoulos, D. (2009). Energy use in the Greek manufacturing sector: A methodological framework based on physical indicators with aggregation and decomposition analysis. *Energy*, *34*, 90–111.
- Sankararaman, S., Daigle, M., Saxena, A., & Goebel, K. (2013). Analytical algorithms to quantify the uncertainty in remaining useful life prediction. 2013 *IEEE Aerospace Conference*, 1–11.
- Sankararaman, S., & Goebel, K. (2014). An Uncertainty Quantification Framework for Prognostics and Condition-Based Monitoring. *16th AIAA Non-Deterministic Approaches Conference*, 1–9.
- Satish, B., Member, S., Sarma, N. D. R., & Member, S. (2005). A Fuzzy BP Approach for Diagnosis and Prognosis of Bearing faults in Induction Motors, 1–4.
- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2010). Metrics for Offline Evaluation of Prognostic Performance, 1–20.
- Schenk, N. J., & Moll, H. C. (2007). The use of physical indicators for industrial energy demand scenarios. *Ecological Economics*, 63, 521–535.
- Scofield, J. H. (2009). Do LEED-certified buildings save energy? Yes, but. *Energy and Buildings*, 41, 1386– 1390.
- Seow, Y., & Rahimifard, S. (2011). A framework for modelling energy consumption within manufacturing systems. CIRP Journal of Manufacturing Science and Technology, 4, 258–264.
- Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal* of Operational Research, 213, 1–14.
- Steuwer, D. S. (2013). Energy Efficiency Governance. doi:10.1007/978-3-658-00681-5
- Sudhakara Reddy, B., & Kumar Ray, B. (2011). Understanding industrial energy use: Physical energy

intensity changes in Indian manufacturing sector. *Energy Policy*, *39*, 7234–7243.

- Tanaka, K. (2008). Assessment of energy efficiency performance measures in industry and their application for policy. *Energy Policy*, *36*, 2887–2902.
- Thiede, S., Bogdanski, G., & Herrmann, C. (2012). A Systematic Method for Increasing the Energy and Resource Efficiency in Manufacturing Companies. *Procedia CIRP*, 2, 28–33.
- Trianni, A., & Cagno, E. (2012). Dealing with barriers to energy efficiency and SMEs: Some empirical evidences. *Energy*, *37*, 494–504.
- Trianni, A., Cagno, E., Thollander, P., & Backlund, S. (2013). Barriers to industrial energy efficiency in foundries: a European comparison. *Journal of Cleaner Production*, 40, 161–176.
- Tsvetanov, T., & Segerson, K. (2013). Re-evaluating the role of energy efficiency standards: A behavioral economics approach. *Journal of Environmental Economics and Management*, 66, 347–363.
- U.S. Department of Energy Energy Efficiency and Renewable Energy. (1989). *Improving Fan System Performance: A Sourcebook for Industry*.
- Udphzrun, R. D. Q. G. (2001). Monitoring energy efficiency performance in New Zealand: A conceptual and mothodological framework.
- Urban, J., & Ščasný, M. (2012). Exploring domestic energysaving: The role of environmental concern and background variables. *Energy Policy*, *47*, 69–80.
- Virtanen, T., Tuomaala, M., & Pentti, E. (2013). Energy efficiency complexities: A technical and managerial investigation. *Management Accounting Research*, 24, 401–416.
- Wang, H. (2002). A survey of maintenance policies of deteriorating systems. *European Journal of Operational Research*, 139, 469–489.
- Weinert, N., Chiotellis, S., & Seliger, G. (2011). Methodology for planning and operating energyefficient production systems. *CIRP Annals -Manufacturing Technology*, 60, 41–44.
- Wiel, S., Egan, C., & delta Cava, M. (2006). Energy efficiency standards and labels provide a solid foundation for economic growth, climate change mitigation, and regional trade. *Energy for Sustainable Development*, 10, 54–63.
- Worrell, E., Price, L., Martin, N., Farla, J., & Schaeffer, R. (1997). Energy intensity in the iron and steel industry: a comparison of physical and economic indicators. *Energy Policy*, 25, 727–744.
- Wu, L.-M., Chen, B.-S., Bor, Y.-C., & Wu, Y.-C. (2007). Structure model of energy efficiency indicators and applications. *Energy Policy*, 35, 3768–3777.
- Yang, Y., Yu, D., & Cheng, J. (2007). A fault diagnosis approach for roller bearing based on IMF envelope spectrum and SVM. *Measurement*, 40, 943–950.

- Zhou, P., & Ang, B. W. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy*, *36*, 2911– 2916.
- Zou, B., Elke, M., Hansen, M., & Kafle, N. (2014). Evaluating air carrier fuel efficiency in the US airline industry. *Transportation Research Part A: Policy and Practice*, *59*, 306–330.

BIOGRAPHIES

Anh HOANG was born in 1982 in Thanh Hoa, Vietnam. He received his M.S. degree in Electrical Engineering from Hanoi University of science and technology (2008). His responsibilities focused on courses of designing power distribution system, electrical equipment and renewable energy system. He was also active in the national energy auditing programs and built up road map for energy efficiency standard. His current research interests includes prognostic, energy audit, maintenance plan and energy management.

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Alexandre VOISIN was born in Metz, France, in 1969, obtained an engineering degree in Electrical Engineering in 1992. In 1999, he received his Ph.D degree in Electrical Engineering from the Lorraine University. He is currently associate professor at the Lorraine University. His primary research were in the field of fuzzy logic and information processing where he applied these techniques to subjective evaluation in the area of car seat comfort. Since 2003 he is involved in a maintenance project, managed by Pr. B. Iung. His research deals with dependability, maintenance decision in a proactive maintenance strategy, prognostics and monitoring, e-maintenance. He is member of French and International projects/groups on e-maintenance such as the MACOD working group (Modeling CNRS and Optimization of Distributed vs. Collaborative Maintenance). the French scientific interest group 3SGS on "Dependability of Complex Systems" in the project DEPRADEM (Degradation and Prognosis Modeling for Maintenance Decision Making), the French project BMCI (Condition monitoring for maintenance and Piloting of naval systems), the European Integrated Project DYNAMITE (Dynamic Decision in Maintenance), and the international project DEPEN-IMPRO (Modeling Policies for the improvement of Production Systems' Dependability). He is involved in

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Aligning PHM, SHM and CBM by understanding the physical system failure behaviour

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ABSTRACT

In this work the three disciplines of condition based maintenance (CBM), structural health monitoring (SHM) and prognostics and health management (PHM) are described. Then the characteristics of the disciplines are compared, which leads to a clear insight in the commonalities, but also in the difference in objectives and scope of the three disciplines. The disciplines are then demonstrated using three different case studies on bearing vibration monitoring, composite panel structural health monitoring and helicopter landing gear prognostics, respectively. After a discussion on the benefits of understanding the system physical (failure) behaviour, an integrated approach is proposed in which the three disciplines are aligned. This approach starts from defining an appropriate monitoring strategy (SHM and CM) and eventually ends in supporting the decision making (PHM) that leads to an optimal maintenance process throughout the life cycle of the asset.

1. INTRODUCTION

The disciplines of condition based maintenance (CBM), structural health monitoring (SHM) and prognostics and health management (PHM) have a lot of commonalities. They all aim to improve the maintenance decision making, with the ultimate goal of reducing maintenance costs and increasing system availability. But at the same time they are focusing on different aspects of the field and are being developed in more or less separate communities. Although implicit links between, for example, CBM and PHM are being made in several occasions (Buderath & Adhikari, 2012), the explicit relation between the disciplines has not often been addressed specifically. In this work we therefore aim to align the three disciplines by identifying the major benefits of the individual approaches and proposing an integrated approach that combines these aspects. Firstly, in section 2 of this paper, we discuss the major differences and commonalities of the three disciplines in a general sense, both in terms of the adopted techniques and methods and underlying philosophy. Secondly, each of the disciplines will be illustrated in section 3 with three (existing) practical cases from our own research in the different disciplines. The CBM illustration case is the rather traditional approach followed in the blind identification of bearing damage. The SHM illustration case concerns the damage assessment in a composite structure using a structural vibration technique, while the PHM illustration case concerns the prognostics of landing gear failure in a helicopter. After that, partly based on the experience from these three cases, the role of understanding the system failure behaviour will be discussed in section 4. It will be demonstrated that knowledge on the physical failure mechanisms, in combination with the monitoring of loads or condition, is a key element in all three disciplines, while this aspect is recognized and covered by only a minority of the cases found in practice. This aspect will thus be taken to align the approaches of CBM, SHM and PHM in section 5. Taking into account the differences in scope and objective of the three disciplines, but fully exploiting their individual strengths, it will be shown that they can be aligned to yield an integral approach for optimizing system life cycle management. The proposed approach will start on the lowest level by monitoring the appropriate parameters and will ultimately provide decision support on the highest level for the optimal life cycle management.

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2. DESCRIPTIONS AND COMPARISON OF DISCIPLINES

In this section the authors' view on the basic concepts of the SHM, CBM and PHM disciplines will be presented. Also the differences and commonalities will be discussed.

2.1. Condition Based Maintenance

Condition based maintenance is the oldest discipline of the three. It is closely associated to Condition Monitoring (CM), which is a term covering a range of techniques that have been developed in the past fifty years to assess the condition of systems and components. Well-known condition monitoring techniques are vibration monitoring, oil analysis, acoustic emission and thermography. These methods are widely applied in industry, where the interpretation of measurement data is mainly experience-based and datadriven. Vibration analysis techniques are mostly applied to rotating equipment (e.g. pumps, compressors, gear boxes, bearings). This means that the source of the vibrations is the machine's normal operation, while faults can be detected as a change in that source (either in frequency or amplitude).

When the results of condition monitoring are used to trigger maintenance activities, a condition based maintenance (CBM) policy emerges. The ISO-13374 standard, Condition Monitory and Diagnostics of Machines (ISO, 2012), defines the functionality in a condition monitoring system in six blocks: data acquisition, data manipulation, state detection, health assessment, prognostics assessment and advisory generation. Further, the Open Systems Architecture for Condition-Based Maintenance (OSA-CBM) (MIMOSA, 2013) provides an implementation of that standard by adding data structures and defining interface methods for the functionality blocks in the ISO standard. Although research on advanced concepts like wireless sensor networks and energy harvesting to power autonomous sensors is ongoing, the data acquisition (sensors) and manipulation are nowadays rather well-established. Therefore, a major portion of the research in this discipline focuses on analyzing the obtained data to retrieve information from it. The methods developed for that are mainly data-driven, e.g. based on trending or on comparing with a baseline measurement, and are seldom based on physical models. Application of the final blocks, the health assessment and prognostics steps, is until now very limited in practice. This discipline is not covered widely in the scientific world, other than the application of CBM policies in maintenance modelling approaches. Also no scientific journals specifically on CM or CBM exist. However, since the field already exists for decades, many books on the topic are available.

2.2. Structural Health Monitoring

Structural health monitoring is a discipline that is closely related to condition monitoring, but has its origin in the inspection of structures. The methods are based on nondestructive testing (NDT) techniques. These techniques, like ultrasonic testing, eddy current and acoustic emission, are traditionally applied using hand-held sensors or scanning techniques, and inspections are only performed occasionally or periodically, not bearing any relation with previous inspections. Due to the increased reliability and availability requirements of many assets, research has focused on developing continuous monitoring techniques, which evolved into the structural health monitoring discipline. A lot of scientific work is currently being done in this field, which also has its own scientific journals. The focus has been on the one hand on the development of new sensing techniques, and on the other hand on the development of advanced damage features and classifiers. Development of sensing approaches are based on new technologies using optical fibers and sensors to measure structural vibrations (e.g. piezo patches) and wave propagation (e.g. ultrasonics). The development of new damage features and classifiers follows a data-driven approach, motivated by the "statistical pattern recognition paradigm" (Farrar & Worden, 2010), which is one of the key foundations of SHM. The application of physical models in this discipline is very limited.

Applications are mainly found in aerospace and infrastructures (e.g. bridges). For vibration based methods, the source of vibrations is generally not the system itself, but the environment it is operated in (e.g. wind, waves). Faults or damage can be detected by observing changes in the response of the system to the vibrations. Note that this field has a strong focus on health assessment, but does not provide a clear approach to apply that to maintenance policies (although a link with CBM is rather straightforward). Instead, developments in SHM techniques mainly focus on increasing the probability of detection of faults, which originates from the NDT background of this discipline. Further, the first standard in this field was established only very recently (SAE, 2013), and in addition there is well-defined structure considering the five levels of SHM (Farrar & Worden, 2010). From levels 1 up to 5 more and more information on the damage in the structure is obtained:

- Level 1: damage detection,
- Level 2: damage localization,
- Level 3: damage characterization,
- Level 4: damage quantification,
- Level 5: prognostics.

The first three levels can now be achieved by many methods, while the final two are still quite challenging.

2.3. Prognostics and Health Management

The prognostics and health management discipline is somewhat different from the previous two, and also emerged more recently. Whereas CBM and SHM focus on the monitoring of the system, PHM is a more integrated approach that aims to provide guidelines for managing the health of the system. In that way, it is a philosophy to perform Life Cycle Management, with a strong focus on the predictability (i.e. prognostics) of failures and maintenance. This is generally achieved by adopting some monitoring strategy, which may be a CM or SHM technique. Also in this field many data-driven approaches emerged to analyze the monitoring data, but in addition to that several physical model based methods have been developed (Orsagh, Roemer, Sheldon, & Klenke, 2004; Roemer, Byington, Kacprzynski, & Vachtsevanos, 2006). As for CM and CBM, this discipline emerged form industry, and has a relatively limited presence in the scientific world. PHM has a background in the military world, especially related to the development of the F-35 fighter aircraft (Brown, McCollom, Moore, & Hess, 2007). Thereafter, PHM approaches have also been developed for other military vehicles, but also for electronics and (civil) aerospace systems.

2.4. Commonalities and differences

Upon analyzing the commonalities and differences between the three disciplines, the following aspects have been found. These aspects are also visualized in Figure 1.

(*i*) the approaches for condition monitoring and structural health monitoring are very similar, since both disciplines



Figure 1. Relation between CBM, SHM and PHM.

look for features that are representative for damage or degradation of the system. However, there are some differences:

• CM is closely related to the CBM policy, which means that the monitoring results are directly applied to guide the maintenance activities. In SHM the focus is completely on the monitoring and no explicit relation to a specific maintenance policy is made. However, linking SHM techniques to CBM seems straightforward.

- In both fields, one of the commonly applied techniques is vibration monitoring, but the approaches are different in the following ways:
 - CM is mostly applied to rotating or reciprocating systems, where the primary vibration source is the system itself. Damage or degradation is diagnosed by detecting changes in that source, e.g. bearing faults that introduce additional vibrations.
 - SHM is mostly applied to load carrying or transferring structures, which are only actuated by their environment (wind, waves). The SHM techniques focus on measuring (changes in) the response of the system or structure and relating those to the presence of damage.
 - The locations of the vibration sensors also vary. In CM the sensor is typically outside the part, whereas in SHM the sensors are commonly on (or even integrated in) the monitored part.

(*ii*) both SHM and PHM include a prognostic capability, while CBM is mainly diagnostic. However, the differences between CBM and SHM in this respect are not that large, since in the SHM field the prognostics is only at level 5, which is not achieved in many cases. At the same time, CM data is often trended in time, which also provides a limited prognostic capability (which is also mentioned in the CBM ISO standard).

(*iii*) PHM is acting on a somewhat higher level than CBM and SHM, since it has a clear ambition to enable health management. The latter is an activity related to Life Cycle Management (LCM), which means that an approach is followed to optimize all (maintenance) activities during the complete life cycle of the asset. This includes the selection of an appropriate maintenance policy, defining the maintenance interval length and deciding on the moment an asset should be discarded. CBM, and SHM to an even lesser extent, do not provide that extensive LCM support.

(*iv*) the PHM field prescribes neither a specific maintenance concept nor a monitoring strategy. However, in typical PHM studies, CBM or other maintenance policies are adopted, and in many cases CM techniques are applied.

3. PRACTICAL CASES

In this section three practical cases will be presented, demonstrating the specific aspects of the three disciplines.

3.1. CBM – bearing blind identification

The field of condition monitoring has matured especially in its application to bearings (Rao, 1996). Since in industry so many bearings are used, a huge amount of experience has been gained on these type of systems. Moreover, the complexity of bearings is rather limited, which makes understanding the failure behaviour feasible in many cases. For these reasons, condition monitoring data, which for bearings most of the time is vibration data, can in many cases be translated into information on the failure mode or the state / condition of the bearing.

This will be demonstrated using the following case study. Vibration data on four different bearings is available: one undamaged (pristine) bearing and three with an artificial damage on the outer race, inner race and rolling element, respectively. In practice, the location and type of damage is unknown, and a so-called blind identification must be performed. However, since a considerable range of failure mechanisms can occur in the different bearing components (inner / outer race, rolling element), identification is quite challenging. Moreover, a recent development is to apply wireless sensor networks for vibration monitoring. Although this development reduces the wiring and installation efforts considerably, it simultaneously introduces additional boundary conditions due to the limits in data transmission bandwidth, power and local (on the sensor node) processing capacity. A generic approach is developed (Sanchez Ramirez, Loendersloot, & Tinga, 2014) to assess the damage.

The vibration patterns observed will have to be matched with the most likely failure modes and failure mechanisms for bearings. Examples of failure modes are cracking, dry rolling, and heating, where the deterioration or failure of the bearing material is caused by mechanisms like fatigue, static overloading, wear, corrosion, etc. Additionally lubricant deterioration is also a key limiting factor of bearing life. For this case, the focus will be on cracking in the outer race, resulting in dynamic behaviour of the bearing related to the response to an impulse excitation. Figure 2 shows the vibration signal for the pristine bearing. The red line in the figures is a sinusoidal signal with the rotor speed frequency and an amplitude approximately equal to the maximum of the pristine bearing vibration.



Figure 2. Vibration signal for pristine bearing.

The signal for the damaged bearing is shown in Figure 3. The first way to identify a failure is to compare the signal of the (damaged) bearing to the baseline signal (red line). Figure 3 clearly shows that the amplitude bandwidth has increased considerably, indicating that a failure is present. However, the challenge is then to characterize or localize the fault. A first step in this analysis is to transform the signal to the frequency domain, and zoom in to the region with the highest energy content by applying a filter. For this bearing, the range of interest appeared to be in the 2500 - 4000 Hz region. Valuable information about the source of the damage can be extracted by looking at the vibration signal, the rate at which the events occur and the possible variation of the amplitude (modulation).

The modulations can be analyzed further by extracting the envelope of the vibration signal, and identifying the main modulating frequency f_m i.e. the frequency of the variation in signal amplitude. This is shown in Figure 4, where a clear frequency peak around 150 Hz occurs, which represents f_m .



Figure 3. Vibration signal for damaged bearing.



Figure 4. Enveloping of the time signal with its corresponding frequency spectrum.

Finally, once the frequency range of interest and the main modulating frequency are known, the analysis will be based on shorter time periods related to the main modulating frequency. Here the instantaneous carrier frequencies are determined from the time signal segments that have been extracted according to the main modulation observed in the signal. Both the instantaneous frequencies and amplitude are extracted, as well as their ratio, as is shown in Figure 5. The variation of these quantities can be used as indicator of developing damage on the bearings.

In summary, this case study showed how a typical condition monitoring technique as vibration monitoring can be used to detect and assess bearing damage. The methods presented here are only a small subset of the large variety of analysis methods available, but a special focus has been put here on computational inexpensive methods that enable application in a wireless sensor network.



Figure 5. Instantaneous frequency and amplitude of the signal.

3.2. SHM - damage assessment in composite structure

Our SHM case study concerns the assessment of damage in a skin stiffener composite structure (Loendersloot, Ooijevaar, Warnet, Boer, & Akkerman, 2011; Ooijevaar, Loendersloot, Warnet, Boer, & Akkerman, 2010; Ooijevaar, Warnet, Loendersloot, Akkerman, & Boer, 2012), shown in Figure 6. Structural vibration techniques are adopted here to detect and locate (and possibly quantify) a delamination in the composite structure. The structure is actuated by a shaker, while the response is measured by piezo electric diaphragms. The damage sensitive parameter extracted from the structure is the mode shape curvature, while the Modal Strain Energy - Damage Identifier (MSE-DI) algorithm (Stubbs & Farrar, 1995) is selected as the damage classifier. The damage feature is selected based on the expected damage (a delamination between the skin and the stiffener, as shown in Figure 7) and the expected change in dynamic response: the local stiffness reduction induced by the damage results in a local change of the mode shapes, and more specifically of the mode shape curvatures.



Figure 6. The composite skin-stiffener structure, equipped with piezo electric diaphragms. The damaged area is indicated in the bottom figure.

This change is an indication of the presence and the location of damage and even serves as an estimation of the severity of the damage, provided a (physical) relation can be established between the size of the delamination and the criticality of the damage.



Figure 7. First-ply delamination failure caused by the impact to which the structure was subjected.

The MSE-DI algorithm is based on the comparison between the curvatures of the mode shapes of the pristine and damaged structure. Given the relative bending energy $\hat{U}_{B,i}^{(n)}$ of the *i*th beam segment, of the *n*th mode, is defined as:

$$\widehat{U}_{B,i}^{(n)} = \frac{U_{B,i}^{(n)}}{EI_i} = \frac{1}{2} \int_{x_{i-1}}^{x_i} \left(\frac{\varepsilon_x^{(n)}(x)}{z}\right)^2 \mathrm{d}x \tag{1}$$

Where $\varepsilon_x^{(n)}$ represents the axial strain amplitude for the *n*th participating mode shape. Note that the strain is directly measured by the piezo diaphragms. The total modal strain energy is approximated by the sum of Eq. (1) over a subset of mode shapes N_{freq} . The damage index value is based on a number of mode shape curvatures, since the location and the size of the damage determine the effect the damage has on the mode shape curvatures.

The damage index β for the *i*th segment of the structure is defined as the summed fractional stiffnesses:

$$\beta_{i} = \sum_{n=1}^{N_{freq}} \left(\frac{\int_{x_{i-1}}^{x_{i}} \widetilde{w}^{(n)} \mathrm{d}x / \int_{0}^{l} \widetilde{w}^{(n)} \mathrm{d}x}{\int_{x_{i-1}}^{x_{i}} w^{(n)} \mathrm{d}x / \int_{0}^{l} w^{(n)} \mathrm{d}x} \right)$$
(2)

Where $w^{(n)}(x)$ represents the integrand of Eq. (1) and the tilde refers to the damaged case. The normalized damage index Z_i , a statistical measure to identify outliers, is defined as:

$$Z_i = \frac{\beta_i - \mu}{\sigma} \tag{3}$$

Where μ is the mean value and σ the standard deviation of the damage index over all elements. The normalized damage index Z is shown in Figure 8. The value of the damage index around x = 0.8 m is close to -4, implying a significant (4 σ) deviation of the fractional stiffness compared to the intact situation. This is a clear indication of the presence of the damage. The actual damage location corresponds to the location indicated by the MSE-DI algorithm.



Figure 8. The normalized damage Z for the entire composite structure. The location of the damage corresponds with the deviating values around x = 0.8 m.

3.3. PHM – predicting helicopter shock absorber failure

The prognostics and health management approach is demonstrated by a case study on a helicopter landing gear. The landing gear contains a shock absorber (see Figure 9), that after some period starts to leak oil, caused by a damaged seal. The shock absorber inspection and maintenance schedule is based on flight hours (as is the case for most aircraft components).



Figure 9. Landing gear shock absorber.

However, for a landing gear, the number of flight hours is not the most appropriate usage parameter for predicting the failures. This is shown in Figure 10, where the number of flight hours at failure are plotted for 11 shock absorber seal failures: there is no correlation between the failures and number of flight hours, and it is difficult to predict when a seal failure will occur. However, this helicopter contains a Health and Usage Monitoring System (HUMS), which collects a large number of parameters on the usage (flight hours, altitude) and health (vibration data) of the helicopter. This data can be used to develop a prognostic method for the seal failure (Tinga, 2013). The physical mechanism causing the seal failure is sliding wear, which is governed by the normal force F_n applied to the seal, the sliding distance *s* and the specific wear rate *k*. Archard's law can then be used to calculate the amount of wear in terms of lost volume *V*:

$$V = kF_n s \tag{4}$$

The values of F_n and k can be obtained from the geometry and material properties of the seal. The sliding distance is governed by the usage of the landing gear, i.e. the number of landings and the weight of the helicopter during the landing. These latter two parameters are available from the HUMS, so for every seal failure the usage history is known and the amount of wear can be calculated, as is shown in Figure 11.



Figure 10. Number of flight hours for 11 failure events.



Figure 11. Calculated amount of wear for 11 failure events.

These results clearly show that the calculated amount of wear, based on the number of landings and landing weight, has much more predictive power than the number of flight hours, since the variation in these values is much lower. Except for the first two cases, the failures either occurred around 30 mm³ of lost volume, or around 50 mm³. The observed difference between the two groups can be explained by the fact that another type of seal was introduced in the absorbers that failed at 50 mm³ of wear. This new seal clearly has a better wear resistance than the original seal, since the oil leakage occurs at a later stage. It can thus be concluded that selection of the appropriate usage parameter, in this case the number of landings and landing weight, and using a suitable physical failure model enables to set-up a prognostic model.

It is now rather straightforward to assess at any moment the remaining useful life (RUL) of the shock absorber in terms of number of landings. The amount of wear can be calculated from the monitored landing information (HUMS) and the amount of landings before seal leakage is expected can be calculated, thus providing a much better RUL assessment than with flight hours.

3.4. Summarizing the cases

The case studies in this section have illustrated many of the aspects mentioned in section 2. The CBM illustration case is mainly data-driven, only a limited amount of system and failure behaviour knowledge is used. Also, the source of the vibration (and its anomalies) is the rotation of the bearing itself. The SHM illustration case is also mainly data-driven, although in this case the dynamic behaviour of the system (i.e. mode shapes) is known as well as the effect the damage (delamination) has on the dynamic response. This information is used to select the damage feature and classifier. Finally, the PHM illustration case clearly has a physical model based approach, where the selection of monitoring data and its processing is motivated by the known physical behaviour of the shock absorber seal.

4. RELEVANCE OF UNDERSTANDING FAILURE BEHAVIOUR

In the case studies in the previous section it can be observed that knowledge on the failure behaviour of the systems is used to some extent in all three cases. This is one of the major differences between the approaches that was already stated in section 2. However, it is the authors' conviction that understanding the failure behaviour and underlying physical mechanisms has the potential to increase the performance of the CBM and SHM disciplines. The motivation for that is in the relation between the usage of a system and the resulting system degradation (or remaining life consumption), as is shown schematically in Figure 12 (Tinga, 2010). The upper three blocks in the figure represent this relation and ideally the dependency of the remaining useful life on the actual usage of the system is explicitly known. However, while the usage of a system is normally known by the operator, its effect on the remaining life consumption is typically unknown. The author believe that zooming in to the level of the physical failure mechanism (e.g. fatigue, wear) enables to quantify this relation, provided that either the usage (operating hours, rotational speed) or loads (strain gauge, thermocouple) are monitored.



Figure 12. Relation between system usage and remaining life consumption is governed by failure mechanism.

The figure also shows that condition monitoring is a third option for monitoring, and since information about the system condition is obtained directly, no detailed understanding of the failure mechanism is required. This is exactly the reason that in CM and SHM many data-driven approaches have been successfully developed. Just monitoring the condition (or some associated damage feature) enables to detect the exceedance of a predefined threshold, and then to trigger some maintenance activity. However, this approach (neglecting the actual physical failure behaviour) has three important drawbacks:

- Selection of quantities to measure, sensor locations and data processing algorithms is mostly based on a trialand-error process;
- The interpretation of the measured data and relating it to the damage or degradation is in many cases rather difficult; In general, it is only possible if a considerable set of failure data is available, which might be difficult to achieve for critical systems and systems that re operated in a variable way;
- The method is only diagnostic, extension to a prognostic method is often difficult.

These drawbacks can be addressed if the physical failure behaviour is understood. The selection of the appropriate monitored quantities and their locations can largely benefit from the knowledge on failure behaviour. The common approach in both CBM and SHM is to apply considerable numbers of sensors and start collecting large amounts of data. Only after a certain period of data collection, the analysis and interpretation of the data is considered. It is then often discovered that non-relevant parameters have been monitored and that other essential quantities are missing. A much better approach is to start with identifying the system's most critical failure mechanisms and their governing loads. These results can then be used to select suitable sensors and locations. For example, if a (rotating) system or component fails due to fatigue, the governing load is a cyclic stress. It is then not useful to monitor the number of operating hours or temperature, but much more useful to monitor the number of starts of the system and the rotational speeds, since that determines the number of stress cycles and their magnitude. Only a limited number of papers advocating this physics-based approach for CM system development is available, see e.g. (Banks, Reichard, Hines, & Brought, 2008).

The next challenge after collecting the appropriate data is the interpretation of the data and retrieving information on the degradation of the system. If the knowledge on the system and its failure behaviour is limited, the only way to obtain that information is the experience-based approach: after collecting a sufficiently large amount of data, patterns or relations may be found in the data. This is the typical approach in data mining processes, but also approaches based on artificial neural networks and fuzzy logic follow this route. The drawbacks are that, firstly, relations can only be found when the data set is sufficiently large. For some (critical) systems the number of failures can be very limited, which significantly reduces the potential of the approach. Secondly, the failure identification is only reliable for conditions that have occurred at least once (and are present in the historic data). For systems that are operated in largely variable conditions (e.g. military, off-shore), this aspect yields a big limitation to the approach. However, when the system behaviour and associated physics of failure is well understood, the data sets no longer consist of anonymous numbers, but contain relevant information. Retrieving that information is generally much more straightforward, and requires much less data and experience, than in the purely data driven approaches.

Finally, the ultimate challenge is to extend the methods to the prognostics. As was mentioned before, the traditional diagnostic methods in CBM and SHM sometimes use trending methods to do some prognostics. However, if the operational conditions of the system vary considerably, a trend based on historical data is not very representative for the present or future behaviour. It therefore has a limited prognostic capability. But, if physical models are used to quantify the failure behaviour, the expected degradation rates can be calculated (also when the conditions change) and reliable prognostic methods can be added to the diagnostic capabilities of CBM and SHM methods.

5. ALIGNING CBM, SHM AND PHM

Now the three disciplines have been described (section 2), have been compared and demonstrated with cases (section 3), and the relevance of understanding the physical failure

mechanisms has been discussed, it will be possible to align them. The proposed integral approach is shown in Figure 13. As was mentioned before, the differences between CM and SHM are not large, and their aim is actually very similar. Except for SHM level 5 (prognostics), they also act at the same level of maturity / complexity (see Figure 1). This means that both methods could be used to monitor the (initiation or progression) of damage in a part or system. The specific application (e.g. rotating or static) will then determine whether a SHM or CBM technique is most suitable. On the next higher level, both monitoring strategies can then be connected to the CBM policy, which is used to govern the maintenance decisions (mainly when to replace a part). Instead of the CBM policy, also a usage based maintenance (UBM) or a load based maintenance (LBM) policy (Tinga, 2010) can be adopted. In that case also another monitoring strategy will have to be selected.



Figure 13. Relation between system usage and remaining life consumption is governed by failure mechanism.

Then, regardless of the adopted maintenance policy, a prognostic approach will have to be selected to assess the RUL at any moment, and there the PHM methods can play an important role. Finally, to guide all the maintenance related decisions (replace, repair, inspect, etc.) during the whole life cycle of the system, a suitable life cycle management approaches developed in the PHM field are very suitable. This means that in the approach proposed in Figure 13, all three disciplines can be combined, where each of them has its own role and scope and the strengths of the individual disciplines are combined.

One important additional aspect of the proposed approach is the inclusion of knowledge on the physical system and failure behaviour. As is indicated in Figure 13, and was also discussed in section 4, this fundamental knowledge improves the approach at three essential stages: (i) in the selection of the quantities to be monitored and their locations; (ii) in the processing of the measurement data to retrieve the required information on the system degradation; (*iii*) in the prognostics, where a physical model-based approach improves the performance.

In summary, instead of considering CBM, SHM and PHM as separate disciplines, the present work has shown how the three fields, their objectives and approaches can be aligned to achieve an integrated strategy to improve the life cycle management of any (complex) system.

6. CONCLUSION

In this paper the three disciplines of condition based maintenance (CBM), structural health monitoring (SHM) and prognostics and health management (PHM) have been described, compared and demonstrated using illustrating case studies. Several commonalities between the disciplines appeared, but also differences in scope and objectives could be identified. This insight enabled us to align the three disciplines and propose an integrated approach, in which the understanding of the physical system failure behavior appears to be an essential aspect. The proposed integral approach starts from defining an appropriate monitoring strategy (CM and SHM), applying the appropriate maintenance policy (CBM), performing prognostics (PHM) and eventually supporting the decision making that leads to an optimal maintenance process throughout the life cycle of the asset.

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REFERENCES

- Banks, J. C., Reichard, K. M., Hines, J. A., & Brought, M. S. (2008). Platform degrader analysis for the design and development of vehicle health management systems. Paper presented at the International conference on prognostics and health management.
- Brown, E. R., McCollom, N. N., Moore, E. E., & Hess, A. (2007). Prognostics and health management. A data-driven approach to suporting the F-35 Lightning II. Paper presented at the IEEE Aerospace Conference, Big Sky, Montana.
- Buderath, M., & Adhikari, P. P. (2012). Simulation framework and certification guidance for condition monitoring and prognostic health management. Paper presented at the European Conference of the Prognostics and Health Management Society, Berlin.
- Farrar, C. R., & Worden, K. (2010). An introduction to Structural Health Monitoring. In A. Deraemaeker (Ed.), New Trends in Vibration Based Structural Health Monitoring. Udine: CISM.

- ISO. (2012). ISO 13374 Condition monitoring and diagnostics of machines ISO.
- Loendersloot, R., Ooijevaar, T. H., Warnet, L., Boer, A. d., & Akkerman, R. (2011). Vibration Based Structural Health Monitoring and the Modal Strain Energy Damage Index Algorithm Applied to a Composite T–Beam. In C. M. A. Vasques & J. D. Rodrigues (Eds.), Vibration and Structural Acoustics Analysis: Current Research and Related Technologies. Amsterdam: Springer Netherlands.
- MIMOSA. (2013). Open System Architecture for Condition-Based Maintenance, V3.3.1 MIMOSA.
- Ooijevaar, T. H., Loendersloot, R., Warnet, L., Boer, A. d., & Akkerman, R. (2010). Vibration Based Structural Health Monitoring of a Composite T– Beam. Composite Structures, 92(9), 2007-2015.
- Ooijevaar, T. H., Warnet, L., Loendersloot, R., Akkerman, R., & Boer, A. d. (2012). Vibration Based Damage Identification in a Composite T-Beam Utilising Low Cost Integrated Actuators and Sensors. Paper presented at the Sixth European Workshop on Structural Health Monitoring, Dresden, Germany.
- Orsagh, R., Roemer, M. J., Sheldon, J., & Klenke, C. J. (2004). A comprehensive prognostic approach for predicting gas turbine engine bearing life. Paper presented at the IGTI Turbo Expo, Vienna.
- Rao, B. K. N. (1996). *Handbook of condition monitoring*. Oxford: Elsevier Science Ltd.
- Roemer, M. J., Byington, C. S., Kacprzynski, G. J., & Vachtsevanos, G. (2006). An overview of selected prognostic technologies with application to engine health management. Paper presented at the ASME Turbo Expo, Barcelona, Spain.
- SAE. (2013). Guidelines for Implementation of Structural Health Monitoring on Fixed Wing Aircraft (Vol. ARP 6461). Warrendale: SAE.
- Sanchez Ramirez, A., Loendersloot, R., & Tinga, T. (2014). Vibration based blind identification of bearing failures for autonomous wireless sensor nodes. Paper presented at the 2nd European conference of the prognostics and health management society Nantes, France.
- Stubbs, N., & Farrar, C. R. (1995). Field verification of a nondestructive damage localization and severity estimation algorithm. Paper presented at the Proceedings of the 13th International Modal Analysis Conference.
- Tinga, T. (2010). Application of physical failure models to enable usage and load based maintenance. *Reliability Engineering and System Safety*, 95(10), 1061-1075.
- Tinga, T. (2013). Predictive maintenance of military systems based on physical failure models. *Chemical Engineering Transactions*, 33, 295-300. doi: 10.3303/CET1333050

BIOGRAPHIES

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Sequential Monte Carlo sampling for crack growth prediction providing for several uncertainties

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ABSTRACT

The problem of fatigue crack growth monitoring and residual lifetime prediction is faced by means of sequential Monte Carlo methods commonly defined as sequential importance sampling/resampling or particle filtering techniques. The algorithm purpose is the estimation of the fatigue crack evolution in metallic structures, considering uncertainties coming from phenomenological aspects and material properties affecting the process. These multiple uncertainties become a series of unknown parameters within the framework of the dynamic state-space model describing the crack propagation. These parameters, if correctly estimated within the particle filtering algorithm, will cover the uncertainties coming from the real environment, improving the prognostic performances. The standard particle filter formulation needs additional methods to augment the state vector and to correctly estimate the parameters. The prognostic system composed by the sequential Monte Carlo algorithm able to account for different uncertainties is tested through several crack growth simulations. The applicability of the method to real structures and the employment in presence of real environmental conditions (i.e. variable loading conditions) is also discussed at the end of the paper.

1. INTRODUCTION

Crack propagation is one of the most widespread phenomena affecting metallic structures. Engineering community dedicated a lot of effort into the comprehension of the fracture mechanism and crack propagation phenomena, especially when fatigue loads affect the cracked structure. The latter case is well known as the fatigue crack growth (FCG) or fatigue crack propagation problem and, intuitively, it causes the need of the time to failure and the residual useful life (RUL) of the cracked structure for maintenance and safety purposes.

The most part of RUL estimation techniques based on fracture mechanics have been developed from the work of Paris & Erdogan (1963) describing the crack growth rate as a function of the stress intensity factor (SIF) range acting during a fatigue load cycle. In the last decades, many works have been dedicated to FCG dealing with multiple aspects. Nonetheless, in spite of these in-depth studies, the RUL predictions cannot overlook the statistical aspects of fatigue crack propagation. The variability affecting FCG was highlighted from Virkler, Hillberry, Goel (1978), when 68 fatigue crack growth tests on Al2024-T3 specimens produced a large variability of the crack growth data. This scatter can increase exponentially dealing with real structures in real environments. As a matter of fact, there are different sources of uncertainty affecting the fatigue crack behavior: (i) the variability of the material properties, (ii) the load sequences, (iii) the environmental conditions and (iv) the intrinsic variability of the phenomenon, that is driven by nano-scale events not accounted for within the usual engineering models.

In order to overcome this variability and to improve the time to failure and RUL predictions, several statistical methods have been developed. Statistical definition of FCG parameters is a very popular technique to address the crack growth variability, since the parameter values comes from fitting procedures like regressions, maximum likelihood estimations etc. (Cross, Makeev & Armanios 2007, Corbetta, Sbarufatti, Manes & Giglio, 2014). Other methods employ stochastic models of the crack, using both analytical solutions and Monte Carlo methods, (Ray & Patankar 1999, Scafetta, Ray & West 2006, Mattrand & Bourinet, 2011).

As mentioned above, the difficulties increase dealing with variable loading conditions. Elber (1970, 1971) introduced the crack closure effect that it has been studied later in presence of variable amplitude loading conditions by Newman (1981). Fatigue crack propagation under variable or

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random loading conditions is still an open issue nowadays. Apart from the Newman's paper (1981), many other works dedicated to crack growth rate are available (Newman 2005, Willenborg, Engle & Wood, 1971) and more recent papers appeared highlighting new methods to describe the prediction of crack propagation under random load spectra (Newman, Irving, Lin & Le, 2006, Mattrand & Bourinet, 2011). Nowadays, the development of real-time Structural Health Monitoring (SHM) techniques paves the way to real-time prognostics of structures. From a structural reliability point of view, the final target of prognostics is the prediction of the structure RUL starting from the information provided by an SHM unit composed by localized or distributed sensor networks and diagnostic algorithms. The output information should be combined with advanced algorithms able to take into account the uncertainties coming from both the SHM unit and the uncertainties affecting the monitored process. Therefore, the estimation of the probability density function (pdf) of the residual lifetime becomes feasible. The two main approaches employed in prognostics are the data-driven approach and the model-based approach. The first uses large amount of data to train algorithms able to predict the future degradation trends based on the previous knowledge, the second takes advantage of physical or phenomenological models to predict the most probable damage evolution. Only the model-based approach is considered in this context, based on the large number of studies on FCG and available models.

Considering the SHM-Prognostics framework, a Sequential Importance Resampling (SIR) algorithm is proposed in this paper to track the damage propagation and update the RUL estimation of a simple structure subjected to fatigue loads. The dynamic state-space (DSS) model of the system is proposed in an *adaptive* form, thanks to the adaptation of model parameters and random processes. These quantities will be estimated during the crack propagation thanks to dedicated techniques within the SIR algorithm. Similar algorithms have just been applied to the fatigue crack growth problem. Cadini, Zio & Avram (2009) have applied particle filter algorithm (in the form of Sequential Importance Sampling/Resampling - SIS/SIR) without the parameter estimation. Corbetta, Sbarufatti, Manes & Giglio proposed a SIS/SIR algorithm with stochastic DSS model (2013a) and updating of the model parameters through Markov chain Monte Carlo (MCMC) techniques (2013b). Chiachio, Chiachio, Saxena, Rus & Goebel (2013) proposed a more complicated prediction problem dealing with composite materials and combined state-parameter estimation within the DSS framework. The SIR algorithm proposed in this work have some novelties with respect to the cited works, making use of the concept of intra-specimen and inter-specimen variability introduced by Bourinet & Lemaire (2008) and explained in detail is section 2. The artificial dynamics (AD) just used by Daigle & Goebel (2011) and Chiachio et al. (2013), and the kernel smoothing (KS) techniques will improve the knowledge of the DSS model parameters describing the crack evolution. These methods will try to cover the inter-specimen variability affecting different specimens of the same structure. The intra-specimen variability is covered by a dynamic noise variance within the SIR formulation, explained in detail in section 3.4. An additional novelty introduced by this work is the evaluation of the Residual Useful Life through the numerical solution of the stochastic integral proposed by Yang & Manning (1996) instead of the long-lasting step-by-step simulation of the crack growth. Unfortunately, this method works in presence of constant-amplitude fatigue loads only. The purpose of this algorithm is to try covering several sources of uncertainties that can appear on real structures subjected to crack propagation. Several virtual tests on crack propagation altered with respect to the theoretical crack growth curve will prove the validity of the method.

The paper organizes as follows: section 2 briefly introduces the FCG equation and its intrinsic variability, focusing on the residual life prediction problem. Section 3 summarizes sequential Monte Carlo methods and Bayesian filtering estimation, describing the adopted techniques for combined state-parameter estimations and dynamic noise variance selection. Section 4 shows the application of the algorithm to a simulated crack propagation and the prognostic formulation. Section 5 is dedicated to the results of the algorithm in terms of parameter estimation and RUL prediction, comparing the *artificial dynamics* and the *kernel smoothing* techniques. Section 6 concludes the paper.

2. PROBLEM STATEMENT: FATIGUE CRACK GROWTH MONITORING AND PREDICTION

Several FCG models are able to describe the growth rate as a function of crack length and a series of model parameters. The most popular model is the Paris-Erdogan equation (Paris & Erdogan, 1963) describing the FCG rate per load-cycle using the SIF range affecting the crack tip, as defined in Eq. (1a), and two empirical parameters commonly defined as C and m, as visible in Eq. (1b).

$$\Delta K(x) = F(x)\Delta S\sqrt{\pi x} \tag{1a}$$

$$\frac{dx}{dN} = C[\Delta K(x)]^m \tag{1b}$$

Where *x* is the current crack length, ΔS is the applied load range, F(x) is a crack shape function depending on the crack length and the structure geometry, and *N* is the general load cycle. If the load range has constant amplitude and constant frequency, the FCG rate domain can easily change from load cycle to time domain, and Eq. (1b) becomes a first-order ordinary differential equation. If the discrete-time domain is used to describe the crack evolution, Eq. (1b) changes into Eq. (2a)¹, where the crack growth rate dx/dN follows the

¹ Supposing a relatively small number of cycles ($\Delta N \rightarrow 1$).
Paris-Erdogan Eq. (1b) or any other FCG rate model (see for instance the NASGRO model, NASA J.S. Centre, 2002).

Considering the RUL of the cracked component, the Paris-Erdogan model allows the direct calculation of the remaining number of cycles by a direct integration of Eq. (1b) using the separation of variable method, Eq. $(2b)^2$.

$$x_k = x_{k-1} + \frac{dx}{dN}\Big|_{x=x_{k-1}} \Delta N$$
 (2a)

$$N_r = \frac{x_{lim}^{\left(1-\frac{m}{2}\right)} - x_0^{\left(1-\frac{m}{2}\right)}}{CF^m \Delta S^m \pi^{\frac{m}{2}} \left(1-\frac{m}{2}\right)}$$
(2b)

The term x_0 indicates the starting crack length, x_{lim} is the limit crack length governed by the fracture toughness and the safety requirements for the structure. N_r is the number of remaining load cycles needed to reach the length x_{lim} starting from x_0 . All the other variables are the same as in Eqs. (1). The application of more complicated models makes unfeasible the direct integration of Eq. (1b), requiring numerical integration or Monte Carlo simulation to estimate the remaining cycles. Obviously, the deterministic definition of N_r cannot be employed in effective lifetime predictions or maintenance strategies, because of the large variability affecting the crack growth process. As a proof of the variability affecting the FCG process on real structures, Figure 1 shows some experimental results coming from fatigue crack growth tests on helicopter fuselage panels. The ordinate axes shows the crack length in millimeters as a function of the load cycles on the abscissa. As clearly visible, there is an high discrepancy between the theoretical curve (built with NASGRO model) and the experimental data. Therefore, a statistical approach is mandatory for an efficient residual lifetime prediction. The interested reader can refer to Corbetta et al. (2014) for further information about the mentioned experimental activity.



Figure 1. Comparison between experimental data and theoretical crack growth curve built with NASGRO model.

2.1. Conceptual definition of fatigue crack growth variability

According to the previous considerations on the scatter affecting FCG data, the Bourinet & Lemaire (2008) approach is proposed here with a little modification. The method can be applied with any kind of FCG propagation model that follows the general form dx/dN = g(x) (in load-cycle domain or time domain).

The variability affecting crack propagation is split into two main contributions, each of them related to one or several sources of uncertainty, according to the Bourinet & Lemaire approach. Firstly, a crack evolution can differ from the theoretical one because of different values of material properties and/or empirical parameters, which cannot be described by a single value for all the structures built with the same material. It is easy to understand this concept giving thought to a large fleet of the same aircraft, or to all the metallic parts constituting a long bridge or an high-rise building. Even though the same material is used, uncertainties due to manufacturing processes and environmental uncertainties are always present in these kind of structures. Moreover, as just mentioned above, the crack propagation event follows a random behavior caused by several variability not considered in the common engineering models of the phenomenon. This random behavior produces discrepancies between the theoretical crack evolution and the expected one, and these discrepancies can appear in a small time-range. The two variability contributions are defined as inter-specimen variability and intra-specimen variability, respectively.

2.1.1. Inter-specimen variability

Usually, the *inter-specimen* variability is described within the FCG model by a randomization of the parameters, for instance C and m affecting the Paris-Erdogan model. This is the most common technique to produce a random FCG model, and the sequential information on the crack length updates the parameter pdfs by means of statistical tools. Corbetta et al. (2014) propose an Adaptive Markov chain Monte Carlo algorithm to update the parameter distributions during real crack propagation on portions of helicopter fuselage. On the other hand, a slightly different approach is proposed hereafter. Checking the discrete-form of crack evolution in Eq. (2a), it can be described as in Eq. (3).

$$x_k = x_{k-1} + \Delta x_{k-1} \,\Delta N \tag{3}$$

Where Δx_{k-1} is the result of the Paris-Erdogan model in this context. Actually, $\Delta x \cdot \Delta N$ describes the crack increment within few load cycles. The model used to evaluate the crack increment Δx can be very complex and composed by a large quantity of empirical parameters and/or material properties; however, the result will be always a crack increment per load

² Considering a constant shape function F(x) = F.

cycle (or per time unit considering constant-amplitude loads). Now, consider that the monitoring of the crack and the subsequent RUL prediction are the main goal of the prognostic system. Thus, one might be not interested in the exact knowledge of the parameters describing the current crack propagation, as the main intent is to correctly monitor the damage and to improve the prognostic performances. Accordingly, the inter-specimen variability is described hereby a single mathematical constant called correction parameter ψ . It will be modulated according to the information related to the crack length during the crack propagation. The correction parameter ψ multiplies the crack increment Δx to adjust the model prediction on the measures coming from a general diagnostic unit (Eq. (4a)). The proposed Paris-Erdogan formulation is highlighted in Eq. (4b).

$$x_k = x_{k-1} + \psi_{k-1} \Delta x_{k-1} \Delta N \tag{4a}$$

$$x_k = x_{k-1} + \psi_{k-1} C \left(F(x) \Delta S \sqrt{\pi x_{k-1}} \right)^m \Delta N \tag{4b}$$

The updating procedure will change the value of the correction parameter ψ instead of the two parameters *C* and *m* during the Bayesian filter operation. The correction parameter, will try to cover the inter-specimen variability affecting the crack propagation phenomenon. From a different point of view, it could be considered a drift of the process noise usually employed to generate the stochastic model. This drift should cover the bias between the expected crack evolution (driven by the deterministic parameters of the model) and the actual crack growth happening on the structure.

2.1.2. Intra-specimen variability

The *intra-specimen* variability can be represented by a random process altering the crack growth at each time step as just presented by Yang & Manning (1996). The FCG rate model is modified by a lognormal random noise Ω , Eq. (5a).

The employment of a lognormal random process to describe \mathcal{Q} is due to the nature of the damage. In fact, cracks can only increase over time (or at least, they remain constant), thus the crack increment during a discrete time step cannot be negative. Others distributions are able to satisfy this requirement, however the lognormal distribution is the easiest way to introduce the correct variability affecting the crack growth process. This random noise is representative of all the possible uncertainties affecting the real environments with respect to the theoretical model describing the FCG phenomenon: variability of the actual state of stress near the crack, environmental conditions, different direction of the applied load with respect to the expected one, just to name a few of them.

Equation (3) modifies according to Ω and it can be employed in a dynamic state-space model of the process, Eq. (5b).

$$\frac{dx}{dN} = \Omega C [\Delta K(x)]^m$$
(5a)

$$x_k = x_{k-1} + C[\Delta K(x_{k-1})]^m \omega_{k-1} \Delta N$$
 (5b)

Where the term ω_{k-1} in Eq. (5b) is a realization of the random process Ω . This variable represents the random noise of the process within the Bayesian filtering framework. Even in this case, the optimal value of the process noise is unknown at the beginning of the crack growth. The first moments of the random noise (for instance the mean and variance) should be properly tuned using previous experimental tests representative of the current condition of the system. However, the amount of uncertainty makes impossible a complete characterization of the random noise. Then, the mean and the variance associated to the random noise Ω will be estimated during the crack propagation according to the data coming from the observation equation, as described in section 3.

2.1.3. Residual useful life prediction

The integration of Paris-Erdogan model is feasible even if the model becomes a random process due to the presence of Ω . The lognormal random process introduced in Eq. (5a) is used to evaluate the probability density function of the RUL according to Eq. (2b). As introduced by Yang & Manning, the integration of $dx/dN = \Omega g(x)$ brings to the equivalence in Eq. (6).

$$\int_{x_0}^{x_{lim}} \frac{1}{g(x)} dx = \int_0^{N_r^0} \Omega \, dN \tag{6}$$

The term N_r^0 is the theoretical number of remaining load cycles calculated with the deterministic FCG rate model g(x). The RUL distribution could be evaluated by means of Monte Carlo sampling and the theory of stochastic processes, avoiding the step-by-step simulation of crack growth samples commonly implemented in standard SIS/SIR algorithms. As a matter of fact, the right-hand side of Eq. (6) can be approximated using the summation of $n^* = N_r^0/\Delta N$ samples coming from the process Ω multiplied by the discretization ΔN , as in Eq. (7).

$$\int_{0}^{N_{r}^{0}} \Omega \, dN \approx \sum_{j=1}^{n^{*}} \omega_{j} \, \Delta N \tag{7}$$

Again, the term ω_j is the *j*-th sample coming from the random process Ω . The repetition of the summation in Eq. (7) for a relatively large number of times produces an approximation of the probability density function of the RUL in agreement with the theoretical curve defined by the stochastic Paris-Erdogan law in Eq. (5a). This simple approach is limited to the case of constant amplitude loading conditions, and it will be explained in detail in section 3 within the pseudo-code of the SIR algorithm (subsection 3.5). Thus, if variable loads are applied to the cracked components, the step-by-step

simulation of the crack should be adopted, as well as more complicated techniques to evaluate the stochastic integrals.

3. SEQUENTIAL IMPORTANCE RESAMPLING, PARAMETER ESTIMATION AND ADAPTIVE NOISE VARIANCE

Literature about sequential Monte Carlo sampling is vast at least as the literature on fatigue crack growth. Therefore, the section summarizes the main features of SIR algorithms with a focus on the crack monitoring and prediction problem only.

3.1. Monitoring and Prediction from a Bayesian filtering perspective

Equations (3-5) presented in section 2 can be generalized with the common dynamic state-space model formulation composed by the state evolution, Eq. (8a) (following the hypothesis of the hidden Markov models of order one) and the observation equation, that is Eq. (8b) (linking the actual state of the system with the information provided by a measurement system).

$$x_k = f(x_{k-1}, \boldsymbol{\theta}, \omega_{k-1}) \tag{8a}$$

$$z_k = h(x_k, \eta_k) \tag{8b}$$

The vector θ contains empirical parameters supposed to be constant during the system evolution. Variables z_k represents the measure related to the state x_k at the general *k*-th step, and η_k is the random noise affecting the measurement system. The objective within the formulation of Bayesian filters is the evaluation of the posterior probability density function of the state *x* given a series of noisy observations *z* at a general timestep *k*; it means the calculation of $p(x_k/z_{1:k})$. From a mathematical viewpoint, the problem statement is described by the Chapman-Kolmogorov equation, Eq. (9a) and the subsequent updating via Bayes' rule, Eq. (9b).

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1}) p(x_{k-1}|z_{1:k-1}) dx_{k-1}$$
(9a)

$$p(x_k|z_{1:k}) = \frac{p(x_k|z_{1:k-1})p(z_k|x_k)}{p(z_k|z_{1:k-1})}$$
(9b)

The analytical solution of the posterior pdf is available if the system is linear and the processes are described by Gaussian distributions. This is not the case for crack propagation phenomena. The SIR algorithm allows approximating the posterior distribution $p(x_k/z_{1:k})$ by a series of samples representative of the system state, usually called *particles* by the widespread definition of the algorithm *particle filter*. Each particle has an associated weight *w* depending on the sequential information coming from the measurement system, diagnostic unit etc. The approximation of the posterior pdf is expressed in Eq. (10).

$$p(x_k|z_{1:k}) \approx \sum_{i=1}^{N_S} w_{n,k}^{(i)} \delta(x_k - x_k^{(i)})$$
(10)

Where N_s is the total number of particles, $x_k^{(i)}$ is the value of the *i*-th particle at the general k-th time step, $w_{n,k}^{(i)}$ is the

normalized weight associated to that particle and δ is the Dirac delta-function. The weight formulation employed in the SIR algorithm agrees with the bootstrap approximation, in which the transition density from x_{k-1} to x_k is used as proposal distribution for the sample generation (Haug, 2005). As a consequence, the weights depend on the value at the previous step k-1 and on the likelihood of the measure given the particle value, as shown in Eq. (11).

$$w_k^{(i)} = w_{k-1}^{(i)} p(z_k | x_k^{(i)})$$
(11)

Then the weights are normalized such that $\Sigma w_k^{(i)}=1$. Arulampalam, Maskell, Gordon & Clapp (2002) and Doucet, Godsill & Andrieu (2000) produced a detailed description of the algorithm for the interested reader.

In case of combined state-parameter estimation, the vector x is augmented such that the *extended system state* is represented by the damage state and the parameter variables $y_k = [x_k, \theta]$. Particles associated to the state $x^{(i)}$ and the parameter sample $\theta^{(i)}$, together with the related weight $w^{(i)}$, will be representative of the combined state-parameter estimation or *extended system state*, Eq. (12a). It has to be remarked that the subscript *k* associated to θ in Eq. (12a) indicates the value of θ at the general *k-th* step, and it does not mean that θ is time-varying. The weight updating follows the same procedure of the standard particle filtering, nevertheless the likelihood of the measure is affected by the value of $\theta^{(i)}$ used to propagate the particle (Eq. (12b)).

$$\left\{ \boldsymbol{y}_{k}^{(i)} = \left(x_{k}^{(i)}, \boldsymbol{\theta}_{k}^{(i)} \right), w_{k}^{(i)} \right\}_{i=1}^{N_{S}}$$
(12a)

$$w_{k}^{(i)} \propto w_{k-1}^{(i)} p(z_{k} | \boldsymbol{y}_{k}^{(i)}) = w_{k-1}^{(i)} p(z_{k} | \boldsymbol{x}_{k}^{(i)}, \boldsymbol{\theta}_{k}^{(i)})$$
(12b)

The combined state-parameter posterior pdf is expressed thanks to Bayes' rule (13) as highlighted by Liu & West (2001).

$$p(\mathbf{y}_k|z_{1:k}) \propto p(z_k|\mathbf{y}_k)p(x_k|\boldsymbol{\theta}, z_{1:k-1})p(\boldsymbol{\theta}|z_{1:k-1})$$
(13)

As clearly visible by Eq. (13), the knowledge of the parameter pdf given the series of observations z is fundamental to approximate the posterior pdf of the augmented state vector y correctly. Thus, the proposal distribution from which to draw the samples of the parameter vector has to be considered in the SIR algorithm. The next sub-section briefly discusses the two main approaches used in this work: the *artificial dynamics* and the *kernel smoothing* techniques (Liu & West, 2001). Both these techniques will be used during the algorithm to update the *correction parameter* ψ shown in section 2. They have been selected because of their simplicity, while other more advanced techniques are available in literature as summarized by Kantas, Doucet, Singh & Maciejowski (2009).

3.2. Artificial dynamics technique

The main drawback in the insertion of constant parameter in the state vector is that the filtering method has to identify two different quantities: one is time-varying, and the other one is constant. The first attempt is to select a DSS equation for the constant parameter on the form $\theta_k = \theta_{k-1}$. However, it leads to the well-known problem of *sampling impoverishment* or *sample degeneracy*. The *sample degeneracy* can be overcome by the addition of a small change in the sample values at each step of the algorithm. This small change is a random noise added to each particle, as presented in Eq. (14).

$$\boldsymbol{\theta}_{k}^{(i)} = \boldsymbol{\theta}_{k-1}^{(i)} + \boldsymbol{\xi}_{k}^{(i)}$$
(14)

where $\xi_k^{(i)}$ is a random value with zero-mean and a variance that decreases in time. This is the idea suggested by Gordon, Salmond & Smith (1993) and recalled by Liu & West (2001). Actually, the statistics of ξ does not depend on the observed data, then $p(\theta|z_{1:k-1})$ is negligible in the posterior formulation of the state distribution.

Noticeably, the simplicity of the method introduces a nonnegligible drawback that is the loss of information between the time steps. It happens because of the introduction of the mentioned artificial changing in the parameter values when they are fixed. Moreover, two questions have to be solved to maximize the performances of the algorithm: the selection of the initial covariance matrix of ξ , $\sigma_{\xi,0}^2$, and the decreasing function depending on the discrete time $\sigma_{\xi}^2 = \sigma_{\xi,0}^2 f(k)$, in order to reach the convergence in a relatively small number of iterations.

3.3. Kernel smoothing technique

Kernel smoothing method was developed by West (1993b) and it is based on the mixture modelling approach. It allows approximating the parameter posterior distribution by a Gaussian mixture using the weights associated to the particles, as shown in Eq. (15).

$$p(\boldsymbol{\theta}|z_{1:k}) \approx \sum_{i=1}^{N_{S}} w_{k}^{(i)} N(\boldsymbol{\theta}|\mu_{\boldsymbol{\theta},k}^{(i)}, \boldsymbol{\zeta}_{k}^{2} \boldsymbol{\Sigma}_{\boldsymbol{\theta},k})$$
(15)

where $\mu_{\theta,k}^{(i)}$ is the *kernel location* for the *i-th* particle of the parameter θ , ζ_k is the *smoothing parameter* and $\Sigma_{\theta,k}$ is the Monte Carlo covariance matrix of θ . Intuitively, $N(\cdot|\mathbf{m}, S)$ indicates a probability that follows a normal distribution with mean \mathbf{m} and covariance matrix S. Effective kernel locations $\mu_{\theta,k}$ are specified according to the *shrinkage rule* proposed by West (1993b) depending on the smoothing parameters ζ_k and another parameter $\mathbf{b} = \sqrt{(1 - \zeta_k^2)}$. Equation (16) defines the kernel location for each particle.

$$\boldsymbol{\mu}_{\boldsymbol{\theta},k}^{(i)} = \boldsymbol{b}\boldsymbol{\theta}_{k-1}^{(i)} + (1-\boldsymbol{b})E(\boldsymbol{\theta}_{k-1})$$
(16)

The term $E(\theta_{k-1})$ is the mean of the parameter vector θ at the k-1 *th* time step. Even though this methodology allows an effective and adaptive sampling technique, the function $\zeta_k = \zeta(k)$ must be properly selected in order to reach the convergence of the algorithm. It should be a small decreasing function of the time as it happens for the variance introduced

in the *artificial dynamics* method. Nevertheless, the loss of information is limited with respect to the previous approach.

3.4. Dynamic noise variance

In the previous sub-section, the problem of constant parameter estimation is faced presenting two different techniques covering the inter-specimen variability affecting the damage propagation phenomenon that can appear on real structures. Now the focus is on the *intra-specimen* variability. In this kind of nonlinear problems with non-Gaussian pdfs, the selection of too small noise features makes the algorithm unable to track the state variations properly. If this happens, the wrong state estimation will produce larger errors in the estimation of the RUL. On the other hand, too large noise features produce unreasonable enlargement of the posterior distributions, then useless information. Moreover, a too large noise variance alters the particle evolutions producing implausible propagation of the crack and falling into unexpected RUL distribution, too. An adaptive noise is proposed hereafter, trying to avoid the tuning of the noise Ω affecting the process.

A suitable process noise for the crack growth problem is the lognormal random process already introduced in section 2. According to the theory of lognormal distributions, Ω can be described as an exponential function of a normal random process Λ , with mean and variance precisely selected, Eqs. (17a, b). In order to produce an unbiased estimation of the mean crack growth curve, the mean and variance of the normal random process Λ must be related according to the formulation in Eq. (17c), such that the mean of the random process approaches one (Eq. (17d)).

$$\Omega = \exp \Lambda \tag{17a}$$

$$\lambda \sim N(\mu_{\Lambda}, \sigma_{\Lambda}^2) \tag{17b}$$

$$\mu_{\Lambda} = -\frac{\sigma_{\Lambda}^2}{2} \tag{17c}$$

$$E(\Omega) = \exp\left\{\mu_{\Lambda} + \frac{\sigma_{\Lambda}^2}{2}\right\} = 1$$
(17d)

In this way, the average of the random process x (the evolution equation of the DSS model) will be centered on the deterministic evolution of x. The *i*-th sample of the process noise ω can be easily drawn according to Eq. (18).

$$\omega^{(i)} \sim \exp\{\lambda^{(i)}\} = \exp\{\mu_{\Lambda} + \sigma_{\Lambda} r\}$$
(18)

Where *r* indicates a random value drawn from the standardized normal distribution; thus $\lambda^{(i)}$ is a single realization of the random process Λ . Despite the link between the mean and the variance of the random process, the selection of σ_{Λ}^2 remains heuristic in the common practice. Then, a non-constant variance tuned on the scatter of the measures could improve the performance of the algorithm.

According to this concept, the simulations presented in section 5 make use of two methods to adjust the noise variance. First, the variance of the process Λ is assumed equal to the variance associated to the observations, which is a function of the estimated state at the previous time-step, as expressed in Eq. (19).

$$\sigma_{\Lambda_{k+1}}^2 = \sigma_{z_k}^2(x_k) \tag{19}$$

This is a very simple approach useful for systems where the variance of the process or the variance of the measurement system can increase over time, like in the structural degradation processes. The other technique makes use of the formulation of Xu and Li (2005) introducing the *similarity parameter* between the observation and the estimated state, defined in Eq. (20). The similarity parameter is proportional to the distance between $E(x_k)$ and the observation z_k in multi-dimensional or one-dimensional spaces (as in this case). The term $V(x_k)$ indicates the Monte Carlo variance of the state at time step k.

$$\varphi_k = \exp\left\{-\frac{\left(z_k - E(x_k)\right)^2}{2V(x_k)}\right\}$$
(20)

The new noise variance is computed according to Eq. (21) through the *similarity parameter* φ_k .

$$\sigma_{\Lambda_{k+1}}^2 = \max\left(\min\left(\sigma_{\Lambda_0^2}\sqrt{\frac{1}{\varphi_k}}, \sigma_{\Lambda,max}^2\right), \sigma_{\Lambda,min}^2\right) \quad (21)$$

Actually, the variance selection is replaced by the tuning of three parameters, so it is not completely avoided. They are the constant $\sigma_{A,0^2}$, the maximum and minimum allowable variances, $\sigma_{A,max}^2$ and $\sigma_{A,min}^2$. However, the selection of these quantities could be simpler than the selection of the optimal variance in some cases. Both the formulations in Eq. (19) and Eq. (21) will be employed in the SIR algorithm.

3.5. Algorithm operation

Sub-sections 3.1-3.4 define the equations adopted in the SIR algorithm, highlighting the artificial dynamics and kernel smoothing techniques to estimate constant model parameters (covering the *inter-specimen* variability), and an adaptation of the process noise variance (accounting for the *intra-specimen* variability). The following points summarize the algorithm operation, while Table 1 explains the variances involved in the algorithm.

1. Initialize the algorithm:

$$z_{0} \sim p\left(x_{0}^{r}, \sigma_{z_{0}}^{2}(x_{0}^{r})\right)$$

$$\forall i = 1, ..., N_{S}$$

$$\theta_{0}^{(i)} \sim p(\theta_{0}, \sigma_{\xi_{0}}^{2})$$

$$x_{0}^{(i)} \sim p(x_{0} | [z_{0} \theta_{0}^{(i)}], \sigma_{x_{0}}^{2})$$

$$w_{0}^{(i)} = \frac{1}{N_{S}}$$

2. Perform the transition:

Update useful parameters

$$\begin{aligned} \sigma_{\xi_{k}}^{2} &= \sigma_{\xi_{0}}^{2} f(k) & \text{for artificial dynamics, or} \\ \boldsymbol{\zeta}_{k} &= \boldsymbol{\zeta}_{0} f(k) & \text{for kernel smoothing} \\ \sigma_{\Lambda_{k}}^{2} &= f\left(\sigma_{z_{k}}^{2}(x_{k}^{r})\right) & \text{according to (19), or} \\ \sigma_{\Lambda_{k}}^{2} &= f\left(\varphi_{k}, \sigma_{\Lambda,0}^{2}, \sigma_{\Lambda,max}^{2}, \sigma_{\Lambda,min}^{2}\right) & \text{according to (21)} \\ \forall i = 1, \dots, N_{S} \\ \boldsymbol{\theta}_{k}^{(i)} \sim p(\boldsymbol{\theta}_{k} | \boldsymbol{\theta}_{k-1}^{(i)}, \sigma_{\xi_{k}}^{2}) & \text{for artificial dynamics, or} \\ \boldsymbol{\theta}_{k}^{(i)} \sim p(\boldsymbol{\theta}_{k} | \boldsymbol{\mu}_{\theta,k}^{(i)}, \boldsymbol{\zeta}_{k}^{2} \boldsymbol{\Sigma}_{\theta,k-1}) & \text{for kernel smoothing} \\ \boldsymbol{x}_{k}^{(i)} \sim p(\boldsymbol{x}_{k} | [\boldsymbol{x}_{k-1}^{(i)} \boldsymbol{\theta}_{k}^{(i)}], \sigma_{x_{k-1}}^{2}) \\ Draw \end{aligned}$$

3. Evaluate the new weights

$$w_k^{(i)} \propto w_{n,k-1}^{(i)} p(z_k | \boldsymbol{y}_k^{(i)} = [x_k^{(i)} \boldsymbol{\theta}_k^{(i)}])$$
$$w_{n,k}^{(i)} = \frac{w_k^{(i)}}{\sum_i w_k^{(i)}}$$

4. Evaluate the posterior pdf

$$p(\mathbf{y}_k|z_{1:k}) = \sum_i w_{n,k}^{(i)} \delta(\mathbf{y}_k - \mathbf{y}_k^{(i)})$$

If the kernel smoothing is adopted, the posterior pdf of parameters becomes:

$$p(\boldsymbol{\theta}|z_{1:k}) = \sum_{i} w_{n,k}^{(i)} N(\boldsymbol{\theta}|\boldsymbol{\mu}_{\boldsymbol{\theta},k}^{(i)},\boldsymbol{\zeta}_{k}^{2} \boldsymbol{\Sigma}_{\boldsymbol{\theta},k})$$

5. Evaluate the Residual useful life up to the limit state x_{lim} .

$$\forall i = 1, \dots, N_i$$

- Estimate the theoretical number of remaining load cycles using Eq. (2b)

$$N_r^{(i)} = N_r(x_{lim}, x_0 = x_k^{(i)}, \boldsymbol{\theta}_k^{(i)})$$

- Alter the estimation of the remaining load cycles using the integral of the random process Ω in (7):

$$N_{r}^{(i)} = \int_{0}^{N_{r}^{(i)}} \Omega \, dN = \sum_{j=1}^{n^{*} = \frac{N_{r}^{(i)}}{\Delta N}} \omega_{j} \, \Delta N$$

Generate the posterior pdf of the remaining load cycles

$$p(N_r|z_{1:k}) = \sum_i w_{n,k}^{(i)} \delta(N_r - N_r^{(i)})$$

6. Resample the particles according to whatever resampling procedure: for instance the systematic resampling scheme (Arulampalam et al. 2002).

$$\forall j = 1, ..., N_S$$
 Assign: $y_k^{(j)} = y_k^{(i)}$ with probability $w_{n,k}^{(i)}$

7. Repeat the steps 2-6 for each *k*-th time step.

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 a_{lim}

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Variance	Description								
$\sigma_{z,k}^2(x_k^r)$	Variance associated to the observations as a function of the real state x_k^r at the <i>k</i> -th step								
$\sigma_{\boldsymbol{\xi},k}^2$	Variance associated to the parameter samples for the AD algorithm at the <i>k-th</i> step								
$\sigma_{x,k}^2$	Variance associated to the state <i>x</i> coming from the state evolution equation at the <i>k</i> -th step								
ζ_k	Smoothing parameter for KS algorithm a the general <i>k-th</i> step								
$\sigma_{A,0}{}^2$	Constant value associated to the noise variance								
$\sigma_{\Lambda,max}^2$	Maximum allowable variance of the random noise Λ								
$\sigma_{\Lambda,min}^2$	Minimum allowable variance of the random noise Λ								
$\Sigma_{\theta,k}$	Monte Carlo variance of θ at the <i>k</i> -th step								

Table 1. Variances used to develop the SIR algorithm.

4. PROGNOSIS OF THE FCG PHENOMENON

This section shows the SIR algorithm of section 3 applied to several simulated crack propagations. The key parameters of the algorithm are set according to the problem and the main features of the simulation are described as well.

4.1. Target crack growth

Target crack propagations are simulated according to Eq. (22) to prove the validity of the method. In this sub-section, the term a indicates the target crack, despite of the term x that indicates the crack samples drawn by the SIR algorithm. Table 2 shows the values of constants and parameters employed in the simulation.

$$a_k = a_{k-1} + \psi_0 C \left(F \Delta S \sqrt{\pi a_{k-1}} \right)^m \omega_{k-1} \Delta N \qquad (22)$$

The correction parameter ψ_0 modifies the theoretical crack propagation, and it constitutes the only parameter that has to be estimated thorough the SIR algorithm. It means that the vector $\boldsymbol{\theta}$ describing the parameters of the model collapse to a single scalar quantity, ψ . Consequently, the vector of random processes ξ becomes scalar, too. Roughly speaking, a different correction parameter in the simulated crack increases or reduces the theoretical crack increment introduced by the Paris-Erdogan model. Several simulations are performed using different correction parameters. Figure 2 shows an example of crack propagation simulated according to the characteristics in Table 2 and in Eq. (22). The target crack length a altered by a normal random noise (driven by σ_n^2) constitutes the observation z provided to the SIR algorithm, visible in Eq. (23a).

The variance of the normal random noise is a function of the crack length itself multiplied by a constant α on the order of 1E-3 as presented in Eq. (23b). This simulated measurement system is adopted in both the simulations with AD and KS approach.

Parameter	Description	Value
F(x)	Crack shape function [-]	1.2
ΔS	Applied fatigue load	30

Table 2. Features of the crack simulation.

[MPa] Empirical constant

[mm/cycle · 1/MPa√mm] Empirical constant [-]

Correction parameter [-]

Random noise Starting crack length

[mm] Critical crack length

[mm] load cycle increment per

time-step [cycles]

$$z_k = h(a_k, \eta_k) = a_k + N(0, \sigma_{\eta_k}^2)$$
 (23a)

2.382e-12

3.2

1.25

 $\sim \log N(1, \exp\{2\}-1)$

5

100

100

$$\sigma_{\eta_k}^2 = \alpha E(a_k)^2 \tag{23b}$$

In this case, the variance of the random process $\sigma_{\eta,k}^2$ coincides to the variance of the measurement system given the Eq. (23a). As a consequence, $\sigma_{z,k}^2 = \sigma_{n,k}^2$.

4.2. SIR algorithm with artificial dynamics

The monitoring-prediction problem of the FCG can be described combining the equations and ideas described in the previous sections. Equations (24a), (24b) and (24c) constitute the core of the SIR algorithm with the AD technique for the estimation of the model parameters.

$$x_{k}^{(i)} = x_{k-1}^{(i)} + \psi_{k-1}^{(i)} C \left(F \Delta S \sqrt{\pi x_{k-1}^{(i)}} \right)^{m} \omega_{k-1}^{(i)} \Delta N \qquad (24a)$$

$$\log \psi_k^{(i)} = \log \psi_{k-1}^{(i)} + \xi_k^{(i)}$$
(24b)

$$\mathbf{z}_k = a_k + \eta_k \tag{24c}$$

The superscript (i) indicates the *i*-th particle of the algorithm. Moreover, since the crack can only increase over time, the parameter ψ should be log-normally distributed so that the values cannot be negative. Therefore, the logarithmic transformation allows computing the artificial dynamics method by means of a normally distributed noise ξ . Equations (25) show the random processes used during the filtering procedure. The random process affecting the measures is the same just described in the Eqs. (23).

$$\omega_k = \exp\{\lambda_k\}; \lambda_k \sim N\left(\mu_{\Lambda_k} = -\frac{\sigma_{\eta_k}^2}{2}, \sigma_{\Lambda_k}^2 = \sigma_{\eta_k}^2\right) \quad (25a)$$

$$\xi_k \sim N\left(0, \sigma_{\xi_k}^2 = \sigma_{\xi_0}^2 f(k)\right) \tag{25b}$$

$$\eta_k \sim N\left(0, \sigma_{\eta_k}^2 = \alpha E(a)_k^2\right)$$
(25c)

Equation (25a) shows the variance of the ancillary quantity Λ (used to define the random process ω_k) as presented in Eq. (19). The *artificial dynamics* for the parameter estimation is generated using a normal random noise as in Eq. (25b) with decreasing variance defined in section 4.4.

4.3. SIR algorithm with kernel smoothing

Similarly to the formulation of the sub-section 4.2, Eq. (26) shows the DSS model of the algorithm using the KS approach for the parameter estimation.

$$x_{k}^{(i)} = x_{k-1}^{(i)} + \psi_{k-1}^{(i)} C \left(F \Delta S \sqrt{\pi x_{k-1}^{(i)}} \right)^{m} \omega_{k-1}^{(i)} \Delta N \qquad (26a)$$

$$\log \psi_k^{(i)} = \mu_{\log \psi, k}^{(i)} + \zeta_k \sqrt{\sigma_{\log \psi, k-1}^2} N(0, 1)$$
(26b)

$$z_k = a_k + \eta_k \tag{26c}$$

 $\sigma_{log\psi,k-1}^2$ is the estimated variance of $log \ \psi$ at the previous time-step. The term μ_{ψ}^k is the kernel location at step *k* and it is represented hereafter in scalar form (27).

$$\mu_{\log\psi,k}^{(i)} = b\log\psi_k^{(i)} + (1-b)E(\log\psi_k)$$
(27)

Where $b=\sqrt{(1-\zeta_k^2)}$. All the other quantities follow the definitions of the previous sections. The random processes defining the noises are the following: the realizations of the state noise Ω follow Eq. (25a). The definition of σ_A^2 is driven by the variance of the measurement system or by the *similarity parameter* of Xu and Li defined in (21), as in the case of artificial dynamics. The value of the smoothing parameter is presented in section 4.4.

4.4. On the influence of initial variances

As reminded in section 3, the *artificial dynamics* approach to estimate the model parameters needs a starting value for the variance used to draw the samples, which is $\sigma_{\zeta,0}^2$. Even the *kernel smoothing* approach requires the selection of the initial variance, but it is less important than the values employed in the AD algorithm. Actually, only the first samples of the parameters *log* ψ are drawn using the starting variance.



Figure 2. Example of target crack growth according to (22) and Table 2.

The Monte Carlo variance $\sigma_{log\psi}^2$ of the previous time step and the smoothing parameter ζ govern the current sampling step. However, a wrong initial variance of the parameter pdf can affect the overall performance of the algorithm even using the KS approach. Besides, prognostic system requires the decreasing function f(k) to update $\sigma_{\xi,k}^2$ and ζ_k , respectively. The values presented afterwards have been preliminary selected following a *trial & error* procedure. These values must not be regarded as the best in absolute terms; nevertheless, they are associated to fairly good performances of the algorithm. A sensitivity analysis of SIR performances with respect to initialization values is matter of future research by the authors.

The quantities presented here represent reasonable values according to the other parameter values, the variability associated to the observations and the magnitude of the observed state *x*. As declared above, they cannot be considered optimal, nor suboptimal variances for the studied process. Equation (28a) shows the starting values employed for the parameter noise variance with both the AD and KS technique, while Eq. (28b) shows the decreasing variance for the *artificial dynamics*. Regarding the KS approach, the initial value and the sub-sequent values of the *smoothing parameters* are defined in (28c-d).

$$\sigma_{\xi,0}^2 = 0.1 \tag{28a}$$

$$\sigma_{\xi,k}^2 = \frac{\sigma_{\xi,0}^2}{k} \tag{28b}$$

$$\zeta_0 = 1 \tag{28c}$$

$$\zeta_k = \frac{1}{\sqrt{k}} \tag{28d}$$

The starting variances of the random noise ω conditioning the state evolution is selected with the same *trial & error* approach. Nevertheless, if the method based on Eq. (19) is adopted, the tuning of the initial variance is not required. As a matter of fact, the variance σ_A^2 is associated to the observation variance from the first measure. The approach proposed by Xu & Li requires the selection of three quantities instead: σ_{A,O^2} , $\sigma_{A,min}^2$ and $\sigma_{A,max}^2$. The magnitudes used in the simulations are expressed in Eq. (29) and can be considered reasonable values for the studied damage propagation process.

$$\sigma_{\Lambda,0}^2 = 1 \tag{29a}$$

$$\sigma_{\Lambda,max}^2 = 1.5 \tag{29b}$$

$$\sigma_{\Lambda,min}^2 = 0.2 \tag{29c}$$

These values are used for both the AD and the KS algorithms. It has to be noticed that the term $\sigma_{A,0}^2$ is not the actual variance associated to the random noise, because it has multiplied by $\sqrt{(1/\varphi)}$, as presented in (21).

5. RESULTS

This section contains the main results of the algorithm. The capability of the developed prognostic unit to assess the residual lifetime of the system is highlighted in terms of model parameter estimation and RUL pdf. The overall behavior of the algorithm is established using both the AD and the KS technique. The crack length monitoring is simulated up to 150000 load cycles, which corresponds to a crack increment of around 7 mm: from 5 mm to 12 mm. The number of employed particles is 5000, the ΔN is set to 100 load cycles, and a measure of the crack length *z* becomes available every ΔN . During these 150000 load cycles, the algorithms try to estimate the most probable crack length (state of the system), the *correction parameter* ψ , and the remaining number of cycles before the critical crack length limit (here arbitrary set to 100 mm).

5.1. Monitoring and prediction of FCG

The estimation of the crack length is the easiest goal because of the construction of the algorithm itself. Almost every estimation of the state contains the actual state, and the results are comparable for both the KS and the AD. The results are satisfactory and do not constitute the nodal point of the proposed algorithm. Then, the following parts will focus on the estimation capabilities in terms of correction parameter and RUL probability density functions.

Figures 3 and 4 shows the results of the algorithm using the *artificial dynamics* approach to estimate the parameter ψ and the RUL, respectively. The simulations involve a small crack increment (from 5 to 12 millimeters) with respect to the critical crack length (100 mm), and the algorithm uses many measures to achieve acceptable results of the parameter ψ (expressed in Figure 3 in its logarithmic form), then adjusting the RUL prediction (Figure 4).

However, the crack increment Δx is very small in the first part of the crack propagation so that the discrimination among good and wrong values of the *correction parameter* is difficult.



Figure 3. *Correction parameter* ($log \psi$) estimation using the SIR algorithm with *artificial dynamics*.

Above all, the convergence velocity depends on the scatter affecting the measures. Hence, less frequent measures provided with larger ΔN could produce the same results because the difference between two distant crack lengths makes easier the identification of good and bad parameter values.

The results of the previous figures have been achieved using the variance updating in (19), in which the variance of the observation equation governs the variance of the process noise σ_A^2 . The implementation of the *similarity parameter* to drive the variance σ_A^2 produces comparable results.

Figure 5 and 6 show the same graphs using a SIR algorithm with the *kernel smoothing* method. As expected, the smoothness of these results is higher with respect to the artificial dynamics case where, actually, the smoothing is missing. The advantages of the *kernel smoothing* technique is clear looking at the results of the whole simulation. The KS algorithm produces more stable results in terms of parameter estimation and above all RUL prediction with respect to the *artificial dynamics* method.

The results of the *kernel smoothing* algorithm relate to the adaptive noise variance in (21), using the similarity parameter proposed by Xu and Li. It is important to underline that the first approach using the same variance of the observation equation does not work in this case. This can be related to the measure variance which is too small with respect to the one required by the algorithm. Figure 7 shows the estimation of the correction parameter using the *kernel smoothing* approach with the adaptive variance of the process noise according to (19).

It obviously produces a wrong RUL prediction. The problem does not appear in the *artificial dynamics* case, where the artificial noise added to the particles is independent from whatever previous estimation. This leads to an higher scatter of the particles with respect to the *kernel smoothing* case.

Therefore, a small variance of ω does not decrease the performance in a marked way.



Figure 4. Residual useful life estimation using the SIR algorithm with *artificial dynamics*.

The approach of Xu and Li based on the similarity between the state estimation and the observations seems better as it works with both the algorithms. However, the tuning of $\sigma_{\Lambda,max}^2$, $\sigma_{\Lambda,min}^2$ and above all $\sigma_{\Lambda,0}^2$ is solved here with a *trial* & error procedure. One more question has to be investigated: the capability of the algorithm with one adaptive parameter only (ψ) , to predict the RUL of a simulated crack built with a different couple of parameters C and m instead of a different value of ψ only. Then, a fictitious crack growth is simulated using (C; m) = (2.39e-11; 2.9) instead of the values presented in Table 2. In this case, the results are compared in terms of RUL distributions only because the *correction parameter* ψ , assumes a value which is not comparable with a target. Figure 9 and 10 show the RUL prediction of the latter case for the artificial dynamics and the kernel smoothing algorithm, respectively. Even in this case, the variance of the random process is set equal to the variance of the observations for the AD and the *similarity parameter* has been employed for the KS approach, respectively. However, the initial variance of the correction parameter, defined as $\sigma_{\xi,0}^2$, has to be properly tuned and differs from the case where a different ψ_0 drives the target crack growth. As visible in the comparison between the figures 4-8 and 6-9, the results remain good. Of course, the validity of the results is limited to the range of crack lengths adopted in these simulations.



Figure 5. Estimation of the *correction parameter* ($log \psi$) using the *kernel smoothing* algorithm.



Figure 6. Estimation of the RUL using the *kernel smoothing* algorithm.

The performances outside this range must be investigated. The AD algorithm produces worse results with respect to the previous case, while the kernel smoothing converges to a slightly biased expected value. This small bias does not appear when the target crack is built with a different parameter ψ . Nonetheless, the estimations remain acceptable. All the analyses and results presented above can be considered a preliminary study of the matter. Of course, they do not have the intent to quantify the errors occurring during the filtering procedure performed by the SIR algorithm. They want to investigate the effectiveness of the proposed methods and to analyze the performances as a tradeoff between different approaches.

6. CONCLUSION

A prognostic unit for FCG grounding on sequential Monte Carlo algorithms has been developed in this work. The kernel smoothing technique introduces more stable parameter estimation and RUL prediction. Its disadvantage is the higher computational effort with respect to the artificial dynamics algorithm. The estimation of the remaining number of cycles N_r using the stochastic integral proposed by Yang & Manning (1996) drastically reduces the computational effort required by common SIR algorithms for FCG prediction. Reporting on the adaptive variance of the process noise, the simple method that links the variance of the random process with the variance of the measurement system does not work in general terms, since the results are good only in the case of artificial dynamics algorithm. The approach based on the similarity parameter produces better results provided that the constant parameter $\sigma_{\Lambda,0}^2$ and the maximum and minimum allowable variances are properly selected. Actually, the tuning of all the parameters introduced in the mathematical formulation is a non-negligible limitation of the algorithm. Although the work highlighted some issues not already solved, the preliminary analysis presented here shows promising results. The authors want to stress the attention on the different kind of uncertainties that can affect the damage propagation process and on the proposed solution, introducing the inter-specimen and the intra-specimen variability within a Bayesian filtering framework. On the other hand, several investigations are mandatory to understand the behavior of the proposed sequential Monte Carlo algorithm. The validity of the correction parameters to cover the inter-specimen variability driven by multiple parameters (for example C and m) has to be proved, even though the results presented in section 5 seems good. Then, an in-depth study of the variances involved in the process could bring to self-adaptive algorithms in which the influence of the selection of the initial variances is very limited. Finally yet importantly, the testing of the proposed system on real structures is fundamental to prove the effectiveness of the method. The implementation of the methodology on real structures remains prohibitive especially because of the difficulties to deal with random load conditions. Even though the scientific community has developed many approaches to solve the problem using efficient statistical ways, the implementation of these methods into a real-time prognostics framework introduces additional complications. For instance the realtime estimation of the loads close to the damage, or the implementation of time-varying variables in the RUL prediction. These questions add up to the current issues of model parameter estimation and optimal variance selection, enlarging the dimension of the prognostic problem.



Figure 7. Wrong estimation of the *correction parameter* (log ψ) using the KS algorithm and a noise variance equal to the variance of the measurement system.



Figure 8. RUL prediction with *artificial dynamics* algorithm, using a target crack built with different *C* and *m* parameters.



Figure 9. RUL prediction with *kernel smoothing* algorithm, using a target crack built with different *C* and *m* parameters.

REFERENCES

- Arulampalam, M. S., Maskell, S., Gordon, N., Clapp, T. (2002). A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking. *IEEE Trans on Signal Processing*, 50(2), pp. 174-188.
- Bourinet J.M., Lemaire, M. (2008). Form sensitivities to correlation: application to fatigue crack propagation based on Virkler's data.4th International ASRANet colloquium, Athens.
- Broek, D. (1988). The practical use of fracture mechanics. Netherlands: Kluwer Academic Publishers.
- Cadini, F., Zio, E., Avram, D. (2009). Monte Carlo-based filtering for fatigue crack growth estimation. *Probabilist Eng Mech*, 24, pp. 367-373.
- Chiachio, J., Chiachio, M., Saxena, A., Rus, G., Goebel, K. (2013). An Energy-Based Prognostics Framework to Predict Fatigue Damage Evolution in Composites. Annual Conference of the Prognostics and Health Management Society, October, 14-17, New Orleans, LA.
- Corbetta, M., Sbarufatti, C., Manes, A., Giglio, M. (2013a). Stochastic definition of state-space equation for particle filtering algorithms. *Chem Eng Trans*, 33, pp. 1075-1080.
- Corbetta, M., Sbarufatti, C., Manes, A., Giglio, M. (2013b). On-line updating of dynamic state-space model for Bayesian filtering through Markov chain Monte Carlo techniques. *Chem Eng Trans*, 33, pp. 133-138.
- Corbetta, M., Sbarufatti, C., Manes, A., Giglio, M. (2014). On dynamic state-space models for fatigue induced structural degradation. *Int J Fatigue*, 61, pp. 202-219.
- Cross, R., Makeev, A., Armanios, E. (2007). Simultaneous uncertainty quantification of fracture mechanics based life prediction model parameters. *Int J Fatigue*, 29, pp. 1510-1515.
- Daigle, M., Goebel, K. (2011). Multiple damage progression paths in model-based prognostics. In *Aerospace conference*, 2011 IEEE, pp. 1-10.
- Doucet, A., Godsill, S., Andrieu, C. (2000). On sequential Monte Carlo sampling methods for Bayesian filtering. *Statistics and Computing*, 10, pp. 197-208.
- Elber, W. (1970). Fatigue crack closure under cyclic tension. *Eng Frac Mech*, 2, pp.37-45.
- Elber, W. (1971). The significance of crack closure. In ASTM STP 486, American Society for Testing and Materials, *Damage Tolerance in Aircraft Structures* (pp. 230-242). Philadelphia PA.
- Haug, A.J. (2005). A tutorial on Bayesian estimation and tracking techniques applicable to nonlinear and non-Gaussian processes. *MITRE technical report*, MITRE McLean, Virginia.
- Kantas, N., Doucet, A., Singh, S.S., Maciejowski, J.M. (2009). An overview of Sequential Monte Carlo Methods for Parameter Estimation in General State-Space Models. In 15th ifac symposium on system identification (Vol. 15).

- Liu, J.S., West, M. (2001). Combined parameter and state estimation in simulation-based filtering, In Doucet, A., De Freitas, J.F.G., Gordon, N.J., (Eds.), Sequential Monte Carlo Methods in Practice. New York: Springer-Verlag.
- Gordon, N. J., Salmond, D. J., Smith, A. F. M. (1993). Novel approach to non-linear/non-Gaussian Bayesian state estimation, *IEEE Proceedings F (Radar and Signal Processing)*, 140(2), pp. 107-113.
- Mattrand, C., Bourinet, J. M. (2011). Random load sequences and stochastic crack growth based on measured load data. *Eng Fract Mech*, 78, pp. 3030-3048.
- NASA J.S. Centre and Southwest Research Institute. (2002). NASGRO reference manual, Version 4.02.
- Newman Jr., J. C. (1981). A crack-closure model for predicting fatigue crack growth under aircraft spectrum loading. *ASTM STP*, 748, pp.53-84.
- Newman Jr., J. C., (2005). Crack growth predictions in aluminum and titanium alloys under aircraft load spectra.In: Proceedings of the XIth international conference of *fracture*, Turin, Italy.
- Newman Jr., J. C., Irving, P.E., Lin, J., Le, D., D. (2006). Crack growth predictions in a complex helicopter component under spectrum loading. *Fatigue Fract Eng Mater Struct*, 29, pp. 949-958.
- Paris, P.C., Erdogan, F. (1963). A critical analysis of crack propagation laws. *Trans ASME J Basic Eng*, 85, pp. 528-534.
- Ray, A., Patankar, R. (1999). A stochastic model of fatigue crack propagation under variable-amplitude loading. *Eng Fract Mech*, 62, pp. 477-493.
- Scafetta, N., Ray, A., West, B. J. (2006). Correlation regimes in fluctuations of fatigue crack growth. *Physica A*, 359, pp. 1-23.
- Virkler, D.A., Hillberry, B.M., Goel, P.K. (1978). The statistical nature of fatigue crack propagation. *Technical report,* Air Force Flight Dynamics Laboratory, AFFDL-TR-78-43.
- West, M. (1993). Mixture Models, Monte Carlo, Bayesian updating and dynamic models, In J. H. Newton (Ed.), *Computing Science and Statistics: Proceedings of the* 24th symposium of the Interface, pp. 325-333. Interface Foundation of North America, Fairfax Station, Virginia.
- Willenborg, J., Engle, R. M., Wood, H.A. (1971). A Crack Growth Retardation Model Using an Effective Stress Concept. *Technical Memorandum*, Air Force Flight Dynamics Laboratory, AFFDL-TM-71-1-FBR.
- Xu, X., Li, B. (2005). Rao-Blackwellised Particle Filter with Adaptive System Noise and its Evaluation for Tracking in Surveillance. In 2nd Joint IEEE International workshop on Visual Surveillance and Performance Evaluation of Tracking and Surveillance, Oct 15-16, Beijing, China.
- Yang, J. N., Manning, S. D. (1996). A simple second order approximation for stochastic crack growth analysis. *Eng Fract Mech*, 53(5), pp. 677-686.

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A Prognostic Approach Based on Particle Filtering and Optimized Tuning Kernel Smoothing

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ABSTRACT

This paper proposes a novel approach based on a Particle Filtering technique and an Optimized Tuning Kernel Smoothing method for the prediction on the Remaining Useful Life (RUL) of a degrading component. We consider a case in which a model describing the degradation process is available, but the exact values of the model parameters are unknown and observations of historical degradation trajectories in similar components are unavailable. A numerical application concerning the prediction of the RUL of degrading Lithium-ion batteries is considered. The obtained results show that the proposed method can provide a satisfactory RUL prediction as well as the parameters estimation.

1. INTRODUCTION

Model-based prognostic methods resort to a mathematical representations of the degradation process (Orchard & Vachtsevanos, 2009; Sankavaram et al., 2009). They typically demand the knowledge of the values of the model parameters, which can be estimated considering the results of experimental tests or by observing the real degradation behaviors of similar components.

However, in some practical situations, e.g. for some safetycritical and high-value components (nuclear, aerospace, military, oil and gas fields), it is not feasible to perform runto failure experimental tests on the component degradation process and observations performed on similar components in the field are not available. Thus, in these cases, the estimation of the degradation model parameters and the prediction of the component RUL can resort only to a sequence of online measurements performed on the operating component as it undergoes degradation.

In this work, this problem has been addressed by developing a Particle Filtering (PF) approach based on the definition of a "joint state" encoding the degradation state and the model parameters (D. An, J. H. Choi, & N. H. Kim, 2012; Daigle & Goebel, 2013). However, the direct application of the PF framework to the problem of parameter estimation typically provides unsatisfactory results due to particle impoverishment, especially in cases of several unknown parameters and very poor knowledge on their prior probability distribution functions (PDF). Some researches solve this problem by adding artificial noise on the particle model parameter values, but the variance of the artificial noise is a parameter difficult to set if complete degradation trajectories are not available. Another solution is to use the Kernel Smoothing (KS) technique whose key idea is to perform a shrinkage of the particle model parameter values (Hu, Baraldi, Maio, & Zio, 2013). The KS method has been shown to solve the particle impoverishment problem without the side effect of increasing the variance of the posterior PDF. However, the application of this algorithm requires the a-priori setting of the smoothing parameter which determines the amplitude of the particle shrinkage. Too large value of this parameter can cause an extra shrinkage and perturbation of the particles, which will result in a bias of the model parameter estimates. On the other side, too small values of the shrinkage parameter can result in the impoverishment of the population of particles. Notice that the proper setting of the smoothing parameter is a very critical problem in the case addressed in this work where historical trajectories describing the component degradation

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from its onset until failure are not available and, thus, a trial and error approach cannot be followed.

In this work, we adopt a scheme proposed in a different context in (Tulsyan, Huang, Bhushan Gopaluni, & Fraser Forbes, 2013) for setting the proper value of the smoothing parameter. The idea is to optimize the smoothing parameter by finding the minimized Kullback–Leibler (KL) divergence between the predicted and posterior PDFs. This method employs only the information of online degradation measurements, which is very suitable for the problem in this paper. A numerical case study concerning the prediction of Lithium-ion battery RUL is considered to verify the performance of the proposed prognostic approach.

The paper is formed by the following sections: section 2 makes a brief description of the problem addressed in this work; in section 3, the combined state and parameter estimation method and optimized turning kernel smoothing is proposed; an application study of Li-on battery is taken in section 4; section 5 summarizes this paper.

2. PROBLEM STATEMENT

We assume to know the physical model describing the degradation process formulated as a first order Markov Process:

$$d_t = g(d_{t-1}, \mathbf{p}_{t-1}, \gamma) \tag{2.1}$$

where $g(d, \mathbf{p}, \gamma)$ is the recursive transition function, d_t is an indicator of the equipment degradation state at time t, \mathbf{p}_t is the vector of the model parameters, whose true values are unknown, γ is the process noise which represents the degradation process uncertainty.

Furthermore, the measurement equation linking the degradation state d and its measurements, z_i , is known. It is typically represented by a possibly non-linear function h:

$$z_t = h(d_t, \sigma_n) \tag{2.2}$$

where σ_n is the measurement noise. We assume a set of online measurements z_t (t = 1, 2, ..., T) collected from the beginning life of component (t=1) to the present time (t=T) is available.

Furthermore, the failure threshold, f, i.e. a value of the degradation state such that if it is exceeded, the equipment is considered failed is assumed to be known and fixed.

3. MODEL-BASED PROGNOSTICS APPROACH

The description of the PF approach can be found in (Arulampalam, Maskell, Gordon, & Clapp, 2002; Orchard & Vachtsevanos, 2009), whereas its application to the problem of predicting the RUL of a degrading component can be found in (Hu et al., 2013; Zio & Peloni, 2011). In

this section, we will discuss the use of the PF method for the problem of jointly estimating the degradation state and the model parameters' values.

3.1. Combined State and Parameter Estimation

The combined estimate of the equipment degradation state and model parameters can be performed by using an extended PF (D. An, J.-H. Choi, & N. H. Kim, 2012; Arulampalam et al., 2002; Ching, Beck, & Porter, 2006; Liu & West, 2001; Tulsyan et al., 2013). The idea is to consider the model parameters as elements of the state vector which is estimated by the PF. Thus, the generic augmented *i*-th particle k_t^i , is represented by: $k_t^i = \{d_t^i, \mathbf{p}_t^i, w_t^i\}$, where d_t^i represents the degradation state, \mathbf{p}_{t}^{i} the model parameters at time t and w_t^i is the weight associated to the particle. Since we need to simultaneously estimate the degradation state and model parameter, we need to extend Eq.(2.1) in order to describe, not only the transition of the degradation state, but also that of the model parameters. Thus, Eq.(2.1) becomes a system of two equations, one describing the transition of the state (g_1) and the other the transition of the parameters (*g*₂):

$$d_{t}^{i} = g_{1}(d_{t-1}^{i}, \mathbf{p}_{t-1}^{i}, \gamma)$$

$$\mathbf{p}_{t}^{i} = g_{2}(\mathbf{p}_{t-1}^{i})$$
(3.1)

The transition function g, describing the degradation evolution, in Eq.(2.1) can be used for g_1 , whereas there are different options to define g_2 . In (Dawn An et al., 2012), the model parameters are kept unchanged during the prediction stage and g_2 is given by:

$$\mathbf{p}_t^i = g_2(\mathbf{p}_{t-1}^i) = \mathbf{p}_{t-1}^i \tag{3.2}$$

this strategy has been shown to suffer the problem of particle impoverishment when several model parameters need to be simultaneously estimated (Daum, 2005): only very few "strong" particles with an associated high weight will survive after the updating phase. This low variety of the model parameter values in the population of particles causes an imprecise estimation of the parameters.

The problem of the particle impoverishment has been addressed by adding an artificial noise to the particles parameters evolution equation (Corbetta, Sbarufatti, Manes, & Giglio, 2013; He, Williard, Osterman, & Pecht, 2011; Higuchi, 1997):

$$\mathbf{p}_{t+1}^{i} = g_{2}(\mathbf{p}_{t}^{i}) = \mathbf{p}_{t}^{i} + N(0, \sigma_{AN}^{2})$$
(3.3)

where σ_{AN}^2 is the variance of the artificial noise. However, this method cannot be applied to our prognostic problem since it requires a proper setting of the value of σ_{AN}^2 , which is difficult to achieve by trial and error attempts, due to the unavailability of complete examples of degradation trajectories in similar components. If too small values of σ_{AN}^2 are used, the convergence of the model parameter values \mathbf{p}_t^i in the population of particles to the model parameter true values is too slow and the problem of particle impoverishment can still be encountered. Whereas, if large values of σ_{AN}^2 are used, the convergence to the parameters true values will never be achieved.

In order to overtake these difficulties, in this work we consider an alternative PF approach based on an Optimized Tuning Kernel Smoothing (OTKS) algorithm which will be object of the next Section 3.2.

3.2. Kernel smoothing approach

Kernel smoothing consists in two different procedures to the population of particles: shrinkage and perturbation. Shrinkage aims at reducing the variability in the particle population by moving the single particle \mathbf{p}_t^i toward the current estimated values $\hat{\mathbf{p}}_t$, whereas perturbation adds a controlled noise on \mathbf{p}_t^i in order to maintain the desired variance in the population (Chen, Morris, & Martin, 2005; Liu & West, 2001; Wan-ping, Sheng, & Ting-wen, 2009).

Shrinkage

The particle shrinkage is performed by:

$$\tilde{\mathbf{p}}_{t}^{i} = \mathbf{p}_{t}^{i} \sqrt{1 - h^{2}} + \hat{\mathbf{p}}_{t} \left(1 - \sqrt{1 - h^{2}}\right)$$
(3.4)

where the vector $\tilde{\mathbf{p}}_{t}^{i}$ contains the parameters values of the *i*-th particle after the shrinkage. The direction of shrinkage is the estimated value of the parameter $\hat{\mathbf{p}}_{t}$. The smoothing parameter, $h \in [0,1]$, determines the degree of shrinkage: higher is its value, deeper is the shrinkage. If h=1, the model parameters completely shrink to the estimated values $\hat{\mathbf{p}}_{t}$; whereas if h=0, no shrinkage is applied.

After shrinkage, the parameters variance in the population of particles will decrease from $V(\mathbf{p}_t^i)$ to $(1-h^2)V(\mathbf{p}_t^i)$. Then, Eq.(2.1) is used to predict d_{t+1}^i based on $\tilde{\mathbf{p}}_t^i$:

$$d_{t+1}^{i} = g_1(d_t^{i}, \tilde{\mathbf{p}}_t^{i}, \gamma)$$
(3.5)

Perturbation

Perturbation is used to maintain the variance of parameter particles by adding an artificial noise of variance $h^2 V(\mathbf{p}_t^i)$:

$$\mathbf{p}_{t+1}^{i} = g_{2}(\mathbf{p}_{t}^{i}) = \tilde{\mathbf{p}}_{t}^{i} + N\left(0, h^{2}V\left(\mathbf{p}_{t}^{i}\right)\right)$$
(3.6)

3.3. Optimization of Smoothing Parameter h

The value of smoothing parameter h is very important for the performance of kernel smoothing. Some authors suggest to use the value h = 0.1, whereas other authors suggest optimizing the value of h using historical data (Chen et al., 2005; Liu & West, 2001). In our work, given that historical trajectories describing the component degradation from its onset until failure are not available, the value of h is continuously updated, considering the newest measurement of the degradation state, according to (Tulsyan et al., 2013). Since the main idea of this algorithm is to find the value of h which projects the prediction PDF in the high density region of the posterior PDF, it can be executed even when just one measurement of the degradation state is available.

The optimization of h is tactfully achieved by minimizing the KL divergence between prediction and posterior PDFs. In our case, the KL divergence is computed by:

$$KL(h_{t}) = \int_{z} \log\left(\frac{p(d_{t} \mid z_{1:t-1})}{p(d_{t} \mid z_{1:t})}\right) p(d_{t} \mid z_{1:t-1}) dd_{t}$$
(3.7)

where $p(d_t | z_{1:t-1})$ and $p(d_t | z_{1:t})$ are the prediction and posterior PDF, respectively. Using the Markov assumption and the Bayes theory, Eq.(3.7) can be rewritten as:

$$KL(h_{t}) = \int_{z} \log \left(\frac{\int_{z} p(z_{t} \mid d_{t}) p(d_{t} \mid z_{1:t-1}) dd_{t}}{p(z_{t} \mid d_{t})} \right) p(d_{t} \mid z_{1:t-1}) dd_{t}$$
(3.8)

which is approximated by:

$$KL(h_{t}) \approx \int_{z} \log \left(\frac{\int_{z} p(z_{t} \mid d_{t}) \sum_{i=1}^{N} w_{t-1} \delta(dd_{t})}{p(z_{t} \mid d_{t})} \right) \sum_{i=1}^{N} w_{t-1} \delta(dd_{t})$$

$$= \sum_{i=1}^{N} w_{t-1} \log \left(\frac{\sum_{i=1}^{N} w_{t-1} p(z_{t} \mid d_{t}^{i})}{p(z_{t} \mid d_{t}^{i})} \right)$$
(3.9)

where $p(z_t | d_t^i)$ is the likelihood of particle *i*, given by Eq.(3.13). Thus, by substituting Eq.(3.13) into Eq.(3.9), one obtains:

$$KL(h_t) \approx -\sum_{i=1}^{N} w_{t-1}^i \log\left(w_t^i\right)$$
(3.10)

where $KL(h_t)$ is the KL divergence at time *t* using the smoothing parameter h_t , and w_{t-1}^i is the weight of the *i*-th particle at time *t*-1 (which also depends on h_t). Finally, the

optimal h_t value, hereafter called h_t^* , is obtained by minimizing $KL(h_t)$:

$$h_t^* = \underset{h_t \in [0,1]}{\operatorname{arg min}} \left[KL(h_t) \right]$$
(3.11)

In order to perform the minimization, given the impossibility of using analytical methods due to the form of Eq.(3.10), we divide the interval [0,1] into 100 discrete values, namely $0.01, 0.02, \dots, 0.99, 1$. For each value, we calculate the corresponding *KL*(*h*) and search the one with minimum *KL*(*h*).

By substituting h_t^* into Eq.(3.4), one obtains the new equation for the particle shrinkage:



Figure 1 Flow chart of PF-OTKS

Notice that the execution of the shrinkage at time *t* requires the knowledge of h_{t+1}^* , which is based on the knowledge of

the measurement z_{t+1} . In practice, at time *t*, once the measurement z_t becomes available, we firstly calculate h_t^* and perform the kernel smoothing of the particle parameter at time *t*-1, \mathbf{p}_{t-1}^i and, then, we can apply the PF procedure to estimate the degradation state and parameters, as well as the RUL prediction, at time *t*.

Figure 1 shows the flow chart of execution.

In practice, the procedure is based on the repetition, at each time *t*, of the following steps:

- 1) Sample the particles $k_0^i = \{d_0^i, \mathbf{p}_0^i, w_0^i\}$ from their prior PDFs. At time *t*=1, the prior PDFs of the degradation state and parameter values are defined according to expert knowledge based on the specific applications.
- 2) At time *t*, using the newest measurement z_t to figure out the optimal h_t^* value using Eq.(3.11)
- 3) Shrink the parameters particles with h_t^* (based on Eq.(3.12)), and get $\tilde{\mathbf{p}}_{t-1}^i$
- 4) Make the prediction using $\tilde{\mathbf{p}}_{t-1}^{i}$ (based on Eq.(3.5)) and get the particles of degradation state d_{t}^{i}
- 5) Perform the particle perturbation using h_t^* (based on Eq.(3.6), and get \mathbf{p}_t^i
- 6) Compute the weight w_t^i :

$$w_t^i = w_{t-1}^i \frac{P(z_t \mid d_t^i)}{\sum_{i=1}^n P(z_t \mid d_t^i)}$$
(3.13)

where $P(z_t | d_t^i)$ is the likelihood of particle *i*.

7) Compute the estimates of the parameters and state \hat{d}_i , $\hat{\mathbf{p}}_i$ as well as their posterior PDFs:

$$\hat{d}_t = \sum_{i=1}^N w_t^i \times d_t^i \tag{3.14}$$

$$\hat{\mathbf{p}}_t = \sum_{i=1}^N w_t^i \times \mathbf{p}_t^i$$
(3.15)

- Perform particle resampling using the systematic resampling method whose description can be found in (Arulampalam et al., 2002; Douc & Capp é 2005)
- 9) Perform the RUL prediction using d_t^i , \mathbf{p}_t^i and w_t^i (based on Eq.(2.1))
- 10) Predict the prior PDFs for d_t^i and \mathbf{p}_t^i at next cycle (using Eq.(2.1)).

11) Set t=t+1, repeat from 2)

4. NUMERICAL APPLICATION

In this Section, we apply the proposal approach on the RUL prediction of a Lithium-ion battery. A detailed explanation of the battery degradation mechanism can be found in (He et al., 2011; Marcicki, Todeschini, Onori, & Canova, 2012; Saha, Goebel, Poll, & Christophersen, 2009; Zhang & Lee, 2011). The quantity which is frequently used to indicate the battery degradation state is the battery capacity q(t). The degradation is mainly represented by a first phase during which the battery capacity slowly decreases, followed by a second phase characterized by a fast decreasing process. These two phases can be described by a double exponential model:

$$q(t) = p_1 \exp(p_2 \cdot t) + p_3 \exp(p_4 \cdot t) + N(0, \sigma_p^2) \quad (4.1)$$

where p_1, p_2, p_3 and p_4 are the four model parameters $(p_1, p_3 \text{ determine the initial state and } p_2, p_4$ the degradation rate), σ_p^2 is the process noise and t is the number of charge/discharge cycles experienced by the battery. The measurement equation is:

$$Q(t) = q(t) + N(0, \sigma_m^2)$$
(4.2)

where Q(t) is the measurement at the *t*-th charge/discharge cycle and σ_m^2 is the measurement noise. The failure threshold of q(t) is set according to expert knowledge.

4.1. Generation of Online measurements

250

200

100

50

0 L 120

100

80

60

true RUL

40

oredicted RUL 150

Motivated to have a test of the performance of the proposed method, one complete battery degradation trajectory has been simulated using Eq.(4.2). The values of the parameters

 p_1, p_2, p_3 and p_4 have been as set in Table 1, the value of process and measurement noises σ_p, σ_m have been both equal to 0.001, and the threshold value equal to 0.7172. These parameters values, as well as the obtained degradation state q and the failure time will be referred to as the "true" values of the battery trajectory.

4.2. Results

The experiment is performed assuming that the true values of p_1, p_2, p_3 and p_4 are unknown, and the measurements performed on the battery of which we want to predict the RUL are available from cycle 1 to the present cycle. The prior PDFs for parameters p_1, p_2, p_3 and p_4 are U(0.85,1.2), U(-0.001,0), U(-0.001,0) and U(0.03,0.13),respectively. Notice that the prior PDFs of p_1, p_2, p_3 and \boldsymbol{p}_{4} are remarkably more dispersed than those used for the simulation of the true values of these parameters (in Table 1). Furthermore, the true of the four parameters are located in the tail of the prior PDFs. This setting has been chosen in order to assess whether the method can work even if the parameter prior PDFs are very uncertain and shifted.

Table 1 True values of the parameters in the considered battery degradation trajectory

Parameter	p_1	p_2	p_3	p_4	life cycle
Value	0.917	-8.19e-4	-2.93e-4	0.0523	115



Figure 2 RUL prediction using PF-KS (left) and PF-OTKS (right)



Figure 3 Parameter estimation using PF-KS (left) and PF-OTKS (right)

Figure 2 shows the RUL predictions obtained at different times, with the red lines representing the 90% confidence interval. Figure 3 shows the estimates of the expected values and 90% confidence intervals of the four parameters of the considered battery. The continue thick horizontal lines represents the true value, the thin continuous line represents the estimates of the parameters expected values and the red lines are the 90% confidence interval of the parameter posterior PDF.

From Figure 2, it can be observed that the RUL prediction given by PF-KS has more uncertainty than PF-OTKS. Furthermore, at the end of life of the battery, the PF-KS's RUL prediction drifts from the true value, due to the unsatisfied estimation of the four parametesrs (in Figure 3), while PF-OTKS does not suffer this problem.

For the parameter estimation, the PF-KS estimation of p_3 is significantly drifted from the true value. And p_2, p_4 have small bias, whereas PF-OTKS provides more satisfied estimates of the parameters. Figure 4 shows the optimal h_{i}^{*} value provided by PF-OTKS. Notice that the value of 0.1, which is suggested by (Liu & West, 2001), appears to be too large in this application. Large h means deeper shrinkage, which causes the bias and drift of the parameter estimation in the PF-KS. It is also interesting to observe that the optimal h value tends to decrease as time passes. At the beginning, since the particles of p_1, p_2, p_3 and p_4 are far away from the true value, the optimal h_t^* value is larger since deeper shrinkage and perturbations are needed to avoid particle impoverishment. On the other hand, at the end of the battery life, the particles are close to the true model parameter values, so the deep shrinkage and perturbation are not necessary.



Figure 4 Optimized smoothing parameter h

5. CONCLUSION

In this work, we have proposed a PF-OTKS approach for the RUL prediction of degrading components based on a model of degradation with unknown parameters. We have assumed to know the model of the degradation process and to be able to perform measurements of quantities related to the component degradation; on the other side, we have assumed that we do not know the true value of the degradation model parameters nor we have available observations of degradation trajectories in similar components.

The results of PF-OTKS obtained in a numerical case study regarding battery degradation have shown that the proposed method can provide estimates of the component RUL and model parameters, which are more satisfactory than those obtained with PF-KS. The proposed approach will be further investigated in a situation in which the degradation model is partly unknown.

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NOMENCLATURE

- d_t Degradation state at time t
- \mathbf{p}_t Vector of parameter values at time t
- γ Process noise representing the degradation process uncertainty
- z_t Measurement of the degradation state d_t
- σ_n Variance measurement noise
- *N* Number of particles
- w_t^i Weight associated to particle *i* at time t
- d_t^i Degradation state of particle *i* at time *t*
- \mathbf{p}_t^i Model parameters contained in particle *i* at time *t*
- RUL_t^i RUL of particle *i* at time *t*
- \hat{d}_{t} Estimate of d_{t}
- $\hat{\mathbf{p}}_t$ Estimate of \mathbf{p}_t
- RUL_t Prediction of RUL at time t
- $\tilde{\mathbf{p}}_{t}^{i}$ Parameter values of particle *i* after shrinkage

REFERENCES

An, D., Choi, J. H., & Kim, N. H. (2012). A comparison study of methods for parameter estimation in the physics-based prognostics, *In* 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 2012

- Arulampalam, M Sanjeev, Maskell, Simon, Gordon, Neil, & Clapp, Tim. (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *Signal Processing, IEEE Transactions on*, 50(2), 174-188.
- Chen, Tao, Morris, Julian, & Martin, Elaine. (2005). Particle filters for state and parameter estimation in batch processes. *Journal of Process Control, 15*(6), 665-673.
- Ching, Jianye, Beck, James L., & Porter, Keith A. (2006). Bayesian state and parameter estimation of uncertain dynamical systems. *Probabilistic Engineering Mechanics*, 21(1), 81-96. doi: <u>http://dx.doi.org/10.1016/j.probengmech.2005.08.003</u>
- Corbetta, Matteo, Sbarufatti, Claudio, Manes, Andrea, & Giglio, Marco. (2013). Stochastic Definition of State Space Equation for Particle Filtering Algorithms. *Prognostic and System Health Management Conference, Milan, Italy.*
- Daigle, M. J., & Goebel, K. (2013). Model-Based Prognostics With Concurrent Damage Progression Processes. *IEEE Transactions on Systems Man Cybernetics-Systems*, 43(3), 535-546. doi: Doi 10.1109/Tsmca.2012.2207109
- Daum, Fred. (2005). Nonlinear filters: beyond the Kalman filter. *Aerospace and Electronic Systems Magazine*, *IEEE*, 20(8), 57-69.
- Douc, Randal, & Capp & Olivier. (2005). Comparison of resampling schemes for particle filtering. *Image and Signal Processing and Analysis, ISPA 2005. Proceedings of the 4th International Symposium on.*
- He, Wei, Williard, Nicholas, Osterman, Michael, & Pecht, Michael. (2011). Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method. *Journal of Power Sources*, 196(23), 10314-10321.
- Higuchi, Tomoyuki. (1997). Monte Carlo filter using the genetic algorithm operators. *Journal of Statistical Computation and Simulation*, 59(1), 1-23.
- Hu, Yang, Baraldi, Piero, Maio, Francesco Di, & Zio, Enrico. (2013). A Particle Filtering and Kernel Smoothing Approach for Component Prognostics based on a Model with Unknown Parameters. *Reliability Engineering & System Safety, under review.*
- Liu, Jane, & West, Mike. (2001). Combined parameter and state estimation in simulation-based filtering: Springer.
- Marcicki, James, Todeschini, Fabio, Onori, Simona, & Canova, Marcello. (2012). Nonlinear parameter estimation for capacity fade in Lithium-ion cells based on a reduced-order electrochemical model. *American Control Conference (ACC)*, 2012.
- Orchard, Marcos E, & Vachtsevanos, George J. (2009). A particle-filtering approach for on-line fault diagnosis

and failure prognosis. Transactions of the Institute of Measurement and Control, 31(3-4), 221-246.

- Saha, Bhaskar, Goebel, Kai, Poll, Scott, & Christophersen, Jon. (2009). Prognostics methods for battery health Bayesian monitoring using а framework. Instrumentation and Measurement, IEEE Transactions on, 58(2), 291-296.
- Sankavaram, Chaitanya, Pattipati, Bharath, Kodali, Anuradha, Pattipati, Krishna, Azam, Mohammad, Kumar, Sachin, & Pecht, Michael. (2009). Modelbased and data-driven prognosis of automotive and systems. Automation Science electronic and Engineering, 2009. CASE 2009. IEEE International Conference on.
- Tulsyan, Aditya, Huang, Biao, Bhushan Gopaluni, R, & Fraser Forbes, J. (2013). On simultaneous on-line state and parameter estimation in non-linear state-space models. Journal of Process Control, 23(4), 516-526.
- Wan-ping, Wang, Sheng, Liao, & Ting-wen, Xing. (2009). Particle filter for state and parameter estimation in passive ranging. Intelligent Computing and Intelligent Systems, 2009. ICIS 2009. IEEE International Conference on.
- Zhang, Jingliang, & Lee, Jay. (2011). A review on prognostics and health monitoring of Li-ion battery. Journal of Power Sources, 196(15), 6007-6014.
- Zio, Enrico, & Peloni, Giovanni. (2011). Particle filtering prognostic estimation of the remaining useful life of nonlinear components. Reliability Engineering & System Safety, 96(3), 403-409.

BIOGRAPHIES

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Degradation prognosis based on a model of Gamma process mixture

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ABSTRACT

A novel method is proposed to exploit jointly degradation measurements originating from a set of identical systems for making a degradation prognosis. The systems experience different degradation processes depending on operational conditions. The degradation processes are assumed to be Gamma processes. The aim is to cluster the degradation paths in classes corresponding to the different operational conditions in order to group properly the data for the estimation of degradation process parameters. A model of Gamma process mixture is considered and an expectation-minimization approach is proposed to estimate the unknown parameters. The feasibility of the method is shown on simulated cases. Prognosis results obtained with the proposed method are compared with results obtained with basic strategies (considering each system alone or all system together).

1. INTRODUCTION

To estimate the remaining useful lifetime (RUL) of a deteriorating system it is necessary to be able to model its deterioration in order to predict when the deterioration leads to a failure i.e. when it reaches a given threshold. To perform this RUL prognosis one generally relies on measurements of the degradation level and on a degradation model which is assumed to describe the degradation evolution in time (Si, Wang, Hu, & Zhou, 2011; Nystad, Gola, & Hulsund, 2012). For example, in the case of a metal pipe corrosion, the thickness provides a deterioration measure.

The Gamma process is widely used for degradation models when deterioration is monotonic and gradual (Van Noortwijk, 2009). This process is defined by a set of parameters, in particular the shape and scale parameters in the case of an homogeneous process. These parameters are usually unknown and must be estimated in order to perform prognosis. Obviously the reliability of prediction is directly related to the estimation precision. Most of the time, in operational conditions the amount of measurement is very limited. So when a set of similar systems is available, one can use the data coming from all the systems in the set to estimate the model parameters. The expected gain of using all measurements together is to improve the estimator precision (reduction of its variance for example).

By considering all systems as a single one while estimating the model parameters it is assumed that the degradation process model is the same for all systems. In most cases, the degradation process depends also on operating conditions that may be partially unknown. In the pipe corrosion example, the evolution of the pipe thickness depends on the used metal but it also depends on the characteristics of the fluid carried by the pipe (liquid/gaz, temperature, pressure...) and on the location (air/ground/underwater...) and on the environmental conditions of the pipe (temperature, humidity...).

In this paper, we consider that we have a limited amount of data from different systems. Each system has one operating condition among an unknown finite number. Then each system evolves in relation with its operating condition, which remains always the same. This is not a system which evolves in different classes corresponding to functioning modes, as in (Ramasso & Gouriveau, 2014).

We propose a method to cluster the observed systems in classes, corresponding to each operating condition. The degradation process is assumed to be ruled by a Gamma process model. The aim is to estimate the parameters of these Gamma processes in order to predict their RUL. In order to tackle the hypothesis of a number of operating conditions, a model of Gamma process mixture is introduced. An expectation-minimization algorithm is proposed to estimate the parameters of each process in the mixture model.

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The problem is formalized in section 2. Then in section 3, the mixture model and the expectation-minimization algorithm (Ambroise & Govaert, 1998)(Hu & Sung, 2006) are presented to determine the clusters. In section 4, the considered prognosis is described and a criterion for comparing the prognosis values obtained according to different strategies of the Gamma process parameter estimation is proposed. In section 5, results on simulated data are presented and analyzed. A conclusion on the selection of process classes number and on future developments ends the paper.

2. PROBLEM FORMULATION

This section first gives a description of the problem and notations and ends with a brief recall about the Gamma process.

2.1. General Aim

The data we consider originates from N paths describing degradation process realizations. Each path p_n , (n = 1, ..., N)is composed of $|p_n|$ observations $l_{n,i}$ with $i = 1..|p_n|$. The observation $l_{n,i}$ is characterized by the time instant $t_{n,i}$, and the deterioration level $x_{n,i} = x(t_{n,i}) \in \Omega_x \subset \mathcal{R}$. Then $p_n = \{l_{n,i} = (t_{n,i}, x_{n,i})\}_{i=1..|p_n|}$.

We suppose that the observation set can be divided into K unknown clusters C_k , (k = 1, ..., K). In practise, each cluster ter would correspond to an operating condition. Each cluster represents a deterioration process characterized by some unknown parameter vector belonging to the parameter set $\Theta = \{\theta_k\}_{k=1}^K$. Besides, the latent membership, or cluster labels of paths are denoted by $\mathbf{z} = \{z_n\}_{n=1}^N$ where $z_n = k$ means that the path p_n belongs to the cluster k. A set of cluster labels defines a partition of all paths. Obviously, for a given path n, all observations $l_{n,i}$, $(i = 1, ..., |p_n|)$ belong to the same cluster.

The aim is to determine the latent cluster label for each observation and jointly the parameter vector of each process. Afterwards this parameter vector can be used to do prognosis. As an illustration, the prognosis we consider in this paper is the mean remaining useful lifetime, defined as the remaining time before reaching a given deterioration threshold which is the failure limit.

In this paper the chosen model for the deterioration processes is the Gamma process, parameterized by 3 parameters, a, band u described in section **??**. The increments, given by $x(t_{n,i}) - x(t_{n,i-1})$ with $t_{n,0} = 0$ and x(0) = 0, are independent. Their density distribution in the cluster k depends on the time and on the parameter θ_k , and can be written as

$$f_k \left(x(t_{n,i}) - x(t_{n,i-1}) \mid t_{n,i}, t_{n,i-1}, \theta_k \right)$$

In the following, for simplicity we will use the notation $f_k(\Delta x_{n,i}|\theta_k)$. It has to be noticed that the density distribu-

tions of all the degradation increments are not the same because the increments are usually all different and/or the process may be not stationary.

The objective is to find out the unknown cluster labels $\{z_n\}_{n=1}^N$ and consequently the distribution parameter set $\theta = \{\theta_k\}_{k=1}^K$, such that paths in the same cluster originate from a process model with the same parameters.

The relevance of a partition described by z and a parameter set θ can be measured using the log-likelihood given by

$$l(\mathbf{z}, \theta) = \sum_{n=1}^{N} \sum_{i=1}^{|p_n|} log f_{z_n}(\Delta x_{n,i} \mid \theta_{z_n})$$
(1)

2.2. Gamma process

Mathematically, the Gamma process is defined as follows: let A(t) be a non-decreasing, right-continuous, real-valued function for $t \ge 0$, with A(0) = 0. The Gamma process with shape function A(t) and scale parameter b > 0 is a continuous-time stochastic process $\{X(t), t \ge 0\}$ such that:

- X(0) = 0 with probability one;
- {X(t), t ≥ 0} is a stochastic process with independent increments;
- X(t) − X(s) follows the Gamma distribution Γ(A(t) − A(s), b) for 0 ≤ s < t

The definition of the Gamma process leads to two straightforward properties:

- $\{X(t), t \ge 0\}$ is a non-decreasing process.
- For all t ≥ 0, the expectation value and the variance of X(t) could be written as:

$$\mathbf{E}(X(t)) = \frac{A(t)}{b} \quad \operatorname{Var}(X(t)) = \frac{A(t)}{b^2} \tag{2}$$

In the degradation modeling framework, a non-homogeneous Gamma process defined by $A(t) = at^u$, (a > 0, u > 0) is often considered. Thus the process is described by three parameters : a, b, and u. In this case, X(t) - X(s) follows the Gamma distribution $\Gamma(a(t^u - s^u), b)$.

Two methods are often mentioned for the parameter estimation of the Gamma process: the moments estimation and the maximum likelihood estimation (Cinlar, Osman, & Bazant, 1977). The maximum likelihood estimator is asymptotically unbiased, which means the estimates converge to the true values as the number of observations increases as: $N \to \infty$. On the other hand, the moments approach leads to simpler formulae of the estimator. It is more straightforward to implement and the computation time is much reduced compared with the maximum likelihood method.

3. PROCESS CLUSTERING

The proposed approach is based on the computation of mixture models using the expectation-maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977). Beside, side information is considered according to (Shental, Bar-Hillel, Hertz, & Weinshall, 2003).

3.1. Related work

The EM algorithm is an iterative method that produces a set of parameters that locally maximizes the log-likelihood of a given sample, starting from an arbitrary set of parameters. It is often used to estimate the unknown parameters of a mixture model of K p.d.f. f_k given by:

$$f(x|\theta) = \sum_{k=1}^{K} \alpha_k f_k(x|\theta_k)$$

where α_k is the probability of class k and $f_k(x|\theta_k)$ the a posteriori probability of class k.

Furthermore the procedure we use is based on the work of Shental et al. (Shental et al., 2003) which describes an EM procedure for a Gaussian mixture model and for handling positive constraints, indicating that some observations arise from the same source. The data set is assumed to be a set of chunklets, and each chunklet is a set of points that originate from the same source. Alternating E steps and M steps leads to the estimation of the probability of each class, and the parameters (mean and variance) of each Gaussian class. The solution can be considered as a soft partition.

3.2. Proposed method

The problem we deal with, in comparison with the problem considered in (Shental et al., 2003), has to lead to a hard partition. Then we add an intermediate classification step between the E and M steps. Such a classification step has been introduced in the CEM algorithm (Celeux & Govaert, 1992, 1995) for hard classification problem using mixture models without constraints.

In comparison with the problem considered in (Shental et al., 2003), there is another main difference. The model is not a Gaussian mixture model and especially the degradation increments have different density distributions. The density distributions of all the degradation increments would be the same only in the case of homogeneous Gamma process, and of regularly sampled paths.

Thus, we have proposed an algorithm based on the mixture models for the problem of statistical process clustering with the two following properties. On the one hand, it takes into account that observations in a same path belong to a same class, and on the other hand it takes into account that a hard classification is searched. The E step at iteration m consists in calculating an estimation of the *a posteriori* probability for each observation using the parameters $\theta^{(m-1)} = (a^{(m-1)}, b^{(m-1)}, u^{(m-1)})$. The posterior probability $c_{nk}^{(m)}$ at iteration m that the path n belongs to class k, given p_n and the parameter $\theta^{(m-1)}$ writes according to

$$c_{nk}^{(m)} = p(z_n = k | p_n, \theta^{(m-1)})$$

=
$$\frac{\alpha_k^{(m-1)} \prod_{i=1}^{|p_n|} f_k(\Delta x_{n,i} | \theta_k^{(m-1)})}{\sum_{r=1}^K \alpha_r^{(m-1)} \prod_{i=1}^{|p_n|} f_r(\Delta x_{n,i} | \theta_k^{(m-1)})}$$
(3)

with

$$f_k(\Delta x_{n,i}|(a_k, b_k, u_k)) \sim \Gamma(a_k(t_{n,i}^{u_k} - t_{n,i-1}^{u_k}), b_k)$$

The expectation of the log-likelihood over all possible assignments which comply the given constraints is given by:

$$E(l(\mathbf{z},\theta)) = \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{i=1}^{|p_n|} log f(\Delta x_{n,i}|k,\theta_k) p(z_n = k|p_n,\theta_k^{(m-1)}) + \sum_{k=1}^{K} \sum_{n=1}^{N} log \alpha_k p(z_n = k|p_n,\theta_k^{(m-1)})$$

The M step at iteration m consists in computing the parameters $\alpha_k^{(m)}$, and $\theta^{(m)}$ that maximize the expected log-likelihood found on the E step. The parameter $\alpha_k^{(m)}$ is given by

$$\alpha_k^{(m)} = \frac{1}{N} \sum_{n=1}^N (z_n^{(m)} = k)$$
(4)

and the parameters $(a^{(m)}, b^{(m)}, u^{(m)})$ are determined by maximization of the log-likelihood.

Then the algorithm is the following one.

- Initialize the parameter set $\theta^{(0)}$
- Repeat until $l(\mathbf{z}^{(m)}, \theta^{(m)}) l(\mathbf{z}^{(m-1)}, \theta^{(m-1)}) < \epsilon$
 - compute $c_{nk}^{(m)}$ for each path n and each class k using relation (3)
 - determine the partition $\mathbf{z}^{(m)}$: choose $z_n^{(m)} = k$ corresponding to the largest value $c_{nk}^{(m)}$
 - determine the parameter vector $\theta^{(m)}$ that maximizes $l(\mathbf{z}^{(m)}, \theta^{(m)})$
 - compute the new value of the probability $\alpha_k^{(m)}$ for each class k using relation (4).

4. PROGNOSIS AND PERFORMANCE EVALUATION

4.1. Considered Prognosis

The considered prognosis is the remaining mean time until a threshold is reached. Let S be a threshold, p_n a path with its last observation $(t_{n,|p_n|}, x_{n,|p_n|})$, its class label z_n , and a set of Gamma process parameters corresponding to the class label $\theta_{z_n} = (a_{z_n}, b_{z_n}, u_{z_n})$. If the last degradation level is smaller than the threshold, i.e. $x_{n,|p_n|} < S$, then it is possible to estimate the remaining mean time until the threshold is reached. This time is noted $T_{n,\theta_{z_n}}(S)$. Since the increment $\Delta X_{n,i}$ follows a Gamma distribution given by $\Gamma(a_{z_n}(t_{n,i}^{u_{z_n}} - t_{n,i-1}^{u_{z_n}}), t_{z_n})$, its mean is

$$E(\Delta X_{n,i}) = \frac{a_{z_n}}{b_{z_n}} (t_{n,i}^{u_{z_n}} - t_{n,i-1}^{u_{z_n}})$$

Then, taking $i = |p_n| + 1$, it leads to the value $T_{n,\theta_{z_n}}(S)$ given by:

$$T_{n,\theta_{z_n}}(S) = \left((S - x_{n,|p_n|}) \frac{b_{z_n}}{a_{z_n}} + t_{n,|p_n|}^{u_{z_n}} \right)^{\frac{1}{u_{z_n}}} - t_{n,|p_n|}$$

For a given value of K, a set $\Theta = \{\theta_k\}_{k=1}^K$ and a set of class labels $\mathbf{z} = \{z_n\}_{n=1}^N$, the remaining mean time until a threshold S is reached can be computed for each path n.

4.2. Prognosis performance evaluation

In the case of simulated data, it is possible to compare the estimated prognosis result with the theoretical one. We have prefered to use the theoretical remaining useful time than a simulated value that we could obtain by running the path up to the failure threshold. The estimated prognosis result for path n, $T_{n,\tilde{\theta}_{\widetilde{zn}}}(S)$, is obtained using the estimated set of parameters $\widetilde{\Theta}$ and the estimated set of class labels \widetilde{z} . The theoretical prognosis is noted $T_{n,\theta_{z_n}}(S)$.

A large number of metrics in the forecasting applications have been proposed, as accuracy and precision, which are classical metrics. The metrics we propose to use in this paper for assessing the prognosis is near to relative accuracy given in (Saxena, Celaya, Saha, Saha, & Goebel, 2010). It is a relative error criterion which allows to give the same importance to all classes. This is critical in our case because the precision depends on the class evolution. For a path n, and a threshold S we define the relative error $e_n(S)$ as:

$$e_n(S) = \frac{T_{n,\tilde{\theta}_{\widetilde{z_n}}}(S) - T_{n,\theta_{z_n}}(S)}{T_{n,\theta_{z_n}}(S)}$$
(5)

Using all the paths for which the threshold is not reached for the last sample, i.e. $x_{n,|p_n|} < S$, it is possible to compute the mean of all the errors e_n to obtain Ee(S) and to compute the standard deviation to obtain Se(S)

$$Ee(S) = \widehat{E}[\{e_n(S)\}_{n|x_{n,|p_n|} < S}]$$
 (6)

$$Se(S)(S) = \widehat{\sigma}[\{e_n(S)\}_{n|x_{n,|p_n|} < S}]$$
(7)

The mean error should be equal to 0. The criterion which characterizes the performance of an approach is the standard deviation of the error.

Table 1. parameters - situations 1 and 2

		class 1	class 2	class 3	class 4
0.4	a	16.67	28.12	41.67	55.80
Situation 1	b	1.67	1.87	2.083	2.23
	u	0.8	0.8	0.8	0.8
			1 0		
		class 1	class 2	class 3	class 4
Situation 2	a	16.67	24.5	33.75	43.21
	b	1.67	1.75	1.87	1.96
	u	0.8	0.8	0.8	0.8

5. **R**ESULTS

Simulations have been done considering two situations. For both of them, there are 4 classes, each class with 6 paths, each path with 3 samples. The time increments are within an uniform distribution between 2 and 8. Parameters for both situations are given in table 1.

The mean theoretical evolution respectively for situation 1 and situation 2 is described in figure 1a and figure 3a. In situation 2, the classes are more similar than in situation 1: at each instant the mean values for 2 different classes are closer than in situation 1. However the standard deviations are the same for both situations.

Example of simulated data respectively corresponding to situation 1 and situation 2 are given in figure 2a and figure 4a.

The simulated data has been used to determine jointly the class of each path and the parameter set of each class, for different values of K (a priori number of classes). Simulations have been done for K between 1 and 7.

For the example of situation 1, the estimated class of each path for K = 3, 4, 5 is described in figures 2b, c, and d. The mean evolution of the degradation corresponding to the estimated parameters is given in figures 1b, c, and d. In the case of K = 4 classes, it is possible to determine the number of paths which are misclassified, since it corresponds to the theoretical number of classes. It can be seen than one path of class 1 ('+' red) is affected to class 2 ('*' green). All other paths are correctly classified.

Similar results for situation 2 are given in figure 4, for the estimated class of each path, and in figure 3, for the mean evolution of the degradation. In the case of K = 4 classes, 3 paths are misclassified: one path of class 1 is affected to class 2 and two paths of class 2 are affected to class 3.

The prognosis $T_{n,\widetilde{\theta_{z_n}}}(S)$ has been determined in 9 cases of estimation of parameter $\widetilde{\theta}$:

- "semi-theoretical case" : the parameter set is estimated assuming the true class of each path is known;
- "path case" : a parameter set is estimated for each path using the 3 observations of the considered path;
- "estimated K-class case" (for K = 1...7): the class of each path and the parameter set of each class are determine jointly.





Figure 1. Evolution of the mean degradation value in situation 1 for (a) the theoretical parameters (b) the estimated parameters with 4 classes (c) the estimated parameters with 3 classes (d) the estimated parameters with 5 classes. Each color corresponds to an estimated class.

Figure 2. Example of simulated data in situation 2 for (a) the theoretical class (b) the estimated class for 4 classes (c) the estimated class with 3 classes (d) the estimated class with 5 classes. Each color corresponds to an estimated class.





Figure 3. Evolution of the mean degradation value in situation 2 for (a) the theoretical parameters (b) the estimated parameters with 4 classes (c) the estimated parameters with 3 classes (d) the estimated parameters with 5 classes. Each color corresponds to an estimated class.

Figure 4. Example of simulated data in situation 2 for (a) the theoretical class (b) the estimated class for 4 classes (c) the estimated class with 3 classes (d) the estimated class with 5 classes. Each color corresponds to an estimated class.



200 300 threshold 350 0.0057 0.0050 0.0055 semi-theor. 1 path 0.0289 0.0276 0.0309 1 class -0.1183-0.0123-0.01042-class -0.01940.0002 0.0009 (a) 3-class -0.00800.0031 0.0037 4-class 0.0067 0.0059 0.0064 5-class 0.0103 0.0089 0.0097 6-class 0.0126 0.0109 0.0119 7-class 0.0143 0.0128 0.0140 threshold 200300 350 semi-theor. 0.0450 0.0520 0.0555 1 path 0.1629 0.1813 0.1954 1 class 0.2960 0.3462 0.3512 2-class 0.1954 0.1897 0.1924 (b) 3-class 0.1117 0.1193 0.1221 4-class 0.0554 0.0615 0.0650 5-class 0.0745 0.0821 0.0868 6-class 0.0859 0.0947 0.1004 7-class 0.0961 0.1062 0.1131

Figure 5. Example of prognosis for (a) the theoretical parameters (b) the estimated parameters for each path (c) the estimated parameters with 4 classes. Each color corresponds to a theoretical class.

The prognosis obtained in the "semi-theoretical case" leads to the minimum error which is reachable, for a given path set. The obtained error is due to the error of the parameters, arising from the estimation with a limited number of paths.

In figure 5, an example of prognosis for situation 2 with a threshold S = 250 shows "theoretical case", "path case" and "estimated 4-class case".

In the "path case" there exists a large variance and the bad estimation is due to the very low number of samples for each path. This is particularly visible when the degradation level at the last inspection time is far from the failure level i.e. when the time of prognosis is far from the failure time. In the case of class 1 (red '+') predicted mean failure times are in [40, 80] instead of [50, 60] for the "theoretical case". In the "estimated 4-class case", the impact of the misclassified paths appears clearly. One path of class 1 is affected to class 2 and two paths of class 2 are affected to class 3. Hence the estimated value for parameter u is smaller than its theoretical value for class 2 (green '*') and the green line on figure 3b is more curved than on figure 3a. As a consequence the estimated mean residual lifetime for class 2 is greater than the theoretical one.

The simulation has been repeated for 200 path sets and for

Table 3. (a) Estimated mean Ee(S) (relation 6) and (b) estimated standard deviation Se(S) (relation 7) for situation 2

	threshold	150	200	250	
ĺ	semi-theor.	0.0073	0.0059	0.0054	
	1 path	0.0333	0.0280	0.0276	
	1 class	-0.1777	-0.0581	-0.0124	
(a)	2-class	-0.0202	-0.0106	0.0003	
(u)	3-class	-0.0010	0.0011	0.0059	
	4-class	0.0098	0.0080	0.0075	
	5-class	0.0138	0.0105	0.0099	
	6-class	0.0159	0.0120	0.0113	
	7-class	0.0186	0.0143	0.0136	
	[1			
	threshold	150	200	250	
	semi-theor.	0.0413	0.0460	0.0500	
	1 path	0.1602	0.1649	0.1769	
	1 class	0.2232	0.2797	0.3007	
(h)	2-class	0.1755	0.1651	0.1642	
(0)	3-class	0.1090	0.1154	0.1169	
	4-class	0.0708	0.0744	0.0769	
	5-class	0.0821	0.0876	0.0913	
	6-class	0.0893	0.0950	0.0995	
	7-class	0.0984	0.1043	0.1099	

Table 2. Estimated mean Ee(S) (relation 6) and estimated standard deviation Se(S) (relation 7) for situation 1

three thresholds. The estimated prognosis values $T_{n,\tilde{\theta}_{\widehat{z_n}}}(S)$ have been compared with the theoretical value $T_{n,\theta_{\widehat{z_n}}}(S)$. The mean error Ee(S) given by relation (6) and Se(S) given by relation (7) have been computed for the 9 cases (described above) of estimated Gamma process parameters and for each threshold. The estimated mean error Ee(S) and the estimated standard deviation Se(S) for situation 1, obtained using 200 path sets, are given in tables 2(a) and (b). For situation 2 they are given in tables 3(a) and (b).

As expected, the estimated mean error is close to 0. For both situations, the worse result is obtained with the "estimated 1class case". From estimated standard deviation point of view, the closest case to the "semi-theoretical case" is the "estimated 4-class case". It corresponds to the theoretical number of classes and to the expected result. As one could expect, results in situation 2 are worse than in situation 1 because the classes are more similar. Consequently the number of misclassified paths is larger than in situation 1 and the Gamma process parameters are estimated with a larger error. For both situations, when the number of classes is larger than the theoretical one, the impact is not very important. On the contrary when the number of classes is smaller than the theoretical one, some paths from different Gamma process are mixed and the parameters are not estimated correctly and consequently the prognosis error can be important.

6. CONCLUSION

In this paper, a method is proposed for making a degradation prognosis based on Gamma process model parameters that are estimated using degradation measurements on different systems. It is assumed that there are a number of operational conditions leading to different degradation processes. Estimating the Gamma process model parameters using only one system leads to poor results due to the limited number of samples. On the contrary, estimating the Gamma process model parameters considering only one Gamma process leads to poor results due to the mixture of systems with different degradation trends.

The proposed method consists in considering a mixture of Gamma process models. It allows to cluster the degradation paths in classes corresponding to the different degradation trends and to estimate the Gamma process parameters. It uses an expectation-minimization approach that takes into consideration that all measurements in a same path belong to the same class.

Simulations have been done and demonstrate the feasibility of the method. They have shown that grouping paths originating from the same process allows to really increase the prognosis performance in comparison with the two basic strategies (all paths in one class, one class per path). The best result has been obtained with the class number equal to the theoretical one ; however if the number of classes is sur-estimated the result evolves slowly. A method for choosing the number of classes, using the Bayesian information criterion (Kass & Raftery, 1995), is currently being studied.

REFERENCES

- Ambroise, C., & Govaert, G. (1998). Convergence of an EMtype algorithm for spatial clustering. *Pattern Recognition Letters*, 19, 919–927.
- Celeux, G., & Govaert, G. (1992). A classification EM algorithm for clustering and two stochastic versions. *Computational statistics & Data analysis*, 14(3), 315–332.
- Celeux, G., & Govaert, G. (1995). Gaussian parcimonious clustering models. *Pattern Recognition*, 28, 781–793.
- Cinlar, E., Osman, E., & Bazant, Z. P. (1977). Stochastic process for extrapolating concrete creep. *Journal of the Engineering Mechanics Division*, 103(6), 1069–1088.
- Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal Statistical Society ,Series B*, 39(1), 1–38.
- Hu, T., & Sung, S. Y. (2006). A hybrid EM approach to spatial clustering. *Computational Statistics & Data Analysis*, 50, 1188–1205.
- Kass, R., & Raftery, A. (1995). Bayes factor. J. Am. Statistical Association, 90, 733-795.
- Nystad, B. H., Gola, G., & Hulsund, J. (2012, July 3-5). Lifetime models for remaining useful life estimation with randomly distributed failure thresholds. In *Proc. of first european conference of the prognostics and health management society 2012* (p. 141-147). Dresden, Germany.
- Ramasso, E., & Gouriveau, R. (2014). Remaining useful life estimation by classification of predictions based on a neuro-fuzzy system and theory of belief functions. *Reliability, IEEE Transactions on*(99).
- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2010). Metrics for offline evaluation of prognostics performance. *International Journal of Prognostics and Health Management (IJPHM)*, 1(1), 20.
- Shental, N., Bar-Hillel, A., Hertz, T., & Weinshall, D. (2003, August 21-24). Computing gaussian mixture models with EM using side-information. In *Proc. of the 20th international conference on machine learning*. Washington DC, USA.
- Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation – a review on the statistical data driven approaches. *European Journal of Operational Research*, 213(1), 1 - 14.
- Van Noortwijk, J. (2009). A survey of the application of gamma processes in maintenance. *Reliability Engineering & System Safety*, 94(1), 2–21.

An efficient simulation framework for prognostics of asymptotic processes- a case study in composite materials.

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ABSTRACT

This work presents an efficient computational framework for estimating the end of life (EOL) and remaining useful life (RUL) by combining the particle filter (PF)-based prognostics with the technique of Subset simulation. It has been named PFP-SubSim on behalf of the full denomination of the computational framework, namely, PF-based prognostics based on Subset Simulation. This scheme is especially useful when dealing with the prognostics of evolving processes with asymptotic behaviors, as observed in practice for many degradation processes. The effectiveness and accuracy of the proposed algorithm is demonstrated through an example for predicting the probability density function of EOL for a carbon-fibre composite coupon subjected to an asymptotic fatigue degradation process. It is shown that PFP-SubSim algorithm is efficient, and at the same time, fairly accurate in obtaining the probability density function of EOL and RUL as compared to the traditional PF-based prognostic approach reported in the PHM literature.

1. INTRODUCTION

The goal of prognostics is to make end of life (EOL) and remaining useful life (RUL) predictions of components, subsystems, and systems that enable timely maintenance decisions to be made under the presence of uncertainty. In practice, different sources of uncertainty are present in a typical prognostic problem, namely, (a) uncertainty in modeling the system, (b) uncertainty in future inputs to the system and (c) measurements noise (Sankararaman & Goebel, 2013). Further it is added the uncertainty that the PF-based prognostics algorithm (Orchard, Kacprzynski, Goebel, Saha, & Vachtsevanos, 2008) introduces itself, since, in general, these prognostics algorithms employ a limited amount of discrete samples for making predictions, unless analytical methods are employed, which are limited to very specific cases in real life applications (Sankararaman & Goebel, 2013).

There is an additional source of error attributable to the prognostics algorithm itself, which is due to the lack of confidence in dealing with the EOL estimate, and it is especially representative of systems whose evolving dynamic exhibit an asymptotic behavior in approaching towards the thresholds. In this situation, prediction accuracy and precision can vary significantly unless higher-density sampling-based methods are employed to characterize fault propagation trajectories achieving higher resolutions in the vicinity of the threshold, which considerably increases the computational cost. On the other hand, choosing a conservative threshold, such that it meets a propagation trajectory prior to the asymptotic region, is one approach but results in throwing away potentially useful component life.

In this work, a novel efficient algorithm, named PFP-SubSim, is presented for estimating the EOL and RUL by combining the PF-based prognostics (Daigle & Goebel, 2011) with the technique of Subset simulation for efficient rare-event simulation, first developed in (Au & Beck, 2001). The result is a especially suited algorithm for the prognosis of asymptotic processes. The idea behind PFP-SubSim algorithm is to split the multi-step-ahead predicted trajectories into multiple branches of selected samples (seeds) at various stages of the process, which are further reproduced into closer approximations to the desired threshold by conditional sampling using the propagation model. A sequence of nested subsets of samples (*simulation levels*) are sequentially defined such that, at

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each simulation level, the samples are increasingly distributed in the vicinity of the threshold, achieving high resolution for the EOL estimate.

A case study is presented for predicting the EOL of a composite coupon subjected to an asymptotic fatigue degradation process, that illustrates some of the challenges in a real-world application of the algorithm. Matrix micro-cracks are considered as the primary degradation mode where the increase in micro-cracks density exhibits asymptotic behavior as fatigue cycling continues. Structural health monitoring in this example is accomplished through Lamb wave-based active interrogation using PZT sensors together with a set of straingauges for measuring stiffness reduction. The data used for this case study is an open-access dataset distributed by NASA Ames Prognostics Data Repository (Saxena, Goebel, Larrosa, & Chang, 2008).

The paper is organized as follows. Section 2 reviews the theory underlying the prognostics problem and overviews the computational architecture we adopt in further sections. In Section 3 the basis of Subset Simulation method is presented before introducing a formal Subset Simulation approach in a prognostic context, which is provided in Section 4. The efficiency of FPF-SubSim is illustrated in Section 5 through a case study. In Section 6, a discussion about the performance of PFP-SubSim algorithm in relation with the standard PFbased prognostic algorithm is provided. Section 7 provides concluding remarks.

2. PF-BASED PROGNOSTICS

Let consider a state-space model which is used to sequentially predicting the state $x_k \in \mathcal{X} \subset \mathbb{R}^{n_x}$ of a dynamic system for observed data vector y_k , where $k \in \mathbb{N}$, is the time index. Let us also consider that the state x_k may depends on a set of model parameters $\theta \in \Theta \subset \mathbb{R}^{n_\theta}$. Mathematically, the state-space model can be described at time k in a generalized manner as:

$$x_k = f_k(x_{k-1}, u_k, v_k, \theta) \tag{1a}$$

$$y_k = h_k(x_k, u_k, w_k, \theta) \tag{1b}$$

where $u_k \in \mathbb{R}^{n_u}$ is the input vector and $v_k \in \mathbb{R}^{n_v}$ and $w_k \in \mathbb{R}^{n_w}$, are uncertain variables introduced to account for the model error and measurement error, respectively. The functions f_k and h_k are possibly nonlinear functions for the state transition evolution and observation equation, respectively. In the last equation, the measurements y_k are assumed conditionally independent given the parameter $\theta \in \mathbb{R}^{n_\theta}$ and the states $x_k \in \mathcal{X}$, follow a Markov model of order one. In addition, it is defined the augmented state z_k in the joint stateparameter space as $z_k = (x_k, \theta) \in Z = \Theta \times \mathcal{X} \subset \mathbb{R}^{n_\theta + n_x}$, so that $p(z_k) = p(x_k | \theta) p(\theta)$. The focus of state-estimation (also known as the *filtering problem*) is on sequentially updating the probability density function (PDF) of the state z_k , given the observed measurements up to time k, $y_{0:k} = \{y_0, \ldots, y_{k-1}, y_k\}$, i.e., $p(x_k, \theta_k | y_{0:k}) \equiv p(z_k | y_{0:k})$. This implies the evaluation of multidimensional integrals parameterized by θ , within a Bayesian framework of prediction and updating (Cappe, Guillin, Marin, & Robert, 2004). These integrals are usually intractable except some especial cases of linear systems and Gaussian noise, hence a generally followed solution is to obtain an approximation to $p(z_k | y_{0:k})$ by means of *particle filters* (PF) (Gordon, Salmond, & Smith, 1993), which may be directly applied to nonlinear systems with non-Gaussian noise terms (Arulampalam, Maskell, Gordon, & Clapp, 2002). Using PF, the approximation to the state distribution $p(z_k | y_{0:k})$ is described through a set of N discrete weighted *particles* $\{(x_k^{(i)}, \theta_k^{(i)}, \omega_k^{(i)})\}_{i=1}^N$ that can be readily sampled from a convenient importance distribution $q(x_{0:k}, \theta_{0:k} | y_{0:k})$ as:

$$p(x_{0:k}, \theta_{0:k}|y_{0:k}) \approx \sum_{i=1}^{N} \hat{w}_{k}^{(i)} \delta(x_{0:k} - x_{0:k}^{(i)}) \delta(\theta_{0:k} - \theta_{0:k}^{(i)})$$
(2)

where $\hat{w}_{k}^{(i)}$ is the unnormalized importance weight for the *i*th particle:

$$\hat{w}_{k}^{(i)} = \frac{p(x_{0:k}^{(i)}, \theta_{0:k} | y_{0:k})}{q(x_{0:k}^{(i)}, \theta_{0:k} | y_{0:k})}$$
(3)

For practical reasons, the PDF $q(x_{0:k}, \theta_{0:k}|y_{1:k})$ is chosen so that it admits a sample procedure by choosing $q(x_{0:k}, \theta_{0:k}|y_{0:k}) = q(x_{0:k}, \theta_{0:k}|y_{0:k-1})$ (Arulampalam et al., 2002), hence it can be factorized in a form similar to that of the target posterior PDF, i.e. :

 $q(x_{0:k},\theta_{0:k}|y_{0:k}) = q(x_{0:k-1},\theta_{0:k-1}|y_{0:k-1})q(x_k|x_{k-1},\theta_{k-1}),$ resulting:

$$\hat{w}_{k}^{(i)} \propto \hat{w}_{k}^{(i-1)} \frac{p(x_{k}^{(i)} | x_{k-1}^{(i)}, \theta_{k-1}^{(i)}) p(y_{k} | x_{k}^{(i)}, \theta_{k}^{(i)})}{q(x_{k}^{(i)} | x_{k-1}^{(i)}, \theta_{k}^{(i)})}$$
(4)

where $p(x_k^{(i)}|x_{k-1}^{(i)}, \theta_{k-1}^{(i)})$ and $p(y_k|x_k^{(i)}, \theta_k^{(i)})$ are¹ the PDFs of state estimation and updating, respectively, which can be obtained using the state-space model defined in Eq. (1) and assuming prescribed PDFs for v_k and w_k . Without lack of generality, we adopt the *bootstrap filter* (Gordon et al., 1993) consisting on adopting $q(x_k|x_{k-1}, \theta_{k-1}) = p(x_k|x_{k-1}, \theta_{k-1})$, so that the expression for the i^{th} unnormalized particle weight yields

$$\hat{w}_{k}^{(i)} \propto \hat{w}_{k-1}^{(i)} p(y_{k} | x_{k}^{(i)}, \theta_{k}^{(i)})$$
(5)

Observe from Eqs. (4) and (5) that the weight values $\hat{w}_k^{(i)}$ are known only up to a scaling factor, which can be overpassed by normalization as: $w_k^{(i)} = \hat{w}_k^{(i)} / \sum_{i=1}^N \hat{w}_k^{(i)}$, $i = 1, \ldots, N$, where $w_k^{(i)}$ denotes the normalized value of the i^{th} particle

¹For simpler notation the conditioning on the model input u_k is dropped from Eq. (1)

at time k. A pseudocode implementation of the PF is given in Algorithm 1, which includes a systematic resampling step (Rubin, 1987) to avoid the well-known degeneracy deficiency of the PF (Cappe et al., 2004).

2.1. Prognostics and RUL prediction

Prognostics is concerned with the performance of the component that lies outside a given region of acceptable behavior. Mathematically, it requires the generation of a ℓ -step ahead prediction of state PDF, namely $p(z_{k+\ell}|y_{1:k})$, using the most up-to-date knowledge of the system at time k (Orchard et al., 2008). By computing the time indexes $t > k \in \mathbb{N}$ when future states z_t violate any previously defined thresholds, an estimate of the end of life (EOL) can be derived.

Algorithm 1 PF with on-line parameter updating

1: inputs:

2: N, {number of particles per time step}

3: Algorithm:

4: Initialize $\left[\left(\theta_0^{(1)}, x_0^{(1)} \right), \dots, \left(\theta_0^{(i)}, x_0^{(i)} \right), \dots, \left(\theta_0^{(N)}, x_0^{(N)} \right) \right],$ where $(\theta, x) \sim p(\theta)p(x|\theta)$ 5: Assign the initial unnormalized weights: $\{ \hat{w}_{0}^{(i)} = p(y_{0}|x_{0}^{(i)}, \theta^{(i)}) \}_{i=1}^{N}$ At $k \ge 1$ {time k evolves as new data point arrives} 6: Resampling of N particles according to weights 6: Resampling C: $w_{k-1}^{(i)}, i = 1, ..., N.$ 7: for i = 1 to N do 8: Sample: $\theta_k^{(i)} \sim p(\theta_k | \theta_{k-1}^{(i)})$ $r_i^{(i)} \sim p(x_k | x_{k-1}^{(i)}, \theta_k^{(i)})$

$$x_k^{(i)} \sim p(x_k | x_{k-1}^{(i)}, \theta_k^{(i)}).$$
9: Update the weight $\hat{w}_k^{(i)} = p(y_k | x_k^{(i)}, \theta_k^{(i)})$
10: end for

- 10: **end for**
- 10: end for 11: Normalize weights $w_k^{(i)} = \hat{w}_k^{(i)} / \sum_{i=1}^N \hat{w}_k^{(i)}$ 12: <u>output:</u> $\{(x_k^{(i)}, \theta_k^{(i)}), w_k^{(i)}\}_{i=1}^N$

The region of unacceptable behavior can be defined by means of a set of thresholds $\mathbf{b} = \{b_1, \dots, b_c\}$ on one or various critical parameters. These thresholds can be combined into a threshold function $T_{EOL} = T_{EOL}(x, \theta) \equiv T_{EOL}(z)$, that maps a given point in the joint state-parameter space to the Boolean domain $\{0, 1\}$ (Daigle & Goebel, 2011). For instance, when a given particle i starting from time k performs a random walk and hits any of the thresholds in **b**, then $T_{EOL}^{(i)} \equiv$ $T_{EOL}(z_k^{(i)}) = 1$, otherwise $T_{EOL}^{(i)} = 0$. The time $t \ge k$ at which that happens defines the EOL_k for that particle. Mathematically:

$$EOL_{k}^{(i)} = \inf\{t \in \mathbb{N} : t \ge k \land T_{EOL}^{(i)} = 1\}$$
(6)

Using the updated weights at the starting time k, an approxi-

mation to the PDF of EOL is given by:

$$p(EOL_n|y_{0:k}) \approx \sum_{i=1}^N \omega_k^{(i)} \delta(EOL_k - EOL_k^{(i)})$$
(7)

Once EOL_n is estimated, the remaining useful life can be readily obtained as $RUL_k = EOL_k - k$. An algorithmic description of the prognostic procedure is provided as Algorithm 2.

Algorithm 2 Standard PF-prognostics and RUL prediction

1:	$\underline{\text{inputs:}} \left\{ \left(x_k^{(i)}, \theta_k^{(i)} \right), \omega_k^{(i)} \right\}_{i=1}^N, \mathbf{b} = \{b_1, \dots, b_c\}$
2:	for $i = 1 \rightarrow N$ do
3:	Calculate: $T_{EOL}\left(x_{k}^{(i)}, \theta_{k}^{(i)}\right)$
4:	while $T_{EOL}^i = 0$ do
5:	Sample: $\theta_t^{(i)} \sim p(\theta_t \theta_{t-1}^{(i)})$
	$x_t^{(i)} \sim p(x_t x_{t-1}^{(i)}, \theta_t^{(i)}).$
6:	$t \leftarrow t+1, \ t > k$
7:	$z_t = \left(x_t^{(i)}, heta_t^{(i)} ight) \leftarrow z_{t+1} = \left(x_{t+1}^{(i)}, heta_{t+1}^{(i)} ight)$
8:	end while
9:	$EOL_k^{(i)} \leftarrow t$
	$RUL_{k}^{(i)} = EOL_{k}^{(i)} - k$
10:	end for "
11:	$\underline{\text{output}} EOL_k, \ RUL_k = EOL_k - k$

3. SUBSET SIMULATION METHOD

Subset Simulation is an adaptive stochastic simulation approach originally proposed to compute small failure probabilities of engineering systems (Au & Beck, 2001). The conceptual idea behind Subset Simulation is to represent a small failure probability as a product of larger probabilities.

In a general way, Subset Simulation is a method for efficiently generating conditional samples that correspond to specified levels of a performance function $g: \mathbb{R}^{n_{\theta}+n_x} \to \mathbb{R}$ in a progressive manner, converting a problem involving rare-event simulation into a sequence of problems involving more frequent events. This general aspect makes Subset Simulation applicable to a broad range of areas of science where the simulation/prediction of unprovable events is required (Au & Beck, 2003; Ching, Au, & Beck, 2005). In this section, the Subset Simulation method is presented using its primary aim on small failure probabilities estimation. In the next section, Subset Simulation is specialized for the use in prognostics, and in particular for asymptotic processes.

Let \mathcal{F} be the region of unacceptable behavior, or failure region, in the z-space, $z \in Z \subset \mathbb{R}^{n_{\theta}+n_x}$, corresponding to exceedance of the performance function q above some specified threshold level b:

$$\mathcal{F} = \{ z \in Z : g(z) > b \}$$
(8)

Let us now assume that \mathcal{F} is defined as the intersection of m regions Z, i.e, they are arranged as nested subsets of regions starting from the entire space Z and shrinking to the failure domain \mathcal{F} , i.e., $\mathcal{F}_1 \supset \mathcal{F}_2 \ldots \supset \mathcal{F}_{m-1} \supset \mathcal{F}_m = \mathcal{F}$, so that $\mathcal{F} = \bigcap_{j=1}^m \mathcal{F}_j$. Each subset \mathcal{F}_j (typically termed as *intermediate failure domain*) is defined as $\mathcal{F}_j = \{z \in Z : g(z) > b_j\}$, with $b_{j+1} > b_j$, such that $p(z|\mathcal{F}_j) \propto p(z)\mathbb{I}_{\mathcal{F}_j}(z)$, $j = 1, \ldots, m$. The term p(z) denotes the probability model for z. By definition of conditional probability, it follows that²:

$$P(\mathcal{F}) = P\Big(\bigcap_{j=1}^{m} \mathcal{F}_j\Big) = P(\mathcal{F}_1)\prod_{j=2}^{m} P(\mathcal{F}_j|\mathcal{F}_{j-1}) \quad (9)$$

where $P(\mathcal{F}_j|\mathcal{F}_{j-1}) \equiv P(z \in \mathcal{F}_j|z \in \mathcal{F}_{j-1})$, is the conditional failure probability at the $(j-1)^{th}$ intermediate failure domain. Observe that the probability $P(\mathcal{F})$ may be relatively small, however it can be approximated by Subset Simulation as the product of larger conditional probabilities involved in Eq. (9), thus avoiding simulation of rare events.

In the last equation, apart from $P(\mathcal{F}_1)$, which can be readily estimated by the standard Monte Carlo method (MC), the remaining factors cannot be efficiently estimated because of the sampling conditional on \mathcal{F}_{j-1} , j = 2, ..., m. However, MCMC methods can be used for sampling from the PDF $p(z_{j-1}|\mathcal{F}_{j-1})$ when $j \ge 2$ giving:

$$P(\mathcal{F}_j|\mathcal{F}_{j-1}) \approx \bar{P}_j = \frac{1}{M} \sum_{n=1}^M \mathbb{I}_{\mathcal{F}_j}(z_{j-1}^{(n)})$$
(10)

where $z_{j-1}^{(n)} \sim p(z_{j-1}|\mathcal{F}_{j-1})$ and $\mathbb{I}_{\mathcal{F}_j}(z_{j-1}^{(n)})$ is an indicator function for the region $\mathcal{F}_j, j = 1, \ldots, m$, that assigns a value of 1 when $g(z_{j-1}^{(n)}) > b_j$, and 0 otherwise.

Observe that it is possible to obtain Markov chain samples that are generated at the $(j-1)^{th}$ level which lie in \mathcal{F}_j , so that they are distributed as $p(z|\mathcal{F}_i)$. Hence they provide "seeds" for simulating more samples according to $p(z|\mathcal{F}_i)$ by using MCMC sampling with no burn-in required, which is an important feature of Subset Simulation to avoid wasting samples (Au & Beck, 2001). As described further below, \mathcal{F}_j is actually chosen adaptively based on the samples $\{z_{j-1}^{(n)}, n =$ $1, \ldots, M$ from $p(z|\mathcal{F}_{j-1})$ in such a way that the worst (in the sense of closer to the intermediate failure threshold) among the M samples define an intermediate level. For practical reasons, the amount of samples defining the intermediate level are chosen as a specified fraction of the total amount of Msamples by fixing a value $P_0 \in (0, 1)$, so that there are exactly NP_0 of these seed samples in \mathcal{F}_j (so $\bar{P}_j = P_0$ in Eq. (10)). For a specified value of P_0 , the intermediate threshold value b_i defining \mathcal{F}_i is obtained in an adaptive manner as

the $[MP_0]^{th}$ largest value among the values $g(z_{j-1}^{(n)})$, $n = 1, \ldots, M$, so that the sample estimate of $P(\mathcal{F}_j | \mathcal{F}_{j-1})$ in Eq. (10) is equal to P_0 . The remaining $M(1 - P_0)$ samples are generated from $p(z|\mathcal{F}_j)$ by MCMC, giving a total of M samples in \mathcal{F}_j . Repeating this process, we can compute the conditional probabilities of the higher-conditional levels until the final region $\mathcal{F}_m = \mathcal{F}$ has been reached.

In Subset Simulation, the choice of an adequate P_0 has a significant impact on the efficiency of the algorithm. Indeed, a small value for the conditional probability $(P_0 \rightarrow 0)$ makes that the distance between consecutive intermediate levels b_i – b_{j-1} becomes too large, which leads to a rare-event simulation problem. In the other hand, if the intermediate threshold values were chosen too close $(P_0 \rightarrow 1)$, the algorithm would take a large total number of simulation levels m (and hence large computational effort) to progress toward the target region of interest, \mathcal{F} . Hence, a rational choice for P_0 is of key importance for the efficiency of the algorithm. In the original presentation of Subset Simulation in (Au & Beck, 2001), $P_0 = 0.1$ was recommended, and more recently in (Zuev, Beck, Au, & Katafygiotis, 2011), the range $0.1 \leq P_0 \leq$ 0.3 was found to be near optimal after a rigorous sensitivity study of Subset Simulation. In this paper, we will adopt $P_0 = 0.2$. For convenience of implementation, P_0 is chosen so that MP_0 and $1/P_0$ are positive integers.

As stated before, to draw samples from the target PDF $p(z|\mathcal{F}_i)$, MCMC methods like Metropolis-Hastings (Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953) are adequate. In the original version of Subset Simulation (Au & Beck, 2001), a modified Metropolis algorithm (MMA) was proposed that worked well even in very high dimensions (e.g. 10^3 - 10^4), because the original algorithm fails in this case (Au & Beck, 2001)). In MMA, a univariate proposal PDF is chosen for each component of the parameter vector and each component candidate is accepted or rejected separately, instead of drawing a full parameter vector candidate from a multi-dimensional PDF as in the original algorithm. To avoid repeating literature, the reader is refered to (Au & Beck, 2001) for further details about MMA. More details about implementation issues can be encountered in the work of (Zuev et al., 2011).

4. SUBSET SIMULATION IN PF-BASED PROGNOSTICS

In this section, the Subset Simulation method presented above is adapted for its application in prognostics. The definition of failure region \mathcal{F} in Eq. (8) is adopted here to establish a nested sequence of prognostic regions \mathcal{F}_j in $Z = \Theta \times \mathcal{X}$, whose points are of the form $z_t^j \equiv (x_t^j, \theta_t^j), t > k$, such that $g(z_t^j) < b_j$, being $g : \mathcal{F} \to \mathbb{R}$ the performance function on Z. The sequence of threshold values $b_{j+1} > b_j, \ j = 1, \dots, m$ are

²In what follows, we use $P(\cdot)$ to denote probability whereas a PDF is expressed as $p(\cdot)$. In addition, we use $P(\mathcal{F}) \equiv P(z \in \mathcal{F})$, for simpler notation

obtained³ sequentially as in Section 3. Observe that the performance function g works analogously to the T_{EOL} function defined in Section 2.1. The main difference between them is that q allows us to know not only whether the state has reached the threshold b, but also how close it is to b if it has not.

Summarizing, the proposed algorithm simulate sequentially the joint state-parameter $z_t^j = (x_t^j, \theta_t^j)$ over a set of nested regions \mathcal{F}_j , $j = 1, \ldots, m$, such that $z_t^j \sim \mathbb{I}_{\mathcal{F}_j}(\theta, x) p(x|\theta) p(\theta)$. Figure 1 schematically describes the performance of the algorithm.

See Algorithm 3 for a pseudocode implementation, which is intended to be sufficient for most cases of application. The algorithm is implemented such that a fixed amount of M samples are drawn per simulation level \mathcal{F}_j , so that $N_T = mM$: the total amount of model evaluations required by the algorithm to reach the final threshold. It is important to remark that it does not imply any restriction but it allows controlling the computational burden. In addition, the conditional probability is set to $P_0 = 0.2$, following the recommendation about Subset Simulation method in (Zuev et al., 2011). Figure 2 provides an algorithm flow-chart to better understand the main steps of the algorithm. For simplicity, the time subscripts are dropped from Step 10, since the time indexing information is implicitly contained at each sample.



Figure 1. Generation of conditional samples in PFP-Sub-Sim: solid disks represent samples in the joint state-parameter space. Darker gray tones are used to represent samples distributed in increasing intermediate regions. Circled disks are the Markov chain samples used as seeds for generating new samples distributed as $p(\cdot | \mathcal{F}_j), j = 1, \ldots, m$.

Algorithm 3 Pseudocode implementation for PFP-SubSim

- 1: Inputs:
- 2: P_0 \in [0,1] {gives percentile selection, chosen so $NP_0, 1/P_0 \in \mathbb{Z}^+; P_0 = 0.2$ is recommended}. $M, \{\text{number of samples per intermediate level}; m,$
- {maximum number of simulation levels allowed}; $\ell = M/N.$

Require: $\left\{(x_k^{(i)}, \theta_k^{(i)}), w_k^{(i)}\right\}_{i=1}^N$; e.g. use Algorithm 1. 4: Algorithm:

- 5: for i : 1, ..., N do
- for $t: k+1, \ldots, k+\ell$ do 6:
- Sample $\theta_t^{0,(i)} \sim p(\theta_t | \theta_{t-1}^{(i)})$ $x_t^{0,(i)} \sim p(x_t | x_{t-1}^{(i)}, \theta_t^{(i)}).$ 7:
- end for 8:

1

- 9: end for
- $\left[(\theta^{0,(1)}, x^{0,(1)}), \dots, (\theta^{0,(M)}, x^{0,(M)})\right]$ 10:
- 11: **for** j : 1, ..., m **do**
- for $n: 1, \ldots, M$ do 12:

3: Evaluate:
$$g_j^{(n)} = g(z^{j-1,(n)});$$

14: end for Sort $[(\theta^{j-1,(n)}, x^{j-1,(n)}), n: 1, \dots, M]$ so that 15: $g_i^{(1)} \leqslant g_i^{(2)} \leqslant \dots g_i^{(M)}$

16: Fix
$$b_j = \frac{1}{2} \left(g_j^{(MP_0)} + g_j^{(MP_0+1)} \right)$$

- 17:
- Fix $b_j = \frac{1}{2} \left(g_j + g_j \right)$ for $n = 1, \dots, MP_0$ do Select as a seed $\left(\theta_{(1)}^{j,(n)}, x_{(1)}^{j,(n)} \right)$ $\left(\theta^{j-1,(n)}, x^{j-1,(n)} \right) \sim p(\theta, x | \mathcal{F}_j)$ 18:
- Run MMA (Au & Beck, 2001) to generate 19. $\begin{bmatrix} 1/P_0 \text{ states of a Markov chain lying in } \mathcal{F}_j: \\ \left[(\theta_{(1)}^{j,(n)}, x_{(1)}^{j,(n)}), \dots, (\theta_{(1/P_0)}^{j,(n)}, x_{(1/P_0)}^{j,(n)}) \right]$

21: Renumber
$$\left[(\theta_{(i)}^{j,(n)}, x_{(i)}^{j,(n)}) \right]$$

$$n = 1, \dots, MP_0; \ i = 1, \dots, 1/P_0$$
 as:

 $\left[(\theta^{j,(1)}, x^{j,(1)}), \dots, (\theta^{j,(M)}, x^{j,(M)})\right]$ 22:

23: if
$$b_j \ge b$$
 then

Record the times indexes of the first-passage

end if 24. 25: end for

³The b_j sequence is an increasing sequence (i.e., $b_{j+1} > b_j$) or a decreasingly sequence $(b_{j+1} < b_j)$ depending wether the process is a nondecreasing or decreasing process, respectively. With no loss of generality, it is considered as an increasing sequence.



Figure 2. PFP-SubSim algorithm flowchart.

5. CASE STUDY

In this section, the performance of the algorithm is investigated on a challenging problem about prognostics of matrix micro-cracks saturation in CFRP laminates using SHM data from a fatigue experiment. The framework for prognostics of fatigue damage in CFRP composites has been recently contributed by the authors in (Chiachío, Chiachío, Saxena, Rus, & Goebel, 2013) and (Chiachío, Chiachío, Saxena, Rus, & Goebel, 2013). To avoid repeating literature but conferring a sufficient conceptual framework, the relevant details are presented here in a brief manner.

5.1. Damage modeling in composites

As already shown in (Chiachío et al., 2013), a physic-based prognostic framework is preferred as a versatile way to deal

with accurate predictions for fatigue damage in composites without much training. It is based on modeling the energy released per unit crack area due to the formation of a new crack between two existing cracks, denoted as G. This energy, known as energy release rate (ERR), can be obtained as (J. A. Nairn, 1989, 1995):

$$G = \frac{\sigma_x^2 h}{2\rho h_{90}} \left(\frac{1}{E_x^*(2\rho)} - \frac{1}{E_x^*(\rho)} \right)$$
(11)

where σ_x is the maximum applied axial tension to the laminate, ρ is the matrix micro-cracks density defined as $\rho = \frac{1}{2i}$ with \overline{l} being the normalized half-crack spacing, and h and h_{90} are the laminate and 90°-sublaminate half-thickness, respectively. See more details in the Nomenclature section. The term $E_x^*(\rho)$, as a function of ρ , is the effective longitudinal laminate stiffness, i.e. the stiffness due to the current damage state, which can be efficiently modeled through microdamage mechanics models like shear-lag models (Garrett & Bailey, 1977; Highsmith & Reifsnider, 1982), variational models (Hashin, 1985), and crack opening displacement based models (Gudmundson & Weilin, 1993; Lundmark & Varna, 2005). In this work, the shear-lag approach is adopted for being simpler and well-suited for symmetric cross-ply laminates, which is the laminate type used in this case study, as shown below. Equation (12) provides the analytical expression for the effective longitudinal stiffness using the classical shear-lag model (Joffe & Varna, 1999):

$$E_x^* = \frac{E_{x,0}}{1 + a\frac{1}{2l}R(\bar{l})}$$
(12)

In the last equation, $E_{x,0}$ is the intact longitudinal Young's modulus of the laminate, $\bar{l} = \frac{l}{h_{90}}$ is the half crack-spacing normalized with the 90° sub-laminate thickness and *a* is a known function of laminate properties (defined in the Appendix). The function $R(\bar{l})$, known as the *average stress perturbation function*, is defined by:

$$R(\bar{l}) = \frac{2}{\xi} \tanh(\xi \bar{l}) \tag{13}$$

where ξ is the shear-lag parameter which is expressed as a function of ply and laminate properties (see the Nomenclature section for further details about the terms involved in the next expression) as:

$$\xi^2 = G_{yz} \left(\frac{1}{E_y} + \frac{1}{\lambda E_x^{(\phi)}} \right) \tag{14}$$

The evolution of crack-density over time is achieved by introducing the ERR into the modified Paris' law (J. Nairn & Hu, 1992), as shown below:

$$\frac{\mathrm{d}\rho}{\mathrm{d}n} = A(\Delta G)^{\alpha} \tag{15}$$

In the last equation, A and α are fitting parameters and ΔG is the increment in ERR for a specific stress amplitude during the fatigue loading: $\Delta G = G(\sigma_{x,max}) - G(\sigma_{x,min})$. Due to the complexity of the expression for ΔG , which involves the underlying micro-damage mechanics model for the computation of $E_x^*(\rho)$ shown above, a closed-form solution for Eq. (15) is hard to obtain. To overcome this drawback, the resulting differential equation can be solved by approximating the derivative using "unit-time" finite differences, considering that damage evolves cycle-to-cycle, as:

$$\rho_n = \rho_{n-1} + A \left(\Delta G(\rho_{n-1}) \right)^{\alpha} \tag{16}$$

5.2. Filtering recursion

As discussed in the last section, the progression of damage is modeled at every cycle n by focusing on the matrix-cracks density, ρ_n , and the normalized effective stiffness, $D_n = \frac{E_{x,0}^*}{E_{x,0}}$, defining a joint response function of two components: $f_n = [f_{1n}, f_{2n}]$ for matrix cracks-density and normalized effective stiffness, respectively. Let denote by $x_n = [x_{1n}, x_{2n}]$ the actual system response, for matrix micro-cracks density and normalized effective stiffness, respectively. Next, the damage model can be embedded stochastically (Beck, 2010) by adding a model-error term $v_n \in \mathbb{R}^2$ that represents the difference between the actual system response x_n and the model output f_n . The following input/output (I/O) state-space model is defined:

$$x_{1_n} = \rho_n = \underbrace{f_{1_n}(\rho_{n-1}, \theta, u_n)}_{\text{Equation 16}} + v_{1_n}$$
(17a)

$$x_{2_n} = D_n = \underbrace{f_{2_n}(\rho_n, \theta, u_n)}_{\text{Equation 12}} + v_{2_n}$$
 (17b)

where θ is a set of updatable model parameters and u_n denotes the set of input parameters to the system at time n. If $y_n = [y_{1_n}, y_{2_n}] = [\hat{\rho}_n, \hat{D}_n]$ are the measurements of the system output x_n , then the following measurement function is added to the discrete state-space model to account for the measurement error $w_n \in \mathbb{R}^2$:

$$y_{1_n} = \hat{\rho}_n = x_{1_n} + w_{1_n} \tag{18a}$$

$$y_{2_n} = D_n = x_{2_n} + w_{2_n} \tag{18b}$$

We use the Principle of Maximum Information Entropy (Beck, 2010) to choose v_n and w_n as i.i.d. Gaussian variables, $v_n \sim \mathcal{N}(0, [\sigma_{v_{1n}}, \sigma_{v_{2n}}] I_2), w_n \sim \mathcal{N}(0, [\sigma_{w_{1n}}, \sigma_{w_{2n}}] I_2)$, being $[\sigma_{v_{1n}}, \sigma_{v_{2n}}]$ and $[\sigma_{w_{1n}}, \sigma_{w_{2n}}]$ the standard deviations of v_n and w_n respectively, and I_2 the identity matrix of order 2, so they can be readily sampled. For this example, we adopt $\sigma_{w_{1n}} = 10^{-2}$ and $\sigma_{w_{1n}} = 10^{-6}$, assuming as known. The model parameters θ are selected among the complete set of parameters that defines the ensemble based on the modified Paris' law through a global sensitivity analysis based on vari-

ances and following the methodology proposed by (Saltelli et al., 2008). As result, the ply properties $\{E_x, E_y, h\}$ together with the modified Paris' law fitting parameter $\{\alpha\}$ emerged as influential parameters in terms of model output uncertainty. Moreover, the set of updatable model parameters θ was completed by adding the error terms to the last choice, i.e., $\theta =$ $\{\alpha, E_x, E_y, h, \sigma_v, \sigma_w\}$. The rest mechanical and geometrical parameters act as static non-updatable input parameters, hence they can be readily fixed at any point within their range of variation, (e.g. the mean value) without significantly influencing the output uncertainty.

5.3. Dataset

The performance of the proposed algorithm is investigated using SHM data obtained from a set of run-to-failure fatigue experiments. Both stiffness data and NDE measurements of internal damage, such as micro-crack density and delamination area, were periodically measured during the fatigue test (Saxena et al., 2011) (although we will only focus here on predicting matrix-micro cracks). Torayca T700G uni-directional carbon-prepreg material was used for 15.24 $cm \times 25.4 cm$ coupons with notched dogbone geometry and stacking sequence defined by $[0_2/90_4]_s$. The nominal values of the laminate ply properties are given in Table 1, along with their statistical description.

The tests were conducted under load-controlled tension cyclic loading, with a maximum applied load of 31.13 KN, frequency f = 5 Hz, and a stress ratio R = 0.14 (defined as the relation between the minimum and maximum stress for each cycle). Lamb wave signals were periodically recorded using a PZT sensor network to estimate internal micro-crack density. The mapping between PZT raw data and microcrack density was done following the methodology proposed in (Larrosa & Chang, 2012). Additionally, periodic X-rays were taken to visualize and characterize subsurface damage features, in particular, the micro-crack damage pattern. More details about these tests are reported in the Composite dataset, NASA Ames Prognostics Data Repository (Saxena et al., 2008) (damage data used in this example correspond to laminate L1S19). A summary of the measurements of matrix microcracks used in this study is provided in Table 2.

5.4. Results

For predicting the estimate end of life (EOL) of the laminate, we are interested in computing the time when the damage grows beyond a predefined damage threshold. In this study, a threshold value of $\rho = 424$ cracks per meter is considered, hence b = 424. A total amount of N = 100 particles trajectories are employed for Algorithm 1 which are further used as initialization samples for Algorithm 3. The results of Algorithm 3 are presented for three different simulation levels (m = 3) in Figure 3a, by using $P_0 = 0.2$ and $M = 2.4 \cdot 10^4$

Туре	Parameter	Nominal value	Units	COV (%)	Prior PDF
Mechanical	E_x	127.55	GPa	10	LN
	E_{y}	8.41	GPa	10	LN
	G_{xy}	6.20	GPa	10	LN
	$\frac{G_m}{d_0}$	$1\cdot 10^5$	GPa/m	50	LN
	$\nu_{xy}^{a_0}$	0.31	_	10	LN
	G_{yz}	2.82	GPa	10	LN
T	\tilde{h}	$1.5 \cdot 10^{-4}$	m	10	LN
Fitting	α	1.80	_	20	LN
-	A	$1 \cdot 10^{-4}$		20	LN
Errors	$\sigma_{v_{1_n}}$	4	$\frac{\# \text{ cracks}}{m \cdot \text{cycle}}$	-	U(0.5, 8)
	$\sigma_{v_{2_n}}$	0.01	$\frac{\# \text{ cracks}}{m \cdot \text{cycle}}$	-	U(0.001, 0.02)

Table 1. Prior information and nominal values of main parameters used in calculations. Classical laminate theory may be used from these parameters to obtain the values of the remaining parameters attributable to the laminate configuration.

Table 2. Experimental sequence of damage for cross-ply $[0_2/90_4]_s$ Torayca T700 CFRP laminate taken from the Composite dataset, NASA Ames Prognostics Data Repository (Saxena et al., 2008). The data are presented for micro-cracks density (ρ_n corresponding to specimen L1S19 in the dataset.)

Fatigue cycles, n	10^{1}	10^{2}	10 ³	10^{4}	$2 \cdot 10^{4}$	$3 \cdot 10^{4}$	$4 \cdot 10^{4}$	$5 \cdot 10^{4}$	$6 \cdot 10^{4}$	$7 \cdot 10^{4}$	$8 \cdot 10^{4}$	9.10^{4}	10^{5}
$\rho_n \left[\# \operatorname{cracks}/m \right]$	98.2	111.0	117.4	208.5	269.6	305.0	355.5	396.4	402.3	402.1	407.0	418.5	424.5
D_n	0.954	0.939	0.930	0.924	0.902	0.899	0.888	0.881	0.896	0.872	0.877	0.885	0.880

samples per simulation level. The results shown in Figure 3 are satisfactory in the sense that our algorithm has the ability to estimate the EOL with high precision with a moderate computational cost.

Figure 3b shows the EOL estimate by a histogram representation. The estimate is calculated by using the set of M samples from the latest subset (\mathcal{F}_3), which contributes in obtaining a higher quality of the estimate, as it is shown below.

6. DISCUSSION

To evaluate the computational improvement and accuracy that can be achieved using PFP-SubSim, the algorithm is compared with a standard PF-based prognostics algorithm in terms of efficiency in obtaining the EOL estimate. To this end, we examine the quality of an estimator based on samples from the different competing algorithms separately. Before proceeding with the analysis, we briefly review here general issues about quality of estimators.

Let $g(z_n) \ge b$, n > k, $n, k \in \mathbb{N}$ represents the fault indicator of our system, such that $P(z_t \in Z | g(z_t) \ge b) = \vartheta$, where ϑ is strictly higher than 0. By definition of T_{EOL} , the next equation also holds: $P(z_n \in Z | T_{EOL}(z_n) = 1) = \vartheta$, (see Section4). We want to obtain an estimator $\hat{\vartheta}$ from ϑ .

Suppose now that, starting at time n > k, N_{T2} samples of the joint state-parameter $\{z_n^{(v)}\}_{v=1}^{N_{T2}}$ are drawn from a state transition evolution model as in Eq. (1a) (or specifically Eq. (17), when the last two cited damage features in composites, are considered). By definition, $\{z_n^{(v)}\}$ are Markov chain samples

of multi-step ahead predictions which are distributed with equally probability among N particle trajectories. The starting points of those trajectories are the latest N updated particles at time k, i.e. $\left\{ \left(z_k^{(i)} \right), \omega_k^{(i)} \right\}_{i=1}^N$, obtained using Algorithm 1, resulting in N independent Markov chains of fixed ⁴ length N_s . Hence $N_s = N_{T2}/N$.

It is straightforward that an unbiased estimator for ϑ can be readily obtained by simulating N i.i.d. trajectories of the process using Algorithm 2 and further compute the ratio of particles that reach the threshold b, as follows:

$$\vartheta \approx \hat{\vartheta} = \frac{1}{N_{T2}} \sum_{i=1}^{N} \sum_{q=1}^{N_s} T_{EOL}^{(i,q)}$$
(19)

where $T_{EOL}^{(i,q)}$ is the value of the T_{EOL} function evaluated at sample q of the *i*th Markov chain, i.e., $T_{EOL}^{(i,q)} = T_{EOL}(z_q^{(i)})$. The coefficient of variation (c.o.v.) of the last estimator is

The coefficient of variation (c.o.v.) of the last estimator is given in Eq. (20) (the proof that Eq. (20) is the c.o.v. of $\hat{\vartheta}$ is given in the Appendix).

$$\delta_{\hat{\vartheta}} = \sqrt{\frac{(1-\vartheta)}{\vartheta N_{T2}}} \left[1+\gamma\right] \tag{20}$$

In the last equation, γ is the autocorrelation factor, which is related with the level of correlation between the samples of any of the N Markov chains (see the Appendix).

⁴Only for this comparative exercise, Algorithm 2 is run using an "ad hoc" time threshold as stopping rule, instead of using a stopping rule based on exceedance of the particle trajectory over specified thresholds, as usual.


Figure 3. Prognostics results for predicting matrix micro-cracks density from cycle $n = 4 \cdot 10^4$ using the modified Paris' law model. (a): PFP-SubSim output using $M = 2.4 \cdot 10^4$ samples per simulation level. Each subset is defined by samples (circles) in the joint state-parameter space Z, where the latest intermediate predictive samples are marked in dark purple circles. (b): Histogram representation of the estimated EOL at cycle $n = 4 \cdot 10^4$. The green triangle represents the time (in cycles) when matrix micro-cracks density will reach the final threshold b = 424 [#cracks $\cdot m^{-1}$], which was reported in (Saxena et al., 2008) (laminate L1S19), and also shown in Table 2.

On the other hand, when Algorithm 3 is used for prognostics, an unbiased estimator from ϑ can be readily obtained as $\hat{\vartheta} = (P_0)^m$, where *m* is the total number simulation levels employed by the algorithm to reach the required threshold. The c.o.v. of $\hat{\vartheta}$ can be calculated as (see Zuev et al. for a detailed demonstration):

$$\delta_{\hat{\vartheta}} = \sqrt{\left(\frac{\log(\gamma)}{\log(P_0)}\right)^2 \frac{(1-P_0)}{P_0 N_{T3}} \left[1+\gamma\right]}$$
(21)

where N_{T3} is the total amount of evaluations employed by Algorithm 3.

Our objective for this comparative exercise is to demonstrate that Algorithm 3 is able to obtain the same, or better, quality of an EOL estimate but employing less model evaluations than Algorithm 2. For simplicity but no loss of generality, let us adopt a configuration in which both algorithms give samples with equal (or similar) level of correlation between them, hence γ is equal for both algorithms. It is reasonable to hypothesize that there exist a configuration for N_{T2} and N_{T3} in which both algorithms give the same quality for the EOL estimate. Then the next equation holds:

$$\frac{(1-P_0)(\log\vartheta)^2\vartheta N_{T2}}{(1-\vartheta)(\log P_0)^2 P_0 N_{T3}} = 1$$
(22)

which is the result of dividing Eq. (21) by Eq. (20). From last equation, it is easy to obtain an expression for the number of samples N_{T2} required for Algorithm 2 to obtain an estimate of EOL with the same level of accuracy as that obtained using Algorithm 3, provided that a total amount of N_{T3} samples are employed:

$$N_{T2} = N_{T3} \underbrace{\frac{(1-\vartheta)P_0}{(1-P_0)\vartheta} \left(\frac{\log P_0^2}{\log \vartheta^2}\right)^2}_{\gg 1}$$
(23)

Observe that the factor that multiplies N_{T3} is always greater than unity, since by definition, $P_0 > \vartheta$. In rare-event problems (like asymptotic processes with conservative thresholds), $P_0 \gg \vartheta$, hence the last cited factor is fairly greater that 1, which demonstrates the high efficiency of our algorithm for prognostics of asymptotic processes.

As a numerical proof of the last postulate, the same exercise of prognostics for fatigue degradation is reproduced here although, in this case, by using the standard PF-based algorithm (Algorithm 2). The same total number of model evaluations as in Algorithm 3 is adopted, i.e. $N_{T2} = N_{T3} =$ $3 \times 2.4 \cdot 10^4 = 7.2 \cdot 10^4$, which are equally distributed among N = 100 particle trajectories. The results reveal that only 231 particles among a total amount of $7.2 \cdot 10^4$ particles reach the threshold, in contrast to 2383 particles scrutinized when PFP-SubSim was employed. Since these particles serve to define the EOL sample size, a poorer EOL estimate is obtained when using Algorithm 2 and only a better estimate may be obtained by employing more simulations, which necessarily increases the computational cost. These results suggest that high efficiency can be gained by employing the PFP-SubSim algorithm for prognostics of asymptotic processes.

7. CONCLUSION

A new algorithm for PF-based prognostics has been presented in this paper. The algorithm combines the prognostics principles with the Subset Simulation method to achieve efficiency for simulating asymptotic processes. We demonstrate the computational efficiency and accuracy that can be gained with the novel algorithm in a case study about predicting the saturation of matrix micro-cracks due to fatigue damage in composites, that illustrate some of the challenges in a real-world application of the algorithm. The main conclusions of this work are:

- PFP-SubSim gets efficiency by adaptively simulating samples over a nested sequence of subsets until the final prognostic threshold is reached. The sequence of subset are adopted in an automated manner, which avoids tedious preliminary calibrations.
- For the case study considered, PFP-SubSim outperforms the standard PF-based prognostic algorithm, typically used by the prognostic community. It is demonstrated that PFP-SubSim is able to obtain the same quality of an EOL estimator by employing significant less evaluations.
- More research effort is required to formally explore the optimal calibration aspects of the algorithm using a variety of examples of application.

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NOMENCLATURE AND BASIC RELATIONS

The next are nomenclature description and basic relations to help understand the case study presented here (Section 5.1).

h Ply thickness

h_{90}	$[90_n]$ -sublaminate half-thickness
h_{ϕ}	$\left[\phi_{\frac{n_{\phi}}{2}}\right]$ -sublaminate thickness
λ	Ply thickness ratio $\lambda = \frac{h_{\phi}}{h_{90}}$
\overline{l}	Average dimensionless half spacing of cracks, $\bar{l} = \frac{l}{h_{00}}$
E_{x}^{90}	Undamaged x-direction $[90_n]$ sublaminate modulus
$E_{x,0}$	Undamaged x-direction laminate Young's modulus
E_x^*	Damaged x-direction laminate Young's modulus
$E_x^{(\phi)}$	Longitudinal Young's modulus
$E_y^{(\phi)}$	Transverse Young's modulus
$ u_{xy}^{(\phi)}$	In-plane Poisson ratio
σ_{x}	Maximum applied stress

The function a in Eq. (12) can is expressed as a function of the laminate and ply properties listed above as:

$$a = \frac{E_y h_{90}}{E_x h_{\phi}} \left(1 - \nu_{xy}^{(\phi)} \frac{\frac{\nu_{xy}^{(\phi)} h_{90}}{E_y^{(\phi)}} + \frac{\nu_{xy} h_{\phi}}{E_y}}{\frac{h_{90}}{E_y^{(\phi)}} + \frac{h_{\phi}}{E_x}} \right) \frac{1 - \nu_{xy} \nu_{xy}^{(\phi)}}{1 - \nu_{xy}^2 \frac{E_y}{E_x}}$$
(24)

REFERENCES

- Arulampalam, M. S., Maskell, S., Gordon, N., & Clapp, T. (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *Signal Processing, IEEE Transactions on*, 50(2), 174–188.
- Au, S., & Beck, J. (2001). Estimation of small failure probabilities in high dimensions by Subset Simulation. *Probabilistic Engineering Mechanics*, 16(4), 263–277.
- Au, S., & Beck, J. (2003). Subset Simulation and its application to seismic risk based on dynamic analysis. *Journal* of Engineering Mechanics, 129(8), 901-917.
- Beck, J. (2010). Bayesian system identification based on probability logic. *Structural Control and Health Monitoring*, 17(7), 825–847.
- Cappe, O., Guillin, A., Marin, J., & Robert, C. (2004). Population Monte Carlo. *Journal of Computational and Graphical Statistics*, *13*(4), 907-927.
- Chiachío, M., Chiachío, J., Saxena, A., Rus, G., & Goebel, K. (2013). Fatigue damage prognosis in FRP composites by combining multi-scale degradation fault modes in an uncertainty Bayesian framework. In *Proceedings of Structural Health Monitoring*, 2013 (Vol. 1).
- Chiachío, J., Chiachío, M., Saxena, A., Rus, G., & Goebel, K. (2013). An energy-based prognostics framework to predict fatigue damage evolution in composites. In *Proceedings of the Annual Conference of the Prognostics and Health Management Society*, 2013 (Vol. 1, pp. 363–371).
- Ching, J., Au, S., & Beck, J. (2005). Reliability estimation of dynamical systems subject to stochastic excitation using Subset Simulation with splitting. *Com*-

puter Methods in Applied Mechanics and Engineering, 194(12-16), 1557–1579.

- Daigle, M., & Goebel, K. (2011). Multiple damage progression paths in model-based prognostics. In *Aerospace conference*, 2011 IEEE (pp. 1–10).
- Garrett, K., & Bailey, J. (1977). Multiple transverse fracture in 90° cross-ply laminates of a glass fibre-reinforced polyester. *Journal of Materials Science*, *12*(1), 157– 168.
- Gordon, N., Salmond, D., & Smith, A. (1993). Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEEE-Proceedings-F*, 140, 107–113.
- Gudmundson, P., & Weilin, Z. (1993). An analytic model for thermoelastic properties of composite laminates containing transverse matrix cracks. *International Journal* of Solids and Structures, 30(23), 3211–3231.
- Hashin, Z. (1985). Analysis of cracked laminates: a variational approach. *Mechanics of Materials*, 4(2), 121–136.
- Highsmith, A., & Reifsnider, K. (1982). Stiffness-reduction mechanisms in composite laminates. *Damage in composite materials, ASTM STP*, 775, 103–117.
- Joffe, R., & Varna, J. (1999). Analytical modeling of stiffness reduction in symmetric and balanced laminates due to cracks in 90 layers. *Composites Science and Technology*, 59(11), 1641–1652.
- Larrosa, C., & Chang, F. (2012). Real time in-situ damage classification, quantification and diagnosis for composite structures. In *Proceedings of the 19th International Congress on Sound and Vibration* (Vol. 15).
- Lundmark, P., & Varna, J. (2005). Constitutive relationships for laminates with ply cracks in in-plane loading. *International Journal of Damage Mechanics*, *14*(3), 235– 259.
- Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., & Teller, E. (1953). Equation of state calculations by fast computing machines. *The journal of chemical physics*, *21*, 1087–1092.
- Nairn, J., & Hu, S. (1992). The initiation and growth of delaminations induced by matrix microcracks in laminated composites. *International Journal of Fracture*, 57(1), 1–24.
- Nairn, J. A. (1989). The strain energy release rate of composite microcracking: a variational approach. *Journal* of Composite Materials, 23(11), 1106–1129.
- Nairn, J. A. (1995). Some new variational mechanics results on composite microcracking. In *Proc. 10th international conference on composite materials (iccm-10) whistler bc, canada.*
- Orchard, M., Kacprzynski, G., Goebel, K., Saha, B., & Vachtsevanos, G. (2008). Advances in uncertainty representation and management for particle filtering applied to prognostics. In *International conference on prognostics and health management.*

- Rubin, D. (1987). A noniterative sampling/importance resampling alternative to the data augmentation algorithm for creating a few imputations when the fraction of missing information is modest: the SIR algorithm (discussion of tanner and wong). *Journal of American Statistical Association*, 82, 543–546.
- Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., ... Tarantola, S. (2008). *Global sensitivity analysis: The primer*. Wiley-Interscience.
- Sankararaman, S., & Goebel, K. (2013). Uncertainty quantification in remaining useful life of aerospace components using state space models and inverse FORM. In AIAA, ASME, ASCE, AHS, ASC, Structures, Structural Dynamics, and materials conference (pp. 1–10). AIAA.
- Saxena, A., Goebel, K., Larrosa, C., & Chang, (2008).CFRP *Composites* F. dataset. (NASA Ames Prognostics Data Repository, [http://ti.arc.nasa.gov/project/prognostic-datarepository], NASA Ames, Moffett Field, CA)
- Saxena, A., Goebel, K., Larrosa, C., Janapati, V., Roy, S., & Chang, F. (2011). Accelerated aging experiments for prognostics of damage growth in composites materials. In *The 8th International Workshop on Structural Health Monitoring, F.-K. Chang, editor.* (Vol. 15).
- Zuev, K., Beck, J., Au, S., & Katafygiotis, L. (2011). Bayesian post-processor and other enhancements of Subset Simulation for estimating failure probabilities in high dimensions. *Computers & Structures*, 93, 283-296.

BIOGRAPHIES

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Guillermo Rus started his research on computational mechanics at the University of Granada (UGR, 1995), where he disputed the PhD thesis on Numerical Methods for Nondestructive Identification of Defects (2001). He applied these experimentally at the NDE Lab at MIT (USA) as a Fulbright Postdoctoral Fellow, rendering novel robust quantitative approaches to ultrasonics monitoring. He started up the NDE Lab at the UGR (www.ugr.es/ endlab) as assistant professor in 2003, focusing on bioengineering applications in collaboration with University College London, Universit Paris VI and the Nanomaterials Technology Lab. (Spain), among others. He is also transferring this diagnosis technology to civil engineering for monitoring structural health of advanced materials, such as FRP damage state monitoring. Rus tenured as associate professor in 2009 at UGR, is the author of 30 SCI papers, 9 books chapters, 3 patents and 18 invited seminars. His research career has been awarded by the Juan Carlos Simo prize for young researchers (Spain, 2007), the Honorary Fellowship of the Wessex Institute of Technology (UK, 2005), Fulbright Fellowship (USA, 2002) and the Excellence PhD award (Granada, 2001).

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APPENDIX

Let $T_{EOL}^{(i,q)}$ be the threshold function as defined in Section 2.1 and applied for the *q*th sample in the *i*th Markov chain, i.e. $T_{EOL}^{(i,q)} = T_{EOL}(z_{(i,q)}), i = 1, ..., N, q = 1, ..., N_s$. Observe that $T_{EOL}^{(i,q)}$ is a Bernoulli random variable of parameter ϑ . It is straightforward to obtain an unbiased estimator for ϑ by simulating N i.i.d. trajectories of the process and further compute the ratio of particles that reach the threshold b, as follows:

$$\vartheta \approx \hat{\vartheta} = \frac{1}{N_{T2}} \sum_{i=1}^{N} \sum_{q=1}^{N_s} T_{EOL}^{(i,q)}$$
(25)

where $T_{EOL}^{(i,q)}$ is the *q*th Bernoulli trial at trajectory *i*. The variance of $\hat{\vartheta}$ can be calculated as:

$$\operatorname{Var}\left[\hat{\vartheta}\right] = \mathbb{E}\left[\hat{\vartheta} - \vartheta\right]^{2} = \mathbb{E}\left[\frac{1}{N_{T2}}\sum_{i=1}^{N}\sum_{q=1}^{N_{s}}\left(T_{EOL}^{(i,q)} - \vartheta\right)\right]^{2}$$
$$\frac{1}{N_{T2}}\sum_{i=1}^{N}\underbrace{\mathbb{E}\left[\sum_{q=1}^{N_{s}}\left(T_{EOL}^{(i,q)} - \vartheta\right)\right]^{2}}_{(*)} \tag{26}$$

Note that (*) can be evaluated by means of the autocovariances of the stationary sequence $T_{EOL}^{(i,q)}$, $q = 1, \ldots, N_s$, as:

$$\mathbb{E}\left[\sum_{q=1}^{N_s} (T_{EOL}^{(i,q)} - \vartheta)\right]^2 = \sum_{q,l=1}^{N_s} \varphi^{(i)}(l)$$
(27)

where $\varphi^{(i)}(l)$ is the autocovariance of the *i*th chain at lag l from q, i.e., $\varphi^{(i)}(l) = \mathbb{E}\left[T_{EOL}^{(i,q)}T_{EOL}^{(i,q+l)}\right] - \vartheta^2$, $l = 1, \ldots, N_s$. In the last equation, it is assumed that each trajectory is probabilistically equivalent, which is motivated by the use of PF with sequential importance resampling (SIR), as in Algorithm 1. Therefore, we will use the term $\varphi(l)$ with independence of the chain index i.

Next, we evaluate Eq. (27):

$$\sum_{q,l=1}^{N_s} \varphi(l) = N_s \varphi(0) + 2 \sum_{l=1}^{N_s - 1} (N_s - q) \varphi(l) \qquad (28)$$

and substitute Eq. (28) into Eq. (26):

$$\operatorname{Var}\left[\hat{\vartheta}\right] = \frac{\varphi(0)}{N_{T2}} \left[1 + 2\underbrace{\sum_{l=1}^{N_s - 1} \left(\frac{N_s - l}{N_s}\right) \frac{\varphi(l)}{\varphi(0)}}_{\gamma}\right] \quad (29)$$

Note that $\varphi(0)$ is the variance of any *i*th Markov chain $T_{EOL}^{(i,q)}$, which is compounded by Bernoulli trials of parameter ϑ , hence $\varphi(0) = \operatorname{Var}\left[T_{EOL}^{(i,q)}\right] = \vartheta(1-\vartheta), q = 1, \ldots, N_s$. Equation (29) can be expressed in a simplified manner, as:

$$\operatorname{Var}\left[\hat{\vartheta}\right] = \frac{\vartheta(1-\vartheta)}{N_{T2}} \left[1+\gamma\right] \tag{30}$$

where γ is a correlation factor who penalizes the quality of the estimator when highly correlated samples for the Markov chains are employed. Note that, in model-based prognostics, the value of γ is directly related with the efficiency of the *artificial dynamics* in drawing samples in Θ although it is not explicitly reflected here, since each Bernoulli trial is previously sampled from $p(\theta_t | \theta_{t-1})$ (see Algorithm 2). An study of the influence of the γ is out of the scope of this work.

Finally, the c.o.v. of $\hat{\vartheta}$, $\delta_{\hat{\vartheta}}$, is expressed as shown bellow:

$$\delta_{\hat{\vartheta}} = \sqrt{\frac{(1-\vartheta)}{\vartheta N_{T2}} \left[1+\gamma\right]} \tag{31}$$

An approach for feature extraction and selection from non-trending data for machinery prognosis

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ABSTRACT

With the paradigm shift towards prognostic and health management (PHM) of machinery, there is need for reliable PHM methodologies with narrow error bounds to allow maintenance engineers take decisive maintenance actions based on the prognostic results. Prognostics is mainly concerned with the estimation of the remaining useful life (RUL) or time to failure (TTF). The accuracy of PHM methods is usually a function of the features extracted from the raw data obtained from sensors. In cases where the extracted features do not display clear degradation trends, for instance highly loaded bearings, the accuracy of the state of the art PHM methods is significantly affected. The data which lacks clear degradation trend is referred to as non-trending data. This study presents a method for extracting degradation trends from nontrending condition monitoring data for RUL estimation. The raw signals are first filtered using a discrete wavelet transform (DWT) denoising filter to remove noise from the acquired signals. Time domain, frequency domain and timefrequency domain features are then extracted from the filtered signals. An autoregressive (AR) model is then applied to the extracted features to identify the degradation trends. Features representing the maximum health information are then selected based on a performance evaluation criteria using extreme learning machine (ELM) algorithm. The selected features can then be used as inputs in a prognostic algorithm. The feasibility of the method is demonstrated using experimental bearing vibration data. The performance of the method is evaluated on the accuracy of RUL estimation and the results show that the method can be used to accurately estimate RUL with a maximum error of 10%.

1. INTRODUCTION

The last one decade has seen focus shifting towards predictive maintenance strategies where maintenance action is taken based on future health state prediction of a component or system. Accurate prediction of the future health or damage propagation of a component provides the maintenance engineers with time to appropriately schedule maintenance without affecting operations. Autonomous systems can also use the predictions to adapt to the prevailing conditions, such that their missions are accomplished. Unlike diagnosis which deals with events that have already occurred, prognosis is much more difficult since it deals with stochastic events that are yet to occur (Kim, Tan, Mathew, & Choi, 2012). Although numerous prognostic methods have been proposed, they are still at the experimental stage (Dragomir, Gouriveau, Minca, & Zerhouni, 2009). This could be attributed to the wide error bounds associated with most algorithms such that maintenance engineers would not have confidence to allow a system to operate once a fault has been identified. Another challenge is the long computational time for both training and prediction, displayed by most methods, rendering them unsuitable for real time prognosis.

Prognosis is a function of the features extracted from the raw data and therefore it is important that the features extracted contain maximum information regarding degradation trend for the predictions to be accurate. Depending on the type of component or system, the observed features may show an increasing or decreasing trend. However, there are situations where the data does not show any observable trend (non-trending data), making long-term prognosis very difficult. Figure 1 (a) shows data with observable degradation trend while (b) shows data with no observable trend until failure.

Various attempts to extract features that represent degradation trends in machinery components have been made. Amongst these attempts is the use of time-frequency methods and autoregressive models. Gu et al., (Gu, Zhao, & Zhang, 2013) introduced a hybrid approach based on autoregressive filter to remove discrete frequencies from a bearing signal and empirical mode decomposition to extract the residual signal which contains the degradation trend. However, the performance of this approach on the ability to provide accurate RUL estimation was not evaluated. Junsheng et al., (Junsheng, De-

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Figure 1. Extracted features from (a) trending data and (b) non-trending data.

jie, & Yu, 2006) presented a fault diagnosis approach based on empirical mode decomposition (EMD) and autoregressive (AR) model which was verified with experimental data on the ability to accurately diagnose bearing faults. Zhang et al., (Y. Zhang, Zuo, & Bai, 2013) proposed a fault diagnosis and performance degradation method based on multiple features, where singular values and autoregressive model parameters are extracted from the results of empirical mode decomposition of the raw signals. Kernel principal component analysis (KPCA) was then employed for feature transformation and reduction. However, the capability of the method to identify performance degradation was not verified. In addition, although PCA has been successfully applied in feature reduction for diagnosis purposes, it may not suitable for prognosis since it orthogonally transforms features which makes them loose important degradation information. Recently, EMD has received a lot of attention as a feature extraction technique for non-stationary signals (Georgoulas, Loutas, Stylios, & Kostopoulos, 2013; Wang, Lu, Wang, Liu, & Fan, 2013; Yu, Dejie, & Junsheng, 2006; Xiong & Yang, 2012). This method is able to enhance impulses in signals, associated with faults and is therefore more suited for fault diagnosis rather than prognosis, where the ability to identify continued degradation is important. Since not all of the extracted features contain important information on degradation trend, it is important to select the features that accurately represent the degradation process.

There has been considerable effort to develop algorithms for automatic feature selection. However, most of these algorithms are focused on feature selection for fault diagnosis or health state based prognosis. In this case, features are selected based on their capability to discriminate between different classes (fault categories or health states). Linear discriminant analysis (LDA) which is based on the assumption that different classes generate data based on Gaussian distributions has been employed in feature selection for fault classification (Bator, Dirks, Monks, & Lohweg, 2012). Distance evaluation technique which computes the largest distance separating data between classes is another feature selection technique that has been employed to select the optimal features that represent the different health states of a degrading component (Kim et al., 2012). Camci et al., (Camci, Medjaher, Zerhouni, & Nectoux, 2012) proposed a feature evaluation method for effective bearing prognostics based on separability value. The features were divided into time segments and the separability of the segments based on 25th and 75th percentile distributions computed. The overall separability value of each feature was then computed as a feature evaluation value. However, the performance of this method for accurate prognosis was not evaluated. The use of separability of features as a method of feature selection can also be found in (Medjaher, Camci, & Zerhouni, 2012). Benkedjouh et al., (Benkedjouh, Medjaher, Zerhouni, & Rechak, 2013) employed isometric feature mapping reduction technique to find a small number of features that represent a large number of observations. The accuracy of the method on ability to improve prognosis was not evaluated. Other methods of feature selection or selection can be found in (Li et al., 2011; Sugumaran, Muralidharan, & Ramachandran, 2007; K. Zhang, Li, Scarf, & Ball, 2011). Saxena and Vachtsevanos, (Saxena & Vachtsevanos, 2007) explored the capabilities of multicore cell processing environment for feature extraction and selection for on-board diagnosis and prognosis. Their effort was concentrated on developing parallel algorithms for Fast Fourier Transforms (FFTs) that could speed up their implementation. Tran and Yang, (Tran & Yang, 2010) presented a method for feature selection based on classification and regression trees. The feature selection was however conducted for classification of faults only and not for prognosis. Ramasso and Gouriveau, (Ramasso & Gouriveau, 2010) proposed a prognostics method involving three modules, observation selection, prediction and classification. A method for feature selection was also presented but found to have high computational requirements. From the literature surveyed, it is evident that there is a need to develop an effective feature selection approach for prognosis based on regression approach.

This paper presents a feature extraction method based on combination of a wavelet denoising filter and autoregressive model with automatic model order selection for feature extraction and the use of kernel based ELM for feature selection based on performance evaluation criteria of the extracted features. This feature extraction approach has the capability of extracting degradation trends from non-trending data. The performance of the method based on ability to provide accurate RUL estimations using ELM is also demonstrated.

2. PROPOSED METHOD

The proposed method involves denoising the raw signals using discrete wavelet transform (DWT) denoising then extracting time, frequency and time-frequency domain features. An AR model is then established for each of the extracted features. The optimum features are then selected using kernel based ELM algorithm. Finally the performance of the method is evaluated using the same kernel based ELM algorithm. Figure 2 shows the workflow of the proposed method.

2.1. Feature Extraction

Feature extraction involves deriving time, frequency and timefrequency domain features from the raw signals which are sampled at suitable frequencies. Signals acquired from some machinery components such as faulty bearing are normally considered non-stationary, that is, frequency varies with time, and hence the extraction of time-frequency features. In this work, wavelet packet decomposition (WPD) is employed for the extraction of the time-frequency features. The denoised signal is decomposed up to 3 levels using bior3.7 wavelet. The detail coefficients from level 1 to 3 and the approximate coefficient for level 3 are then obtained. The wavelet energy is then computed from the wavelet coefficients. Fast Fourier Transform (FFT) is employed to extract the frequency domain features. A total of 19 features, 12 time domain, 3 frequency domain and 4 time-frequency domain from each signal may be extracted from the denoised signals. A summary of these features is presented in Table 1 (Galar, Kumar, & Zhao, 2012; Maio et al., 2012).

2.2. Autoregressive (AR) Model

AR model represents a time series in which the next value in the sequence is predicted based on a certain number of previous values. The AR model parameters may contain important information regarding the condition of a component (Y. Zhang et al., 2013). The following model is established to each of the extracted features f to obtain degradation trend:

$$f_n = \sum_{k=1}^p a_k f_{n-k} + e_n, \qquad n = 1, 2...N$$
(1)

where a_k are the model parameters, p is the model order, e_n is the residual of the model and N is the number of data points in f. In this work, the model parameters were determined using the Yule-Walker method (Stoica, Friedlander, & Son-



Figure 2. Workflow of the proposed method.

Time demain	factures	Chana	DMC	Dowor	חכח
nine domain	reatures	Shape	$SF = \frac{KMS}{2}$	Power	PSD
		factor	$\frac{1}{2}\sum_{i=1}^{n} x_i $	spectral	$\tilde{\Sigma}$
			$n^{2l=1}$	density of FFT	$= \sum r_k e^{-i\omega k}$
					<u>k=</u> −∞
RMS	n	Line	\sum_{n}^{n}	Time –frequence	cy domain
	$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}$	integral	$LI = \sum_{i=0} x_{i+1} - x_i $		
Variance	var	Peak to	$PP = \max(x_i) - \min(x_i)$	Energy of	$\sum_{n=1}^{n_1}$
	$1\sum_{n}^{n}$	peak value		WPD detail	$D_1 = \sum cD1_i$
	$=\frac{1}{2}\sum_{i}(x_{i}-\bar{x})^{2}$	•		coefficient	$\sum_{i=1}^{n}$
	$n \underset{i=1}{\sqsubseteq} $			one	1-1
Peak value	$PvT = \max(x_i)$	Shannon	n	Energy of	<u>n2</u>
		entropy	$Ent = -\sum_{i} x_{i}^{2} \log(x_{i}^{2})$	WPD detail	$D_{2} = \sum cD_{4}$
				coefficient	
			1-1	two	1=1
Croct factor	P12T	Skowposs	Cl.	Eporav of	n3
Clesi laciol	$CF = \frac{T V T}{T V T}$	Skewness	<i>3к</i>	Ellergy OI	∇ ∇ ∂
	RMS		$\frac{1}{n}\sum_{i=1}^{n}(x_{i}-\bar{x})^{3}$		$D_3 = \sum cD3_i$
			$=\frac{n}{\sqrt{1-\frac{3}{2}}}$	coefficient	$\overline{i=1}$
			$\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2}\right)$	three	
Kurtosis	$\sum_{i=1}^{n} (x_i - \bar{x})^4$	Frequency of	domain	Energy of	<i>n</i> 3
	$Kurt = \frac{n \times nar^2}{n \times nar^2}$			WPD	$A_3 = \sum cA_{3i}$
	-3			approximate	$\sum_{i=1}^{n}$
	0			coefficient	v - 1
				three	
Clearance	PvT	Peak	$PvF = \max(r_k)$.		
factor	$Clf = \frac{1}{(1-1)^2}$	value of			
	$\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{ x_i }\right)$	FFT	$r_{i} = \sum r(t)e^{-i\omega t}$		
	(11		$\frac{1}{\kappa} \sum_{i=-\infty}^{\kappa} \kappa(i) e^{i \pi i \pi}$		
Impulse	<i>PvT</i>	Eneray of	<u>N</u>		
factor	$IF = \frac{1}{1} \sum_{n=1}^{n} \frac{1}{n} \sum_{n=1}^{n}$	FFT	$En = \sum r_{h}$		
	$\frac{1}{n} \sum_{i=1}^{n} x_i $		$\sum_{k=1}^{r_k} r_k$		

Table	1.	Features	extracted	from	denoised	signals
rabic	1.	1 catures	extracted	nom	uchoiseu	orginais

derstrom, 1988). The performance of the AR model depends on the choice of the model order. In this study, the Akaike information criteria, *AIC* introduced by Akaike was employed (Ayalew, Babu, & Rao, 2012):

$$AIC(p) = log(\hat{\sigma}_p) + \frac{2p}{N},$$
(2)

where,

$$\hat{\sigma}_p = \frac{1}{(N-p)} \sum_{n=p+1}^{N} (f_n - \sum_{k=1}^{p} a_k f_{n-k})^2, \qquad (3)$$

The model order is varied from 1 to 100 and the model order yielding the minimum AIC is selected. The feasibility of this approach is demonstrated using the impulse factor IF, extracted from the filtered signal. For each sampled signal with M data points, IF is obtained as follows:

$$IF = \frac{\max(x_K)}{\frac{1}{M}\sum_{K=1}^{M} |x_K|}, \qquad K = 1, 2, ..M$$
(4)

Figure 3(a) shows the impulse factor of a bearing vibration signal before application of AR model, in which the degradation trend is not clearly identifiable. Figure 3(b) shows the AR model (f_{IF}) of the feature, which presents a clearer degrada-

tion trend or fault evolution trend. The AR model also acts as a filtering method, thus eliminating the noise within the extracted feature.

2.3. Extreme Learning Machine (ELM)

Extreme learning machine is a relatively new simple learning algorithm for single-hidden layer feedforward neural network (SLFN) which was first proposed by Huang in 2005 (Huang, Zhu, & Siew, 2006). Figure 4 shows the structure of a SLFN with radial basis function (RBF) hidden neurons. x_j is the input vector at the input neuron j, a_i is the input weight connecting the hidden neuron i and the input neurons, b_i is the bias of the hidden neuron β_i is the output weight of the hidden neuron i and y is the output (Huang et al., 2006).

In ELM, the input weights and hidden layer biases of SLFN are randomly generated, while the output weights linking the hidden layer to the output layer are determined through simple generalized inverse operation of the hidden layer output matrices (Huang et al., 2006). The ELM learning process is extremely fast compared to other machine learning algorithms such as support vector machines and artificial neural networks with back propagation (Huang et al., 2006). The kernel based ELM has two parameters (regularization parameter C and kernel parameter γ) that tuning. In this work, C = 7000 and $\gamma = 2.9$ were employed.



Figure 3. Extracted feature (a) Feature before application of AR model and (b) after applying AR model.



Figure 4. Structure of SLFN with RBF hidden neurons.

2.3.1. ELM Based Feature Selection

Feature selection is important for machinery prognosis in order to reduce computational time and effort, and also to avoid over-fitting of data which results to large prediction errors. In this work, kernel based extreme learning machines was employed for feature selection due to its robust predictions and fast training and prediction times. The AR features are first evaluated individually on their ability to provide accurate prognosis. The input to the ELM method is the AR features while the target vector is the fraction of the remaining useful life. The mean square error computed from the target fractional RUL and estimated fractional RUL of the training data for each individual input feature is obtained and values for all the inputs are normalized between 0 and 1. A performance evaluation criterion, *PEC* is then defined by:

$$PEC = 1 - \frac{mse}{\max(mse)} \tag{5}$$

where μ is the normalized training mean square error, *mse*.

Figure 5 shows the workflow of the feature selection algorithm.



Figure 5. Workflow of the ELM-based feature selection algorithm. i is the feature index and N is the total number of features.

To obtain the selection criteria PEC_{sc} , the PEC is varied from 0 to 1 and the mse of the training data set is obtained. The PEC value that yields the minimum mse is taken as the feature selection criteria.

2.3.2. ELM Based RUL Estimation

During the training stage of the method, the selected features are used as inputs to the PHM algorithm while the fractional remaining useful life is used as the target vector. The fractional RUL is used to take care of the varying lifetimes of machinery components. A degradation model is obtained after training, which is used together with the testing input features to predict the fractional RUL of the test data.

Given the current time, t_c , and the fractional RUL, F_c , the es-



Figure 6. Estimating the RUL from the current time and fractional RUL.

timated remaining useful life RUL can be obtained by similar triangles as follows:

$$RUL = t_{EOL} - t_c = \frac{t_c}{1 - F_c} F_c \tag{6}$$

where t_{EOL} is the time to end of life of the component.

3. APPLICATION EXAMPLE

To demonstrate the applicability of the method, a case study was conducted. Run to failure rolling element bearing data provided for the 2012 PHM data challenge was employed (Nectoux et al., 2012). The data consists of run to failure vibration data recorded by two accelerometers, along the vertical direction and along the horizontal direction, sampled at a frequency of 25.6 kHz with 2560 samples recorded at intervals of 10 seconds. Two complete run to failure data sets are provided for algorithm training and five truncated run to failure data are provide for testing. The challenge is to provide an estimation of the remaining useful life of the test bearings (Nectoux et al., 2012).

The features detailed in section 2.1 were extracted and an AR model applied. The proposed feature selection method described in section 2.3.1 was then applied. Figure 7 shows the mse as a function of PEC.



Figure 7. Mean square error, mse as a function of performance evaluation criteria, PEC for the training data set.

From Figure 7, it is evident that features with a performance evaluation criteria value of 0.65 yield the lowest mse. Therefore a selection criterion of $PEC_{sc} = 0.65$ was employed in this study. Based on this selection criterion, 11 out of 38 features were selected. Figure 8 shows the PEC value of each feature. It can be observed that not many features from the vertical acceleration were selected. The vibration signal from the vertical accelerometer was highly impulsive which led to high mean square errors. Although the features extracted from the vertical accelerometer may not be suitable for prognosis, they may provide valuable information about the nature and location of faults within the bearings.



Figure 8. Performance evaluation criteria of the extracted features described in section 2.1, (a) horizontal vibration and (b) vertical vibration.

The selected features were then extracted from the denoised signals of the training and test data. An AR model was applied to the resulting features in order to obtain inputs to the ELM algorithm. The ELM method was then trained with the AR features as the input and fractional lifetime as the target vector. A degradation model consisting of the number of neurons, the input and output weights of the hidden layer was obtained. The AR features from the test data were then used as inputs to the degradation model and the estimated fractional lifetime obtained as the output.

Using Eq. 6, the RUL of the five test bearings were computed from the fractional lifetime obtained as the output from the ELM algorithm. Figure 9 shows curves of the estimated RUL, the actual RUL and predicted RUL of bearing 1_3. RUL_c is the RUL at the current time. The predicted RUL is obtained by fitting a linear curve from the current time to the point where the RUL is zero

Figure 9 shows that the accuracy of the method increases towards the end of life of the component. This is the most critical stage of the prognosis since it signifies that the maintenance engineers should start planning for maintenance.



Figure 9. Estimated, actual and predicted RUL for bearing 1_3 versus the operation time.

The performance of the method was evaluated based on performance metrics such as percentage RUL error and percentage accuracy as shown below:

$$\% Error = \frac{ActRUL - estRUL}{ActRUL} \times 100, \tag{7}$$

where ActRUL is the actual RUL of the test data provided for validation of the prognostic methods and estRUL is the estimated RUL. Table 2 shows the performance of the proposed method based on percentage error and percentage accuracy. The estimated RUL is based on the current time.

Table 2. Performance of the proposed method based on prognostic performance metrics.

Test	% Error
Bearing 1_3	0.44
Bearing 1_4	5.31
Bearing 1_5	-4.94
Bearing 1_6	-8.41
Bearing 1_7	3.71

The negative percentage error signifies late prediction or overestimation of RUL, which is usually not desirable in machinery prognosis since the machine may breakdown before the scheduled maintenance, depending on the margin of error of the estimation. Table 1 shows the proposed method yields accuracies within 10% error bounds. This would be a good reference for maintenance.

4. CONCLUSION

The accuracy of any prognostic algorithm is a function of the information contained in the input features which are extracted from the raw condition monitoring data. A method for feature extraction and selection for machinery prognosis based on autoregressive modeling and extreme learning machine is presented. The proposed feature extraction method is able to identify degradation trends in condition monitoring data for effective prognosis. The feasibility of the method is demonstrated using bearing run-to-failure experimental data. The results show that the proposed method is effective in estimating the remaining useful life of machinery components, with error bounds within a 10% bandwidth. The results also show that feature selection improves the accuracy of RUL estimation significantly. Therefore, we conclude that the proposed method of feature extraction and selection can be used as an effective tool for estimating the remaining useful life of machinery components.

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REFERENCES

- Ayalew, S., Babu, M. C., & Rao, L. K. M. (2012). Comparison of new approach criteria for estimating the order of autoregressive process. *IOSR Journall of Mathematics*, 1(3), 10–20.
- Bator, M., Dirks, A., Monks, U., & Lohweg, V. (2012). Feature extraction and reduction applied to sensorless drive diagnosis. 22. Workshop, Computational Intelligence, Dortmund, 163–178.
- Benkedjouh, T., Medjaher, K., Zerhouni, N., & Rechak, S. (2013). Remaining useful life estimation based on nonlinear feature reduction and support vector machines. *Engineering Application of Artificial Intelligence*, 26, 1751–1760.
- Camci, F., Medjaher, K., Zerhouni, N., & Nectoux, P. (2012). Feature evaluation for effective bearing prognostics. *Quality and Reliability Engineering International.*
- Dragomir, O. E., Gouriveau, F. D., Minca, E., & Zerhouni, N. (2009). Review of prognostic problem in conditionbased maintenance. *European Control Conference*, *ECC'09*.
- Galar, D., Kumar, U., & Zhao, W. (2012). Remaining useful life estimation using time trajectory tracking and support vector machines. In 25th international congress on condition monitoring and diagnostic engineering.
- Georgoulas, G., Loutas, T., Stylios, C. D., & Kostopoulos. (2013). Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition. *Mechanical Systems and Signal Processing*, 41(1-2), 510– 525.
- Gu, H., Zhao, J., & Zhang, X. (2013). Hybrid methodology of degradation feature extraction for bearing prognostics. *Mainten ance and Reliability*, 15(2), 195–201.
- Huang, G.-B., Zhu, Q.-Y., & Siew, C.-K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, 70, 489–501.
- Junsheng, C., Dejie, Y., & Yu, Y. (2006). A fault diagnosis

approach for roller bearings based on emd method and ar model. *Mechanical Systems and Signal Processing*, 20, 350–362.

- Kim, H.-E., Tan, A. C. C., Mathew, J., & Choi, B.-K. (2012). Bearing fault prognosis based on health state probability estimation. *Expert Systems with Applications*, 39, 5200–5213. doi: 10.1016/j.eswa.2011.11.019
- Li, B., Zhang, P.-L., Tian, H., Mi, S.-s., Liu, D.-s., & Ren, G.-q. (2011). : A new feature extraction and selection scheme for hybrid fault diagnosis of gearbox. *Expert Systems with Applications*, *38*, 10000–10009.
- Maio, F. D., Hu, J., Tse, P., Petch, M., Tsui, K., & Zio, E. (2012). Ensemble-approaches for clustering health status of oil sand pumps. *Expert Systems with Applications*, 39, 4847-4859.
- Medjaher, K., Camci, F., & Zerhouni, N. (2012). Feature extraction and evaluation for health assessment and failure prognostics. *Proceedings of First European Conference of the Prognostics and Health Management Society*,.
- Nectoux, P., Gouriveau, R., Medjaher, K., Ramasso, E., Morello, B., Zerhouni, N., & Varnier, C. (2012). Pronostia: An experimental platform for bearing accelerated degradation tests. *IEEE International Conference on Prognostics and Health Management, Denver, CO, USA.*
- Ramasso, E., & Gouriveau, R. (2010). Prognostics in switching systems: Evidential markorvian classification of real-time neuro-fuzzy predictions. In *Ieee international* conference on prognostics and system health management, macau.
- Saxena, A., & Vachtsevanos, G. (2007). Optimum feature selection and extraction for fault diagnosis and prognosis. In *Proceedings of the 2007 aaai fall symposium on artificial intelligence for prognosis.*
- Stoica, P., Friedlander, B., & Sonderstrom, T. (1988). A high-order yule-walker method for estimation of the ar parameters of an arma model. *Systems and Control Letters*, 99–105.
- Sugumaran, V., Muralidharan, V., & Ramachandran, K. I. (2007). Feature selection using decision tree and classification through proximal support vector machine for fault diagnostics of roller bearings. *Mechanical Systems and Signal Processing*, 21, 930–942.
- Tran, V. T., & Yang, B.-S. (2010). Machine fault diagnosis

and condition prognosis using classification and regression trees and neuro-fuzzy inference systems. *Control and Cybernetics*, *39*, 22-54.

- Wang, Z., Lu, C., Wang, Z., Liu, H., & Fan, H. (2013). Fault diagnosis and health assessment for bearings using the mahalanobis-taguchi system based on EMD-SVD. *Transactions of the Institute of Measurement and Control*, 35(6), 798–807.
- Xiong, X., & Yang, S. (2012). A new procedure for extracting fault feature of multi-frequency signal from rotating machinery. *Mechanical Systems and Signal Processing*, 32, 306–319.
- Yu, Y., Dejie, Y., & Junsheng, C. (2006). A roller bearing fault diagnosis method based on emd energy entropy and ann. *Journal of Sound and Vibration*, 294, 269– 277.
- Zhang, K., Li, Y., Scarf, P., & Ball, A. (2011). Feature selection for high-dimensional machinery fault diagnosis data using multiple models and radial basis function networks. *Neurocomputing*, 74, 2941–2952.
- Zhang, Y., Zuo, H., & Bai, F. (2013). Classification of fault location and performance degradation of a roller bearing. *Measurement*, 46, 1178–1189.

BIOGRAPHIES

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Investigating Computational Geometry for Failure Prognostics in Presence of Imprecise Health Indicator: Results and Comparisons on C-MAPSS Datasets

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ABSTRACT

Prognostics and Health Management (PHM) is a multidisciplinary field aiming at maintaining physical systems in their optimal functioning conditions. The system under study is assumed to be monitored by sensors from which are obtained measurements reflecting the system's health state. A health index (HI) is estimated to feed a data-driven PHM solution developed to predict the remaining useful life (RUL). In this paper, the values taken by an HI are assumed imprecise (IHI). An IHI is interpreted as a planar figure called polygon and a case-based reasoning (CBR) approach is adapted to estimate the RUL. This adaptation makes use of computational geometry tools in order to estimate the nearest cases to a given testing instance. The proposed algorithm called RULCLIP-PER is assessed and compared on datasets generated by the NASA's turbofan simulator (C-MAPSS) including the four turbofan testing datasets and the two testing datasets of the PHM'08 data challenge. These datasets represent 1360 testing instances and cover different realistic and difficult cases considering operating conditions and fault modes with unknown characteristics. The problem of feature selection, health index estimation, RUL fusion and ensembles are also tackled. The proposed algorithm is shown to be efficient with few parameter tuning on all datasets.

1. INTRODUCTION

Knowledge-based systems and Case-Based Reasoning approaches (CBR) have appeared as suitable tools for data-driven Prognostics and Health Management (PHM) (Saxena, Wu, & Vachtsevanos, 2005; T. Wang, Yu, Siegel, & Lee, 2008; T. Wang, 2010; Ramasso, Rombaut, & Zerhouni, 2013). In CBR, historical instances of the system - with condition data and known failure time - are used to create a library of degradation models or health indices. Then, for a test instance, the similarity with the degradation models is evaluated generating a set of *Remaining Useful Life* (RUL) estimates which are finally aggregated.

The required assumptions for CBR implementation are limited, the main issues consisting in, on the one hand, the choice of an appropriate similarity measure and, on the other hand, the selection of the relevant training instances. CBR approaches are also flexible since it is simple to incorporate quantitative and qualitative pieces of knowledge such as measurements and expertise.

We consider applications for which the noise due to various sources, such as operational conditions or fault modes, can not be well characterised and where filtering may change the meaning of the health index. We assume that the health index can not be well defined by a single real value but only by *Imprecise Health Index* (IHI). To fix ideas, an illustration taken from the turbofan engine dataset (Saxena, Goebel, Simon, & Eklund, 2008) (used and detailed in experiments) is given in Figure 1. The figure pictorially represents the IHI taken from the fourth dataset (made of two fault modes and six operating conditions) for the 8th training data (P_1), the 100th training data (P_2) and the 1st testing data (P_3) of this dataset. As depicted, fault modes may generate

- sudden changes in wear (e.g in P₁, t ∈ [225, 275]) that may increase the lifetime of the unit. It may be due to both fault modes and operating conditions, for example a drastic decrease of speed to cope with mechanical incidents or meteorological phenomenons.
- Unexpected changes in the trend, such as increasing instead of decreasing (e.g. P_2 , t > 125) that may disturb the algorithm. It may be due to component failures such

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as sensors or electronics.

Sudden bursts characterised by low signal-to-noise ratio (SNR) on a possibly short duration which deeply affect the HI (e.g. on P₃ with t ∈ [10, 75]) that may affect the lifetime accordingly to the fault type which is generally unknown.



Figure 1. Effect of fault modes and operating conditions on health indices estimation. HIs (here obtained from training instances) are described with planar figures called polygons.

The representation and the propagation of imprecision (or uncertainty) is of paramount importance in engineering analyses (Vachtsevanos, 2006; Orchard, Kacprzynski, Goebel, Saha, & Vachtsevanos, 2008; Beer, Ferson, & Kreinovich, 2013). Several mathematical theories (Klir & Wierman, 1999) have been used in prognostics such as probability theory (including Bayesian approaches) (Peng et al., 2012), set-membership approaches (including fuzzy-sets) (Chen, Zhang, Vachtsevanos, & Orchard, 2011; El-Koujok, Gouriveau, & Zerhouni, 2011) and Dempster-Shafer's theory of belief functions (Serir, Ramasso, & Zerhouni, 2012; Ramasso et al., 2013). Facing imprecision in HIs for prognostics is thus not new but the way to handle it can be considered differently.

We assume 1-D health index to be available but obtained from noisy measurements. The data points are supposed to represent vertices of a simple planar polygon. The IHI is thus a polygon-shaped health index represented by a planar figure. Three polygons are depicted in Figure 1. Using computational geometry tools, a prognostics method is proposed that handles IHI without knowing nor estimating the noise properties. The method is based on CBR for which a similarity measure adapted to IHI and polygon is developed. The set of cases is made of training instances represented by polygons and the similarity with a testing instance recorded on the in-service system is made dependent on the degree of *inter*section between both training and testing polygon instances. The prognostics algorithm introduced is called "RULCLIP-PER" (Remaining Useful Life estimation based on impreCise heaLth Index modeled by Planar Polygons and similaritybasEd Reasoning").

The next Section is dedicated to the presentation of a methodology to build imprecise health index and perform prognostics. The methodology is then applied on C-MAPSS datasets.

2. PROGNOSTICS BASED ON IMPRECISE HEALTH INDEX: A CBR APPROACH

A health index (HI) takes the form of a 1-dimensional real-valued signal $H = [x_1 \ x_2 \dots \ x_j \dots \ x_T]^T, x_j \in \mathbb{R}$ obtained at some instants $t_1, t_2 \dots \ t_T$.

2.1. Polygon-shaped representation of IHI

An IHI is defined as a polygon where each vertex is represented by a data point estimated from the original HI. The set of vertices is obtained by first rearranging the data points to define an ordered sequence that is made possible by extracting the upper and lower envelopes of the noisy HI. For that, let's define $\tilde{H} = [\tilde{x}_1 \ \tilde{x}_2 \dots \ \tilde{x}_j \dots \ \tilde{x}_T]^T$ a smooth HI obtained by applying a *filter* over H such that the extraction of both envelopes of H is made *easier*. The filter used in this paper was a 15-point moving average.

A polygon (representing an IHI) is thus defined as a set of pairs (x_j, t_j) made of HI values x_j at time index t_j .

The upper envelope of H denoted S is defined by

$$S = \{ (x_j, t_j) | x_j \ge \tilde{x}_j \} \cup \{ (x_{j-1}, t_j) | x_j < \tilde{x}_j \} , \quad (1)$$

meaning that, for a given data point j, if the HI value x_j at time t_j is greater than the filtered value \tilde{x}_j then the upper envelope is equal to the HI value, otherwise it takes its previous value. The lower envelope \mathcal{I} is defined similarly by

$$\mathcal{I} = \{ (x_j, t_j) | x_j < \tilde{x}_j \} \cup \{ (x_{j-1}, t_j) | x_j \ge \tilde{x}_j \} .$$
 (2)

The ordered pairs of vertices listed counterclockwise represents a bounding closed polygonal chain that separates the plane into two regions. The word "polygon" refers to a plane figure bounded by the closed path defined as:

$$\mathcal{P} = \left\{ (x_1, t_1)^{\mathcal{S}}, (x_2, t_2)^{\mathcal{S}} \dots (x_j, t_j)^{\mathcal{S}} \dots (x_T, t_T)^{\mathcal{S}}, (x_T, t_T)^{\mathcal{I}}, (x_{T-1}, t_{T-1})^{\mathcal{I}} \dots (x_1, t_1)^{\mathcal{I}}, (x_1, t_1)^{\mathcal{S}} \right\}$$
(3)

with $(x_j, t_j)^{\mathcal{S}} \in \mathcal{S}$ and $(x_j, t_j)^{\mathcal{I}} \in \mathcal{I}$. To close the polygon, the first and last vertices are the same. The pairs of vertices define a finite sequence of straight line segments representing the polygon.

More specifically, a polygon is a region of the plane enclosed by a simple cycle of straight line segments where nonadjacent segments do not intersect and two adjacent segments intersect only at their common endpoint (Rosen, 2004). However, the second part of the definition of the bounds may generate some segment intersections. These inconsistencies can be corrected easily by exchanging the corresponding values of the lower and upper bounds when an intersection is detected. When consistent bounds are obtained, the polygon is made of nonintersecting line segments which characterise a Jordan's simple closed curve also called *simple* polygon (Filippov, 1950). This category of polygon enables one to apply some standard algorithms from Computational Geometry (Rigaux, Scholl, & Voisard, 2002; Rosen, 2004; Longley, de Smith, & Goodchild, 2007). Note that some of the most efficient algorithms for operations on polygons can manage self-intersections (Vatti, 1992; Greiner & Hormann, 1998) but these inconsistencies generally increase time-consumption.

2.2. CBR approach for prognostics based on IHI

2.2.1. Training dataset

We assume the training dataset to be composed of N training instances:

$$\mathcal{L} = \{\mathcal{P}_i, \mathcal{K}_i\}_{i=1}^N \tag{4}$$

where \mathcal{P}_i is the *i*th polygon attached to the *i*th imprecise health index H_i and $\mathcal{K}_i = [y_1 \ y_2 \dots \ y_j \dots \ y_T]^T, y_j \in$ \mathbb{N} represents a discrete-valued signal reflecting a system's state. The component \mathcal{K}_i may be useful in some applications where the system can be described by means of latent variables (Ramasso & Denoeux, 2013; Javed, Gouriveau, & Zerhouni, 2013). In that case, \mathcal{K}_i may represent a partial knowledge about the state. For example, in (Ramasso et al., 2013), partial knowledge was encoded by belief functions to express imprecision and uncertainty about the states.

2.2.2. Determining the nearest case

A testing instance takes the form of a health index H^* from which the envelopes can be estimated as explained in the previous paragraph, leading to the polygon representation \mathcal{P}_* . As in usual CBR approaches for prognostics (T. Wang, 2010; Ramasso et al., 2013), the goal is to sort the training instances with respect to their similarity to the testing instance. However, since the training instances are made of polygons, the usual Euclidean distance is not adapted. We propose the following similarity measure.

Getting inspired from the Computer Vision community (Powers, 2011), recall, precision and F_{β} indices are used to quantify the relevance of a training instance compared to the testing one. Precision represents the fraction of the retrieved instance that is relevant, while recall is the fraction of the relevant instance that is retrieved. The F_{β} is an harmonic mean which gives equal weight to recall and precision when $\beta = 1$. Note that the three indices are normalised into [0, 1].

More precisely, for the *i*th training instance:

1. Estimate the area of the intersection between the polygon \mathcal{P}_i and \mathcal{P}_* :

$$\mathcal{A}_{\cap} = \operatorname{Area}\left(\mathcal{P}_i \cap \mathcal{P}_*\right) \tag{5}$$

2. Compute the "recall":

$$R_{\rm ec} = \frac{\mathcal{A}_{\cap}}{\mathcal{A}_i} \tag{6}$$

3. Compute the "precision":

$$P_{\rm rec} = \frac{\mathcal{A}_{\cap}}{\mathcal{A}_*} \tag{7}$$

4. Compute the " $F_{\beta,i}$ ", in particular for $\beta = 1$, characterizing the similarity with the *i*th training instance:

$$F_{1,i} = 2\frac{R_{\rm ec} \cdot P_{\rm rec}}{R_{\rm ec} + P_{\rm rec}} \tag{8}$$

where A_i, A_*, A_{\cap} represent the area of polygons $\mathcal{P}_i, \mathcal{P}_*$ and of their intersection respectively.

Example 1 An illustration of intersection is given in Figure 2 where the darkest polygon represents a training instance and the two other polygons are testing ones. The whitest polygon is within the testing instance meaning that the precision is high, but the recall is pretty low since it covers only a small part of the testing instance. On the opposite, the third polygon covers entirely the testing instance leading to a high recall but its spread decreases the precision.



Figure 2. Illustration of recall and precision.

Practically, intersection construction is the main difficulty and was tackled quite recently in computational geometry for arbitrary planar polygons. It consists in determining the region of geometric intersection which can be performed in three phases (Rosen, 2004) (Chap. 38):

- Compute the intersection between the boundaries of the objects using the linearithmic plane sweep algorithm (Bentley & Ottmann, 1979);
- 2. If the boundaries do not intersect then determine whether one object is nested within the other;
- 3. If the boundaries do intersect then classify the resulting boundary fragments gathered to create the final intersec-

)

tion region (Margalit & Knott, 1989; Chazelle & Edelsbrunner, 1992), which can be performed in linearithmic time. Regularized Boolean operations ensure the closure of the interior of the set-theoretic intersection.

In this paper, the Vatti's algorithm (Vatti, 1992) has been used because it is generic and can manage most of pratical cases. Several implementations of this algorithm have been proposed, especially in (Greiner & Hormann, 1998) which was shown to be particularly efficient.

2.2.3. Estimating the Remaining Useful Life (RUL)

The F_1 measure is used to sort the N training polygon instances in descending order: $\mathcal{P}_{(1)} > \mathcal{P}_{(2)} \cdots > \mathcal{P}_{(j)} \cdots > \mathcal{P}_{(N)}$ so that $\mathcal{P}_{(1)}$ is the closest instance to the testing one and $\mathcal{P}_{(N)}$ the farthest one. The index (i) in $\mathcal{P}_{(i)}$ represents a reordering and the symbol > in $\mathcal{P}_{(i)} > \mathcal{P}_{(j)}$ means that the *i*th polygon is more similar to the testing instance that the *j*th.

CBR assumes that a limited number of instances, say K, are enough to approximate the testing instance. The K closest training instances can then be combined to estimate the RUL. The length of a training instance minus the length of a testing instance provides an estimation of the RUL (Figure 3). Given the definition of a polygon (Section 2.1) and of the training dataset (Eq. 4), the length of both the training and testing polygon instances is given by T_i and T_* respectively. Therefore, the estimated RUL is given by

$$\hat{RUL} = T_i - T_* . \tag{9}$$

Example 2 Two polygons are illustrated in Figure 3, one coming from the training dataset #1 (the tenth instance) and one from the testing dataset #1 (the first instance). Since $T_1 = 222$ and $T_* = 31$, the estimated RUL is 191 time-units.



Figure 3. Polygon instances: training (\mathcal{P}_1) and testing (\mathcal{P}_*) .

Each closest training instance $\mathcal{P}_{(i)}$ can be accompanied by a state sequence $\mathcal{K}_{(i)}$ so that K estimations of the RUL, denoted $\hat{\text{RUL}}_{\mathcal{K}}$, can be obtained from the state sequences in addition to the ones obtained with $\mathcal{P}_{(i)}$ and denoted $\hat{\text{RUL}}_{\mathcal{P}}$.

Using $\mathcal{K}_{(i)}$, the last transition in the sequence is supposed to represent a jump of the system to a faulty state. This assumption relies on the fact that the last part of a training instance represents the system's end-of-life (Ramasso et al., 2013; Ramasso & Gouriveau, 2013; Javed et al., 2013).

The 2K estimations of the RUL can then be pooled in one set: $\hat{RUL}_{PK} = \{\hat{RUL}_{P}, \hat{RUL}_{K}\}$ and an information fusion process can then be performed to combine these partial RUL estimates. According to the application, the fusion rule can be adapted (Kuncheva, 2004).

A plot chart of RULCLIPPER algorithm is depicted in Figure 4. Some of the elements will be illustrated in the next section dedicated to experiments.

3. EXPERIMENTS: METHOD

RULCLIPPER is tested on the datasets obtained from the turbofan engine degradation simulator (Saxena, Goebel, et al., 2008). Before presenting results, several details about the datasets have to be presented, in particular how to select the features and how to compute the health index.

3.1. Turbofan engine degradation simulator

The simulation model (Saxena, Goebel, et al., 2008) was built on the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) developed at NASA Army Research Lab., able to simulate the operation of an engine model of the 90.000 lb thrust class. A total of 21 output variables were recorded to simulate sensor measurements to the system. Another 3 variables representing the engine operating conditions were recorded, namely altitude (kilo feet), Mach number (speed) and Throttle Resolver Angle (TRA) value which is the angular deflection of the pilot's power lever having a range from 20% to 100%. In the sequel, references to variables are made by using their column position in the data files as provided on the data repository of the Prognostics Center of Excellence website: it begins by number 6 and finishes to 26 (see (Saxena, Goebel, et al., 2008) for details).

3.2. Datasets

Six datasets generated from independent simulation experiments were provided, each with some specificities (Saxena, Goebel, et al., 2008).

Datasets #1 and #2 include only one fault modes (HPC degradation) while datasets #3 and #4 include two (HPC degradation and fan degradation). Datasets #1 and #3 include a single operational condition against six for datasets #2 and #4. Dataset #4 represents the most complex case study. Datasets # 5_T (semi-final testing dataset) and # 5_V (final validation dataset) were generated for the 2008's PHM data challenge with one fault mode and six operating conditions. The two last datasets have common training instances. A summary of



Figure 4. The sequence of operations involved in the proposed approach.

the six datasets are shown in Table 1 according to information taken from (Saxena, Goebel, et al., 2008).

Each dataset is divided into training and testing subsets. The training set includes instances with complete run-to-failure data (to develop life prediction models), and the actual failure mode for training instances in #3 and #4 is not labeled. The testing datasets include instances with data up to a certain cycle and are used for RUL estimation and algorithm performance evaluation.

The testing instances are also simulated run-to-failure and only an earlier portion of the history is provided. The actual life (RUL) of the testing instances are known only for datasets #1, #2, #3 and #4 and can only be used for testing algorithm. For datasets $\#5_T$ and $\#5_V$, results have to be uploaded to the data repository: uploading is allowed only once a day for $\#5_T$ whereas only a single try is possible for dataset $\#5_V$.

The validation can be performed by many performance measures (Saxena, Celaya, et al., 2008) among which accuracybased measures such as the *timeliness*, also called scoring function in the sequel since it has been used in the data challenge to sort participants algorithm. The review of papers using the C-MAPSS datasets show that the timeliness was the most used performance measure (about 30% of papers). Note that, for datasets $\#5_T$ and $\#5_V$, this performance measure is returned for each submission by the data challenge chairs.

For comparison purpose, the scoring function is also used in

this paper with the same parameters as in the challenge:

$$S = \sum_{n=1}^{N} S_n \tag{10a}$$

$$S_n = \begin{cases} e^{-d_n/13} - 1, d_n \le 0\\ e^{d_n/10} - 1, d_n > 0 \end{cases}, n = 1 \dots N$$
(10b)

$$d_n = \text{estimated RUL} - \text{true RUL}$$
 (10c)

This function, that assigns higher penalty to late predictions, has to be minimised. In addition to the scoring function (computed for all datasets), a second performance measure was used (on datasets #1 to #4 for which we know the RUL) called accuracy measure A that evaluates the percentage of testing instances for which the RUL estimate is within the interval [-13, +10] around the true RUL (Saxena, Celaya, et al., 2008). These values are the same as the scoring function and was used in several papers such as (Ramasso et al., 2013) for dataset #1.

3.3. Related results on C-MAPSS

For comparison purpose, results of predictions from other researchers (as exhaustive as possible) on these datasets are summarised below for each dataset. Note that some authors also used the simulator to create their own datasets (Sarkar, Jin, & Ray, 2011; Zein-Sabatto, Bodruzzaman, & Mikhail, 2013; Al-Salah, Zein-Sabatto, & Bodruzzaman, 2012). References have been put on the NASA PCOE website.

To our knowledge, the full testing dataset of #1 was only used in two papers: In (Liu, Gebraeel, & Shi, 2013) where

	C-MAPSS DATASETS						
Datasets		FURBI	FOFAN	1	CHALLENGE		
	#1	#2	#3	#4	$#5_T$	$\#5_V$	
Nb. of faults	1	1	2	2	1	1	
Nb. of operating conditions	1	6	1	6	6	6	
Nb. training instances	100	260	100	249	2	218	
Nb. testing instances	100	259	100	248	218	435	
Minimum RUL	7	6	6	6	10	6	
Maximum RUL	145	194	145	195	150	190	

Table 1. Datasets characteristics according to the organisers. In this paper, results for all datasets are provided in the experiments, but more details are given specifically for datasets #1 and #3. Note that the datasets called "data challenge" have a common training datasets made of 218 instances. The "semi-final" testing dataset ($\#5_T$) is made of 218 instances and the "final" validation dataset ($\#5_V$) is made of 435 instances.

the authors reported results by using an average error between true RUL and prediction; and to evaluate the EVIPRO algorithm in (Ramasso et al., 2013) where the performance was assessed by using the accuracy measure which was equal to 53% on the testing dataset #1. The full testing datasets of #2, #3, #4 were not used in the past (only a few instances were considered in a few papers).

Testing datasets $\#5_T$ (corresponding to a "semi-final" testing dataset) and $\#5_V$ (corresponding to the "final" validation dataset) represent datasets for which the true RULs is *not known*. These datasets were used in many papers summarised in Table 2 (for published work after 2008) and in Table 3 (for results of challengers during the competition in 2008). The complete review of scores on these datasets were found on the web or obtained by request to the conference chairs. In Table 3, methods (1), (2) and (3) were published in (T. Wang et al., 2008), (Heimes, 2008) and (Peel, 2008) respectively.

It can be observed that no score has been mentioned in the literature on the final validation dataset $\#5_V$ since 2008, whereas the semi-final testing dataset $\#5_T$ was used in several papers. The final dataset is complex and the performances obtained by the challengers are high. According to our knowledge, good performances (in terms of scoring) can be obtained on the final dataset only if the algorithm is robust. Indeed, a few important mistakes (too late or too early predictions) can lead to bad scores. This was also observed with RULCLIPPER on the other datasets. Robustness can be evaluated by computing several PHM metrics (Saxena, Celaya, et al., 2008) as proposed in (T. Wang, 2010).

Therefore, the generalisation capability of the algorithm should be ensured before trying the final dataset. This is illustrated in Tables 2-3 and Figure 6 which depict the scores obtained on the semi-final dataset $\#5_T$ and on the final dataset $\#5_V$. Some algorithms exhibited very low score on $\#5_T$ (made of 218 instances), whereas a relatively poor score was obtained on the final dataset. The winner obtained 737 on $\#5_T$ (according to the conference chairs) which is not the best score, but only 5636 on the final dataset $\#5_V$.

Algo. (pseudo.)	$#5_T$	$\#5_V$
RULCLIPPER	752	11572
SBL (P. Wang, Youn, & Hu, 2012)	1139	n.a.
DW (Hu, Youn, Wang, & Yoon, 2012)	1334	n.a.
OW (Hu et al., 2012)	1349	n.a.
MLP (Riad, Elminir, & Elattar, 2010)	1540	n.a.
AW (Hu et al., 2012)	1863	n.a.
SVM-SBI (Hu et al., 2012)	2047	n.a.
RVM-SBI (Hu et al., 2012)	2230	n.a.
EXP-SBI (Hu et al., 2012)	2282	n.a.
GPM3 (Coble, 2010)	2500	n.a.
RNN (Hu et al., 2012)	4390	n.a.
REG2 (Riad et al., 2010)	6877	n.a.
GPM2B (Coble, 2010)	19200	n.a.
GPM2 (Coble, 2010)	20600	n.a.
GPM1 (Coble, 2010)	22500	n.a.
QUAD (Hu et al., 2012)	53846	n.a.

Table 2. Performance of the state-of-the-art approaches on $\#5_T$ (semi-final dataset) and $\#5_V$ (final dataset) after 2008 (published work).

Note that some papers using the datasets of the data challenge are not mentioned in the table because error measures (accuracy-based) were given and that is not possible by using the original testing datasets for which the *true RULs are not known*: testing errors are not possible on testing datasets $\#5_T$ and 5_V , but only on the training dataset. This rule (defined from 2008 to 2014) may change in the near future so that other metrics (in addition to the scoring function) could be obtained on demand to the data challenge chairs.

3.4. Priors about the datasets

Some rules were used to improve prognostics on these datasets, some have been proposed in previous papers:

R1: The first rule is related to the fact that, according to (Saxena, Goebel, et al., 2008), the maximum RUL in testing instances for $\#5_T$ was greater than 10 and lower than 150 time-units, while being greater than 6 and greater than 190 in testing instances for $\#5_V$. Moreover, most of previous approaches agreed on limiting the RUL estimates around 135 (depending on papers (T. Wang et al., 2008;

A1 (1) / D (11 11 11 11 11 11 11 11 11 11 11 11 11
Algo. (pseudo.) / Data	$\# \mathfrak{I}_T$	$\# \mathfrak{I}_V$
heracles (1)	737 (3rd)	5636 (1st)
FOH (2)	512 (2nd)	6691 (2nd)
LP (3)	n.a.	25921
sunbea	436.8 (1st)	54437 (22nd)
bobosir	1263	8637
L6	1051	9530
GoNavy	1075	10571
beck1903	1049	14275
Sentient	809	19148
A	975	20471
mjhutk	2430	30861
RelRes	1966	35863
phmnrc	2399	35953
SuperSiegel	1139	154999

Table 3. Pseudonyms and scores (known on *both* $\#5_T$ and $\#5_V$) during the 2008's PHM data challenge. Methods (1), (2) and (3) were published

T. Wang, 2010; Heimes, 2008; Riad et al., 2010)) because too large and late estimates are greatly penalized by the scoring function. So, for most of tests presented below, the RUL was given by $\max(6, \min(\hat{RUL}, 135))$ where \hat{RUL} was the estimated RUL.

- **R2:** The difference between 1 and the average of the first 5% of an instance was used as an offset to compel the health index (HI) to begin around 1. Even though the health index function (Eq. 11) already compels it, there are some cases, in particular for #2, #3 and #4, for which the health index was strongly disturbed by fault modes and operating conditions.
- **R3:** To limit the impact of fault modes (datasets #3 and #4), a detection of the monotonicity (Coble, 2010) is performed. When the testing instance is less than the half of the training instance and if more than 25 consecutive samples are above the training instance, then the training instance is not taken into account. This simple rule was applied on all datasets considered (even without fault modes or without operating conditions).
- **R4:** To decrease the risk of overpredictions, the sequence of states \mathcal{K} were made of two states, the second state being activated only 15 samples before the end-of-life. This setting similar to (Ramasso & Gouriveau, 2013), was the same for all tests and all datasets.

3.5. Local/global health index estimation

To reflect a real-world and practical cases, the health indices (HI) for both training and testing datasets were not given by the organisers (Saxena, Goebel, et al., 2008). An adaptation of the approach proposed in (T. Wang, 2010) is presented below to estimate the HI for each instance. These HIs (highly corrupted by noise) are the basis of the proposed methodology described in previous sections (Fig. 4).

The set of features for the *i*th unit is $\mathbf{X}_i = [\mathbf{x}_1 \ \mathbf{x}_2 \dots \mathbf{x}_t \dots \mathbf{x}_{T_i}]^{\mathsf{T}}$

where $\mathbf{x}_t = [x_{t,1} \ x_{t,2} \dots x_{t,m} \dots x_{t,q}]$ is the q-dimensional feature vector at t (composed of sensor measurements), and \mathbf{u}_t is the vector of operating conditions at t. The operational conditions variables can be clustered into a finite number of operating regimes (T. Wang, 2010). Crisp outputs are obtained such that the current regime at time t, C_t , is precisely known. Then, for samples $(\mathbf{u}_t, \mathbf{x}_t)$ collected at early age of the system, e.g. $t < \sigma_1$, the health index attached to the *i*th training unit is $HI(\mathbf{x}_t, \boldsymbol{\theta}^p) = 1$, where the set of parameters $\boldsymbol{\theta}^p$ depends on the model used to link regimes and sensor measurements.

At late age of the system, e.g. $t > \sigma_2$, the corresponding output is HI($\mathbf{x}_t, \boldsymbol{\theta}^p$) = 0. In (T. Wang, 2010), the author used only the data at $t > \sigma_2$ and $t < \sigma_1$ in addition to 6 models (one for each operating mode) built on all data. In comparison, we propose to make use of samples between σ_1 and σ_2 while building a local model for each operating mode in each training instance. Moreover, we have used one HI for each training instance while in (T. Wang, 2010) a global HI model was estimated using all instances.

The corresponding output of the index is set to

$$\widehat{\mathrm{HI}}_{i}(\mathbf{x}_{t}, \boldsymbol{\theta}^{p}) \equiv 1 - \exp\left(\frac{\log(0.05)}{0.95 \cdot T_{i}} \cdot t\right) , t \in [\sigma_{1}, \sigma_{2}].$$
(11)

This function allows to compel the health index to be globally decreasing, from 1 (healthy) to 0 (faulty). As proposed in (T. Wang, 2010), $\sigma_1 = T_i \cdot 5\%$ and $\sigma_2 = T_i \cdot 95\%$ where T_i is the length of the *i*th training instance. We used local linear models for multi-regime health assessment so that $\boldsymbol{\theta}_i^p = [\theta_{i,0}^p \ \theta_{i,1}^p \dots \theta_{i,q}^p]$ represents the parameters of a linear model defined conditionnally to the *p*th regime. The health index at time *t* given the *p*th regime can be estimated as

$$\operatorname{HI}_{i}(\mathbf{x}_{t}, \boldsymbol{\theta}_{i}^{p}) = \theta_{i,0}^{p} + \sum_{n=1}^{q} \theta_{i,n}^{p} \cdot x_{t,n}$$
(12)

where θ^p can be estimated by standard least-squares algorithms. In experiments, in case the estimation of HI is performed by considering the three operating conditions, then it will be called a *local* approach (Fig. 4) and *global* otherwise. HIs are then transformed into IHIs as proposed in previous sections (Fig. 4).

3.6. Information fusion for improved RUL estimation

The first family of rules is a combination of minimum and maximum RUL estimates suggested in (T. Wang, 2010):

$$\alpha m M(R) = \alpha \cdot \min R + (1 - \alpha) \cdot \max R \qquad (13)$$

where R is a set of RUL estimates and $\alpha mM(R)$ the combination result. For example, in (T. Wang, 2010), $\alpha = 13/23$. In this paper, we considered $\alpha \in \{0.1, 0.2, 0.3, \dots 0.9, 13/23\}$. The authors in (T. Wang, 2010) also added two outlier removal (OR) rules to keep RULs within the interquartile range:

$$OR: \{a \in R : a \in [q_{25}, q_{75}]\}$$
(14)

and

$$WL: \{a \in R: q_{50} - 3 \cdot (q_{50} - q_{25}) < a < q_{50} + 2 \cdot (q_{75} - q_{50})\}$$
(15)

The set of RUL estimates provided by the algorithm, considering either discrete (\mathcal{K}) or continuous predictions (\mathcal{P}), is denoted

$$R \equiv \hat{\mathrm{RUL}}_{\mathcal{P}[\mathcal{K}]}^{[OR|WL],[th],M}$$
(16)

Only the M first RULs estimates were taken into account (sorted according to the F_1 measure) with $M \in \{11, 15\}$ in this study. OR|WL means that one of the outlier removal operators was applied. The optional parameter [th] means that only training instances with F_1 measure greater than 0.5 were kept.

Weighted average is the second family of rules:

$$mw_L^{[e],[OR]} = \sum_{i=1}^L \omega_i^{[e],[OR]} \cdot R_{(i)}$$
(17)

where the weights are made dependent on the similarity $F_{1,i}$ (Eq. 8) between the testing instance and the *i*th training instance; $R_{(i)}$ is the *i*th RUL estimate in set of RULs R sorted in descending order with respect to the similarity $(F_{1,i})$; $L \in$ $\{3, 5, 7, 9, 11, 15\}$ is the number of RULs kept to compute the average while applying or not the outlier removal rule OR. The weights are given by the following equations:

$$\omega_i = F_{1,i} / \sum_{k=1}^{L} F_{1,k} , \qquad (18)$$

with softmax normalisation:

$$\omega_i^e = \exp(F_{1,i}) / \sum_{k=1}^L \exp(F_{1,k}) , \qquad (19)$$

using outlier removal (OR):

$$\omega_i^{OR} = OR(F_{1,i}) / \sum_{k=1}^{L} OR(F_{1,k}) , \qquad (20)$$

and combining OR and softmax:

$$\omega_i^{e,OR} = \exp(OR(F_{1,i})) / \sum_{k=1}^{L} \exp(OR(F_{1,k})) .$$
 (21)

The third kind of rules is a combination of the previous ones:

$$\hat{\text{RUL}} = 0.5 \cdot \alpha m M(R) + 0.5 \cdot m w_L^{[e],[OR|WL]}$$
(22)

Considering several combinations of parameters, about 3168

rules were considered.

3.7. Selecting the subset of sensors

As shown by the literature review presented beforehand, many combinations of features can be used (among 21 variables), and a subset was particularly used made of features $\{7, 8, 12, 16, 17, 20\}$ (involving key sensors for the turbofan degradation (Sarkar et al., 2011)). To this preselection, a subset of sensors was added from every possible subsets with cardinality equal to 1, 2, 3 and 4 in $\{\emptyset, 9, 10, 11, 13, 14, 18, 19, 22, 25, 26\}$ as well as subsets of cardinality 5 comprising sensor 9 leading to a total of 511 cases. For each combination (511 cases for each dataset), we applied the prognostics algorithm RULCLIPPER introduced previously and the best subset was selected by minimising the scoring function.

3.8. Testing datasets

Given the training instances of a given dataset, the first task is to create a testing dataset in order to estimate 1) the input features and 2) the fusion RUL of RULCLIPPER. The training instances were truncated at a time instant randomly selected from a uniform distribution between 10% and 80%of the half-remaining life. This procedure allowed to obtain instances with small enough RULs to allow the occurrence of substantial degradation, and also large enough RULs to test the robustness of algorithms (Hu et al., 2012). The obtained testing datasets were used in RULCLIPPER with all subsets of features (511 subsets, 3168 fusion rules) and with two subsets of features (511 × 511 combinations for each fusion rule).

4. RESULTS AND DISCUSSIONS

Results are presented and compared to past work for all datasets (turbofan and data challenge). More details are given for datasets #1, #3 and $\#5_T$ and $\#5_V$.

4.1. Performances on datasets #1 and #3

The results can be represented in the penalty – accuracy plane for all combinations of features. A point in that plane with coordinates $(P_1(S_1, A_1))$ is obtained by considering the accuracy (A_1) for the lowest penalty score (S_1) given a subset of features. In order to represent the imprecision concerning the performances, a second point $P_2(S_2, A_2)$ is taken and defined by the lowest score plus 25% $(S_2 = S_1 + 25\%S_1)$ with accuracy (A_2) : these two points define a rectangle in the penalty – accuracy plane.

Figure 5 represents the accumulation of these rectangles for all combinations of features in the testing datasets #1 and #3. The whitest part corresponds to the area where most of rectangles are located and thus to the likeliest performances given several subsets of features. If the white area is large then it means that the subset of features should be carefully

selected. If the area is concentrated then several subsets of features provided similar performances: it is an image of the robustness with respect to the choice of the subsets. The scores have been divided by the number of testing instance for comparison purpose.

For dataset #1, the performance's centroid is located around (60%; 4.0) (or (60%; 400)). One can draw any subset of features (among the 511 combinations considered) and can expect a score between S = 310 and S = 440 with an accuracy between A = 56 and A = 64. A few "optimal" subsets led to better performances (reported in Table 4 for the testing datasets). The effect of the fault mode on the performances is important. The scores are more spread and a clear global decrease of the accuracy is observed (translation of the cluster of performances to the left hand-side). The level of the colorbar indicates that the choice of the features becomes more and more crucial as the difficulty of the dataset increases: it is simpler to find a subset of features for dataset #1 leading to low penalty and high accuracy because the level is quite similar on a large area (with a value around 8). However, it is more sensitive for dataset #3 for which the level is around 12 on a very local area. A similar (and magnified) observation was obtained on the other datasets.



Figure 5. Performances for #1 (top) and #3 (bottom).

Based on these results obtained on the testing datasets, the fusion rule and the subset of features were selected for final evaluation of the testing datasets by minimising the scoring function (as done for the PHM data challenge) and maximising the accuracy. The results obtained on the testing datasets #1 and #3 are summarised in Table 4 (note that the features indicated in the table have to be assembled with features 7, 8,

12, 16, 17, and 20). For each dataset, the combinations of features are given with respect to the two best scores ("Best S") and the two best accuracies ("Best A"). For example, the first line of Table 4 concerns dataset #1 for which the best score is S = 261 (with A = 63%) when using features 9, 10, 14, 25 and 26, and the RUL fusion " $0.9mM(\hat{\text{RUL}}_{\mathcal{P}}^{th,11}) \oplus mw_7$ " which corresponds to the combination of two elements: 1) the output of the min/max operator (Eq. 13) with parameter $\alpha = 0.9$ applied on the 11 first RUL estimates and keeping only estimates with a similarity greater than 0.5, and 2) the weighted average (Eq. 17) of the L = 7 first RUL estimates after outlier removal. The high value of α (0.9) implies more weight to the minimum (early) estimate. An accuracy of 70%on #1 was obtained with the same subset of features while keeping a low score at S = 301. This accuracy obtained by the RULCLIPPER algorithm is significantly higher (+16%)than the previous known results given by the EVIPRO-KNN algorithm (Ramasso et al., 2013) which yielded 53%. Other metrics were computed (see Table 6) for performance comparison with previous approaches: An exponential-based regression model with health index estimation proposed in (Liu et al., 2013) that provided MAPE = 9% on #1 and an Echo State Network with Kalman filter and submodels of instances presented in (Peng et al., 2012) with¹ MSE = 3969.

The part entitled (#1, #3)/S indicates the best scores for the same subset of features tested with the same fusion method on both datasets. Considering simultaneously #1 and #3 is equivalent to a situation where the engine is degrading while developing a fault. As the score is low and the accuracy high on both datasets using the same subset of features and the same method, it means that this parameterisation makes the prognostics robust to the introduction of the fault mode.

4.2. RULCLIPPERs ensemble to manage sensors faults

Two RULCLIPPERs were considered, each with one particular subset of features. All couples of subsets of features were studied (about 130000 combinations) on each testing dataset. The best couples are given in Table 5.

Beyond the important improvement of scores and accuracies compared to the previous results (Table 4), it shows it is not enough to take the two subsets leading to the two best results and expecting an improvement of the performances. Indeed, in most cases, performances for the single feature subsets selected are not the best ones, but their combination yielded to significative improvement of the performances compared to Table 4. For example, for dataset #1, combining RUL estimates provided by subset of features {10, 11, 14, 22} (in addition to 7, 8, 12, 16, 17, 20) with {13, 18, 19, 22} led to S = 216 and P = 67%. It represents 27% of improvement on the score and +4% on accuracy compared to the best per-

¹Authors in (Peng et al., 2012) actually provided the best RMSE obtained equal to 63, so MSE was computed as $3969 = 63^2$.

TYPE	DATA	FEATURES	FUSION	S	A
Best /S	#1	9, 10, 14, 25, 26	$0.9mM(\hat{\text{RUL}}_{\mathcal{P}}^{th,11}) \oplus mw_7$	272	68
Best /A	#1	9, 10, 14, 25, 26	$0.9mM(\hat{RUL}_{\mathcal{P}}^{th,11}) \oplus mw_{13}$	301	70
Best /S	#3	9, 13, 14, 22, 26	$0.9mM(\hat{RUL}_{\mathcal{PK}_{11}}^{WL,11}) \oplus mw_3^{OR}$	353	57
Best /A	#3	9, 19, 25	$0.8mM(\hat{RUL}_{\mathcal{PK}}^{WL,11})$	632	63
Best /A (2)	#3	18, 25, 26	$\mid mw^{e,OR}_{e,5} \oplus mw_5$	580	63
Best /A (3)	#3	9, 10, 14, 18, 25	$0.8mM(\hat{RUL}_{\mathcal{PK}}^{WL,11}) \oplus mw_3$	476	60
(#1, #3) /S	#1	9, 11, 14, 25, 26	$0.9mM(\hat{RUL}_{\mathcal{P}}^{th,11}) \oplus mw_9^{e,OR}$	294	64
	#3	—	-	480	55
(#1, #3) /S(2)	#1	9, 10, 14, 25, 26	$0.9mM(\hat{\mathrm{RUL}}_{\mathcal{P}}^{tn,11}) \oplus mw_{13}^{OR}$	299	63
	#3	-	-	480	56
(#1, #3) /S(2)	#1	9, 10, 14, 25, 26	$0.9mM(\hat{\mathrm{RUL}}_{\mathcal{P}}^{th,11}) \oplus mw_5^{OR}$	315	66
	#3	_		435	54

Table 4. Subset of features (in addition to 7, 8, 12, 16, 17, 20) leading to the best performances in terms of scores (and the corresponding accuracies) for each dataset using a single RULCLIPPER.

Data	Туре	Subset 1	S_1	$Fear P_1$	atures Subset 2	S_2	P_2	Fusion	S	Р
1	Best /S	10, 11, 14, 22	301	64	13, 18, 19, 22	325	62	$0.9mM(\hat{\text{RUL}}_{\mathcal{P}}^{th,11}) \oplus mw_5^{OR}$	216	67
#1	Best /A	10, 11, 14, 22	301	64	13, 18, 19, 22	325	62	$0.9mM(\hat{\mathrm{RUL}}_{\mathcal{P}}^{th,11}) \oplus mw_7^{OR}$	224	70
	Best /S	13, 19, 25, 26	525	61	9, 13, 14, 22, 26	353	58	$0.9mM(\hat{\text{RUL}}_{\mathcal{P}}^{th,11})$	317	59
#3	Best /A	14, 18, 19, 26	499	61	9, 10, 13, 14, 26	399	58	$0.9mM(\hat{\mathrm{RUL}}_{\mathcal{P}}^{WL,15}) \oplus mw_{11}^{OR}$	332	63

Table 5. Combination of subsets of features (in addition to 7, 8, 12, 16, 17, 20) leading to the best performances in terms of scores (and the corresponding accuracies) for each dataset using the fusion of two RULCLIPPERs.

formances obtained in Table 4 with subset $\{13, 14, 18, 25\}$, and more when considering the performances of single subsets ($S_1 = 301$ and $P_1 = 64\%$, or $S_2 = 325$ with $P_2 = 62\%$). Similar observations can be made on #3.

4.3. Results on the PHM data challenge $(\#5_T, \#5_V)$

Based on the 218 training instances provided, RULCLIPPER was run on the testing dataset using the 511 combinations of features with the 3168 fusion rules. The results were sorted by ascending order with respect to the scoring function. The first five best subsets of features were then selected: $\{9, 11, 26\}$, $\{9, 18, 22, 25\}$, $\{9\}$, $\{9, 10, 13, 25\}$, $\{9, 10, 18, 25, 26\}$ (in addition to 7, 8, 12, 16, 17, 20 for each subset).

These combinations of features were considered and evaluated on the dataset $\#5_T$. The best score was given by averaging three configurations of RULCLIPPERs, each with ensembles based on three subsets of features:

- RULCLIPPER 1 with inputs {9, 11, 26}, {9, 18, 22, 25} and {9};
- RULCLIPPER 2 with inputs {9, 11, 26}, {9, 18, 22, 25} and {9, 10, 13, 25};
- RULCLIPPER 3 with inputs {9, 11, 26}, {9, 18, 22, 25} and {9, 10, 18, 25, 26}.

The RUL limit was set to 135 as described in Section 3.4 and the fusion rule was the same for all individual RULCLIP-PER, namely $0.9mM(\hat{RUL}_{PK}^{11}) \oplus mw_{15}^{OR}$. The score obtained on dataset $\#5_T$ (on the NASA's website) was equal to 752, which is the 3rd score compared to published works. An alternative was considered by increasing the RUL limit from 135 to 175. The fusion rule was the same as previously and the score obtained was 934 which is quite low relatively to the high risk taken by setting the RUL limit to 175.

The average of the three configurations given above provided a set of RULs parameterised by both a RUL limit (135, 175) and a fusion method. Three parameterisations were considered and combined: $\Omega_1 = (135, 0.8 m M (R \hat{U} L_{PK}^{11}) \oplus m w_5^{OR})$, $\Omega_2 = (175, 0.9 m M (R \hat{U} L_{PK}^{11}) \oplus m w_9^{OR})$, and $\Omega_3 = (175, 0.9 m M (R \hat{U} L_{PK}^{11}) \oplus m w_{15})$. The motivation of this configuration was to make long-term predictions possible while minimising the risk of making late predictions. The RULs obtained by Ω_2 and Ω_3 were averaged and the resulting combined by a weighted average with with Ω_1 . The weights were set by a sigmoid (with shape parameter: 0.3 and position: 120) to increase the importance of RULCLIPPERs Ω_2 and Ω_3 when the estimation is greater than 120 while giving more importance to Ω_1 otherwise. This methodology was then applied with the final testing dataset $(\#5_V)$ yielding 11672. The comparison with approaches can be quantified on Figure 6. The generalisation of RULCLIP-PER parameterised as proposed in this paper is lower than the first five algorithms (see square markers on the left-hand side). Indeed, some of these algorithms provided higher scores on $\#5_T$ but lower on the final dataset $\#5_V$. One explanation accounting for the lack of generalisation capability compared to the first five algorithms may hold in the "rules" integrated in RULCLIPPER (section 3.4). These rules have been tuned according to observations on the five other datasets but may be not relevant for dataset $\#5_V$ if the statistics governing the generation of instances have been modified (Saxena, Goebel, et al., 2008). In order to show the applicability of RULCLIP-PER algorithm with as less parameterisation as possible, the author intentionally kept the same settings for all datasets without distinction in particular concerning the number of fault modes or thresholds on RUL limits.

However, the generalisation is better than the 23 remaining algorithms, for which lower scores on $\#5_T$ have been obtained with higher ones on $\#5_V$ (see square markers on the right-hand side). RULCLIPPER provided a relatively low score on both datasets using the same parameters (816 on $\#5_T$ and 11672 on $\#5_V$). The authors remarked on the previous datasets (#1 to #4) that a few instances can disturb the algorithm (in particular to test the robustness), generating very late or very early predictions, degrading drastically the scores. The important difference on scores between $\#5_T$ and $\#5_V$ can be due to this particularity.

A summary of results of RULCLIPPER on C-MAPSS datasets is given in Table 6. The best performances were selected according to the scoring function (better accuracies can be obtained as shown in previous tables but with lower scores). Metrics are defined in (Saxena, Celaya, et al., 2008).

5. CONCLUSION

The RULCLIPPER algorithm is proposed to estimate the remaining lifetime of systems in which noisy health indices are assumed imprecise. RULCLIPPER is made of elements inspired from both the computer vision and computational geometry communities and relies on the adaptation of casebased reasoning to manage the imprecise training and testing instances. The combination of these elements makes it an original and efficient approach for RUL estimation as shown in experiments.

RULCLIPPER was validated with the six datasets coming from the turbofan engine simulator (C-MAPSS), including the so-called turbofan datasets (four datasets) and the data challenge (two datasets), and compared to past work. These datasets are considered as complex due to the presence of fault modes and operating conditions. In addition to RUL-CLIPPER, a method was proposed to estimate the health indicator (in presence of faults and operating conditions) and the problem of the selection of the most relevant sensors was also tackled. Information fusion rules were finally studied to combine RUL estimates as well as ensemble of RULCLIPPERs. The review of past work, the presentation of the datasets, as well as the results on sensor selection, health index estimation, information fusion rules and RULCLIPPER ensembles are expected to give a hand to other researchers interested in testing their algorithms on these datasets.

The use of the same algorithm (RULCLIPPER) for all datasets lets suppose that, more generally, computational geometry seems promising for PHM in presence of noisy HIs. However, as for all similarity-based matching algorithm (T. Wang, 2010), the computational cost associated to sort instances is the most important limitation of RULCLIPPER. Two solutions can be considered. Firstly, since operations on convex polygons are simpler (and faster), a procedure can be used to approximate the bounds and to decrease the number of segments.

The second solution concerns implementations, particularly of the intersection algorithm. Computational geometry has become a very active field in particular to improve memory and time requirements, with applications in multimedia (computer graphics such as games). CUDA implementations on processor arrays (using graphic cards) can be pointed out as a promising solution. With such implementations, real-time and anytime prognostics can be considered. The extension of RULCLIPPER to multiple health indices is also under study, in particular by using polytopes.

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REFERENCES

- Al-Salah, T., Zein-Sabatto, S., & Bodruzzaman, M. (2012). Decision fusion software system for turbine engine fault diagnostics. In *Southeastcon*, 2012 proceedings of ieee (p. 1-6).
- Beer, M., Ferson, S., & Kreinovich, V. (2013). Imprecise probabilities in engineering analyses. *Mechanical Systems and Signal Processing*.
- Bentley, J., & Ottmann, T. (1979). Algorithms for reporting and counting geometric intersections. *IEEE Trans. Comput.*, C28, 643-647.
- Chazelle, B., & Edelsbrunner, H. (1992). An optimal algorithm for intersecting line segments in the plane. J.



Figure 6. Comparison of RULCLIPPER with other state-of-the-art approaches. Some scores on the testing dataset $\#5_T$ are missing. Scores have to be minimised.

RULCLIPPER performance							
Dataset	#1	#2	#3	#4	$#5_T$	$#5_V$	
Score	216	2796	317	3132	752	11672	
Accuracy (%)	67	46	59	45	n.a.	n.a.	
FPR (%)	56	51	66	49	n.a.	n.a.	
FNR (%)	44	49	34	51	n.a.	n.a.	
MAPE (%)	20	32	23	34	n.a.	n.a.	
MAE	10	17	12	18	n.a.	n.a.	
MSE	176	524	256	592	n.a.	n.a.	

Table 6. Summary of results.

Assoc. Comput. Mach, 39, 1-54.

- Chen, C., Zhang, B., Vachtsevanos, G., & Orchard, M. (2011). Machine condition prediction based on adaptive neuro-fuzzy and high-order particle filtering. *IEEE Transactions on Industrial Electronics*, 58(9), 4353-4364.
- Coble, J. (2010). Merging data sources to predict remaining useful life - an automated method to identify prognostic parameters (Unpublished doctoral dissertation). University of Tennessee, Knoxville.
- El-Koujok, M., Gouriveau, R., & Zerhouni, N. (2011). Reducing arbitrary choices in model building for prognostics: An approach by applying parsimony principle on an evolving neuro-fuzzy system. *Microelectronics Reliability*, 51(2), 310 - 320.
- Filippov, A. (1950). An elementary proof of Jordan's theorem. Uspekhi Mat. Nauk, 5, 173-176.
- Greiner, G., & Hormann, K. (1998). Efficient clipping of arbitrary polygons. ACM Trans. on Graphics, 17, 71-

83.

- Heimes, F. (2008). Recurrent neural networks for remaining useful life estimation. In *Ieee int. conf. on prognostics* and health management.
- Hu, C., Youn, B., Wang, P., & Yoon, J. (2012). Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. *Reliability Engineering and System Safety*, 103, 120 - 135.
- Javed, K., Gouriveau, R., & Zerhouni, N. (2013). Novel failure prognostics approach with dynamic thresholds for machine degradation. In *Ieee industrial electronics conference*.
- Klir, G., & Wierman, M. (1999). Uncertainty-based information. elements of generalized information theory. In (chap. Studies in fuzzyness and soft computing). Physica-Verlag.
- Kuncheva, L. I. (2004). *Combining pattern classifiers: Methods and algorithms*. Wiley-Interscience.
- Liu, K., Gebraeel, N. Z., & Shi, J. (2013). A data-level fu-

sion model for developing composite health indices for degradation modeling and prognostic analysis. *IEEE Trans. on Automation Science and Engineering.*

- Longley, P., de Smith, M., & Goodchild, M. (2007). *Geospatial analysis : A comprehensive guide to principles, techniques and software tools.* Matador, Leicester.
- Margalit, A., & Knott, G. (1989). An algorithm for computing the union, intersection or difference of two polygons. *Computers & Graphics*, 13, 167-183.
- Orchard, M., Kacprzynski, G., Goebel, K., Saha, B., & Vachtsevanos, G. (2008). Advances in uncertainty representation and management for particle filtering applied to prognostics. In *Int. conf. on prognostics and health management*.
- Peel, L. (2008). Data driven prognostics using a Kalman filter ensemble of neural network models. In *Int. conf. on prognostics and health management.*
- Peng, T., He, J., Liu, Y., Saxena, A., Celaya, J., & Goebel, K. (2012). Integrated fatigue damage diagnosis and prognosis under uncertainties. In *Annual conference of* prognostics and health management.
- Powers, D. (2011). Evaluation: From precision, recall and F-factor to ROC, informedness, markedness & correlation. *Journal of Machine Learning Technologies*, 2, 37-63.
- Ramasso, E., & Denoeux, T. (2013). Making use of partial knowledge about hidden states in hidden Markov models: an approach based on belief functions. *IEEE Transactions on Fuzzy Systems*, 22(2), 395-405.
- Ramasso, E., & Gouriveau, R. (2013). RUL estimation by classification of predictions: an approach based on a neuro-fuzzy system and theory of belief functions. *IEEE Transactions on Reliability, Accepted*.
- Ramasso, E., Rombaut, M., & Zerhouni, N. (2013). Joint prediction of observations and states in time-series based on belief functions. *IEEE Transactions on Systems*, *Man and Cybernetics - Part B: Cybernetics*, 43, 37-50.
- Riad, A., Elminir, H., & Elattar, H. (2010). Evaluation of neural networks in the subject of prognostics as compared to linear regression model. *International Journal* of Engineering & Technology, 10, 52-58.
- Rigaux, P., Scholl, M., & Voisard, A. (2002). *Spatial databases with application to gis* (E. Science, Ed.). Kauffman Publishers.
- Rosen, K. (2004). Handbook of discrete and computational geometry, second edition (J. E. Goodman & J. O'Rourke, Eds.). Chapman and Hall/CRC.
- Sarkar, S., Jin, X., & Ray, A. (2011). Data-driven fault detection in aircraft engines with noisy sensor measurements. *Journal of Engineering for Gas Turbines and Power*, 133, 081602.

Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B.,

Saha, S., & Schwabacher, M. (2008). Metrics for evaluating performance of prognostic techniques. In *Int. conf. on prognostics and health management* (p. 1-17).

- Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage propagation modeling for aircraft engine runto-failure simulation. In *Int. conf. on prognostics and health management* (p. 1-9). Denver, CO, USA.
- Saxena, A., Wu, B., & Vachtsevanos, G. (2005). Integrated diagnosis and prognosis architecture for fleet vehicles using dynamic case-based reasoning. In *Autotestcon* (p. 96-102).
- Serir, L., Ramasso, E., & Zerhouni, N. (2012). E2GKpro: An evidential evolving multi-modeling approach for system behavior prediction with applications. *Mechanical Systems and Signal Processing*. doi: 10.1016/j.ymssp.2012.06.023
- Vachtsevanos, G. (2006). Intelligent fault diagnosis and prognosis for engineering systems. Wiley, Hoboken, NJ.
- Vatti, B. R. (1992). A generic solution to polygon clipping. Communications of the ACM, 35, 56-63.
- Wang, P., Youn, B., & Hu, C. (2012). A generic probabilistic framework for structural health prognostics and uncertainty management. *Mechanical Systems and Signal Processing*, 28, 622 - 637.
- Wang, T. (2010). Trajectory similarity based prediction for remaining useful life estimation (Unpublished doctoral dissertation). University of Cincinnati.
- Wang, T., Yu, J., Siegel, D., & Lee, J. (2008). A similaritybased prognostics approach for remaining useful life estimation of engineered systems. In *Int. conf. on prognostics and health management* (p. 1-6).
- Zein-Sabatto, S., Bodruzzaman, J., & Mikhail, M. (2013). Statistical approach to online prognostics of turbine engine components. In *Southeastcon, 2013 proceedings of ieee* (p. 1-6).

BIOGRAPHY



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Comparison of binary classifiers for data-driven prognosis of jet engines health

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ABSTRACT

A reliable prognosis is crucial to manage asset health and predict maintenance needs of large civil jet engines, which in turn contribute to enhanced aircraft airworthiness, longer time on wing and optimized lifecycle costs. With the accumulation of large amount of data over the last decade, one can relate the number of components serviced during a maintenance visit to the history of parameters inside and outside the engine (temperatures, pressure, shaft rotation speeds, vibration levels, etc.). While established statistical models had been developed for small samples, more recent computer-intensive statistical techniques from the field of Machine Learning (ML) can handle more complex datasets. In particular, binary classifiers constitute an attractive option to predict the probability of servicing the components of a given jet engine at the next maintenance visit. This paper demonstrates the validity of such data-driven methods on an industrial case study involving failures of thousands of compressor blades in aeronautical turbomachines. The prediction accuracy obtained with the ML techniques presents a significant improvement over the state-of-the-art. Moreover, the performance of six binary classifiers with different characteristics - logistic regression, support vector machines, classification trees, random forests, gradient boosted trees and neural networks - was compared according to four qualitative and quantitative criteria. Results show that there is no clear winner, although ensemble models based on trees (random forests and boosted trees) offer a good overall compromise while neural networks offer the best absolute performance. In the industrial world, the business objectives, the environment in which the models are deployed and the users' skills should dictate the choice of the most adequate statistical technique.

1. INTRODUCTION AND MODELING APPROACH

A jet engine is complex machine subject to particularly demanding operating conditions that explains the deterioration of the engine components. Therefore, a proper maintenance of jet engines is crucial to ensure airworthiness, reduce fuel consumption and ultimately lower operating cost. Large amount of data are acquired on a permanent basis by jet engine manufacturers to help engineers in predicting future maintenance needs. On the one hand, the health of a jet engine is monitored in real-time by dozens of sensors measuring hundreds of variables inside and outside the engine (temperature, pressure, rotation speeds, vibration levels...); the data from this Engine Health Monitoring (EHM) system are recorded in corporate databases for later analysis. On the other hand, for every maintenance shop visit performed all around the world, the number of components scrapped are registered by maintenance technicians and engineers and sent to the engine manufacturer. These two major types of data can be combined to establish a prognosis of the health of the fleet of engines.

To predict future maintenance needs, reliability engineers rely on multiple techniques that can be divided into two categories:

- 1. Analytical inductive methods based on engineering reasoning and analysis of failure modes of the part, such as Failure mode, effects, and criticality analysis (FMECA) (Jordan, 1972). Methods in this category typically require a deep technical expertise and knowledge of the product but limited volumes of historical data.
- 2. Deductive statistical techniques inferring risk of failure using actual past data from similar cases. Many such statistical methods have been applied to reliability engineering (Meeker & Escobar, 1998): analysis of

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failure time data (Kalbfleisch & Prentice, 2011), biostatistics-inspired survival analysis (Lawless, 2003), Poisson-related models based on count data with excess zeros such as zero-inflated models (Lambert, 1992) or hurdle models (Grogger & Carson, 1991).

This paper covers a set of methods belonging to the second category. Most of such statistical methods currently in use by industrial corporations are based on established statistical models developed for dealing with small samples. However, the large volumes of monitoring data acquired over the last decade allowed resorting to more data-driven, computerintensive methods for predicting maintenance needs (Jardine, Lin, & Banjevic, 2006). In this paper, we intend to validate a statistical approach for PHM of jet engine parts based on binary classifiers from the field of machine learning. Such binary classifiers predict whether a given part in the engine is likely to be scrapped (output variable Y =1) or not (Y = 0) at the next maintenance visit, given its own history and the history of similar components. Compared to the aforementioned statistical models, the literature on binary classifiers applied to reliability engineering and maintenance planning is still scarce. For instance, Kim, Tan, Mathew, Kim, and Choi (2008) used Support Vector Machines to predict the remaining useful life of elements in high pressure liquefied natural gas pumps. Caesarendra, Widodo, and Yang (2010) used logistic regression to evaluate the degradation of bearings. Rafiee, Arvani, Harifi, and Sadeghi (2007) used neural networks to monitor the condition of gearbox components. Nevertheless, there are few examples in the literature comparing rigorously the predictive performance of several binary classifiers concurrently, which is the objective of our paper.

According to our approach, the statistical model of part failure can be expressed in the most general way as:

$$Y = f_{\theta}(X) + \varepsilon \tag{1}$$

where *Y* is the $N \times 1$ output vector to be predicted (containing the probability of failure or the occurrence of failure in our case study), *X* is the $N \times (p + 1)$ matrix of predictors (including intercept), f_{θ} is the actual function to estimate and ε is an $N \times 1$ vector of residuals (i.e. errors) of the model. The function f_{θ} is potentially complex, nonlinear and depends on a set of parameters θ – varying from model to model - to be estimated via model fitting. In equation (1), the residuals ε are assumed to be centered and normally distributed with constant variance σ^2 , i.e. $\varepsilon \sim \mathcal{N}(0, \sigma^2)$). In fact, it is impossible to identify the actual function f_{θ} : instead, the statistical models provide an estimate \hat{f}_{θ} of the actual f_{θ} . The role of the statistician is to find the model that is as close as possible to f_{θ} by 1) finding the most relevant type of model and 2) by tuning the parameters θ .

Following the description of the context in this introduction, the article will present the case study and the dataset in Section 2 before detailing the methodology – including simple mathematical formulation behind the classifiers - in Section 3. The results of the comparison of the binary classifiers are covered in Section 4 and commented in Section 5, which also opens discussion for potential improvements and next steps.

2. CASE STUDY AND DATASET DESCRIPTION

2.1. Description of the compressor blades

We tested the validity of our approach on a case study involving blades in the intermediate pressure (IPC) and high pressure compressors (HPC) of Rolls-Royce Trent 500 engines (Figure 1). Such compressor blades are made of titanium (in the front and middle stages) or nickel alloys (in the rear stages of the HPC) and manufactured by forging or machining processes. We selected compressor blades as our case study as they are relevant candidates to test the validity of the statistical approach:

- There are numerous stages in a Trent 500 (8 in the IPC and 6 in the HPC), each containing dozens of blades. Thus, in total, there are hundreds of compressor blades in a Trent 500 engine. This leads to a dataset with more observations (higher *N*), an important condition for making the statistical approach viable.
- The 14 different types of blades are located all along the gas path of the engine, and therefore subject to very diverse operating conditions (amplitude of temperature and pressure, rotation speeds and vibration levels in the IPC and HPC shafts, etc.). This large diversity of situations also improves the meaningfulness and quality of the statistical estimates.



Figure 1 - Location of the blades in Trent 500 engine

Knowing the deterioration mechanisms of the component is important to select the most adequate type of statistical model and the predictors entering the model as inputs. Compressor blades are subject to demanding conditions during engine operations and their degradation is influenced mostly by gas temperature and pressure, shaft rotation speed and vibration levels.

2.2. Structure of the dataset

Our dataset comprises a total of N = 12132 serviced components, corresponding to 36 components per engine, for 337 maintenance visits performed on 176 different engines between 2000 and 2012. The number of components serviced during the maintenance visits comes from the analysis of maintenance invoices while the predictors of the model have been extracted from the Engine Health Monitoring (EHM) database.

Out of the hundreds of variables recorded by the EHM system, we have selected only the p = 11 most relevant ones (Table 1). Selecting a limited number of variables fulfills several objectives: 1) keep the predictors most pertinent to the failure mechanisms of the components in the case study, 2) make the approach more tangible for the reader by exposing few, meaningful variables and 3) not to compromise industrial confidentiality.

Table 1. Variables selected as model predictors.

Variable	Description
Cycles	Number of cycles (i.e. flights) done by the engine between two maintenance visits
Average TGT margin	Average of the margin (i.e. difference with the admissible value) of the temperature in the turbine (highest temperature in the engine) over the period between two maintenance visits
Delta TGT margin	Difference between the initial and final values of the turbine temperature margin over two maintenance visits
Average N2 margin	Average of the margin of the rotation speed of the intermediate shaft over the period between two maintenance visits
Delta N2 margin	Difference between the initial and final values of the intermediate shaft speed margin over two maintenance visits
Average N2	Average of the absolute rotation speed of the intermediate shaft over the period between two maintenance visits
Delta N2	Difference between the initial and final values of the intermediate shaft absolute speed over two maintenance visits
Average VB2	Average of the vibration level in the intermediate shaft over the period between two maintenance visits
Delta VB2	Difference between the initial and final values of the intermediate shaft vibration level over two maintenance visits
Average OAT	Average of the absolute Outside Air Temperature over the period between two maintenance visits
Delta OAT	Difference between the initial and final values of the absolute Outside Air Temperature over two maintenance visits

The number of cycles and the Turbine Gas Temperature (TGT) are usually considered by maintenance engineers as the best proxies for overall deterioration of a jet engine. The rotation speed N2 of the intermediate shaft can be considered as a proxy for fatigue due to centrifugal forces and fluid-structure interaction. Taking both the margin and absolute values of some of those engine parameters allowed us to include in the statistical models two complementary types of information about the engine operations. The average and delta values over the period between two maintenance visits provide us with information about the average and variability of the engine parameters, respectively.

3. METHODOLOGY

In this Section 3, we describe the general modeling approach that we followed, as well as the simple characteristics of the binary classifiers compared in the paper.

3.1. General approach and data cleaning

Our objective is to obtain an estimate \hat{f}_{θ} that is as close as possible to the actual true function f_{θ} explaining Y as a function of the engine parameters defined in the matrix X of predictors in equation 1. The choice of the model \hat{f}_{ρ} depends on the probability distributions of the output Y and the structure of the predictors X. The predictors X being all numeric, it is possible to use a large variety of models. After preliminary data exploration, we found that the probability distribution of the output Y discarded models based on the Poisson distribution or count data. Instead, binary classifiers appeared more adapted to our case study: the output Y thus takes the value of 1 for a failed component and 0 for a nonfailed component. Y can alternatively be a probability of failure, in which case a threshold has to be defined so as to classify the probability as corresponding - or not - to a failed component.

The list of predictors X being defined, we pre-processed the data to make them more suitable for subsequent statistical analysis. First, the few outliers were removed or their value reattributed by usual imputations techniques: imputations of the mean or median by relevant groups and regression on other predictors. Second, the predictors were scaled ¹ in order to increase the quality of the estimates and increase the convergence of the algorithms, as some are known for their instability, notably neural networks. Scaling the predictors thus ensures giving a common ground for comparing all the binary classifiers.

¹ Scaling means that each predictor X_i in X was transformed as $X'_i = (X_i - \mu_{X_i})/\sigma_{X_i}$ where μ_{X_i} and σ_{X_i} are respectively the mean and standard error of the variable X_i

3.2. Characteristics of binary classifiers

Many binary classifiers have emerged from the field of Machine Learning over the last two decades to predict phenomena involving binary outcomes in a large diversity of applications (e.g. disease diagnosis, image recognition). We cover in this section 6 of the most popular ones, presenting a gradual increase in terms of model complexity, from the easily interpretable linear logistic regression to the complex, highly nonlinear neural networks. This section is based on the widely acknowledged text of Hastie, Tibshirani, and Friedman (2009) and intends to initiate the reader - especially the one not versed in statistical methods - to the main characteristics and differences between binary classifiers. An intuitive presentation of the principle and a simple formulation of the mathematics of the techniques are presented; moreover, the tuning parameters (aka hyperparameters) of the models are described so as to illustrate their complexity. Indeed, behind the sometimes fancy names attributed by statisticians or computer scientists to those binary classifiers, one should be aware of the explanatory power and predictive accuracy of these techniques, but also the amount of skills required to use them properly.

3.2.1. Logistic regression

In logistic regression the binary output *Y* is transformed so that the natural logarithm of its $odds^2$ is expressed as a linear function of *X*, the matrix of predictors. It can also be written as the probability³ of the outcome of *Y* given *X*:

$$\log \left(\frac{P(Y = 1 | X = x)}{P(Y = 0 | X = x)} \right) = \beta_0 + \beta^T x$$

$$P(Y = 1 | X = x)$$

$$= \frac{\exp(\beta_0 + \beta^T x)}{1 + \exp(\beta_0 + \beta^T x)}$$

$$= 1 - P(Y = 0 | X = x)$$
(1)

Therefore, the logistic regression is a binary classifier depending on a linear function of the predictors. The model provides the linear coefficients β_i that quantify the risks on the output *Y*:

$$\exp(\beta_i) = 1 + \alpha \tag{2}$$

where α is the increase (and symmetrically decrease if $1 + \alpha < 1$) of the relative risk of failure provoked by an increase in one unit of the predictor X_i . Thanks to the coefficients of the logistic regression, it is thus possible to

estimate the marginal effect of each predictor on the output variable *Y*, rendering the model more interpretable. This unique characteristic combined with the simplicity of the model assumptions makes the logistic regression particularly attractive and popular amongst analysts with little statistical background. Moreover, the logistic regression doesn't require tuning parameters (aka hyperparameters) which often represent a considerable part of the modeling process.

Nonetheless, the deterioration of jet engine components is a nonlinear stochastic process and predictors are usually correlated. Unable to capture this added complexity of the dataset, the logistic regression is limited in terms of goodness-of-fit and prediction accuracy: more sophisticated models thus have to be used.

3.2.2. Support Vector Machines

Support Vector Machines (SVM) became popular two decades ago after the research on statistical learning theory of Vapnik (1996). It is a nonlinear and non-parametric method based on transforming, via a complex transform function Φ , the initial (often non separable) dataset into a new space of much higher – and potentially infinite – dimension. In this new space, the likelihood of having a separable dataset is much higher and it becomes possible to obtain a linear decision boundary, in lieu of a nonlinear decision boundary in the initial space. In this article, we used a particular type of SVM classifier called "C-SVM" which can be formulated mathematically as an optimization problem under constraints (Chang et al., 2011):

$$\min_{\beta,\beta_0,\xi} \frac{1}{2} \|\beta\|^2 + C \sum_{i=1}^N \xi_i \text{ under}$$

$$y_i(\langle \beta, \Phi(x_i) \rangle + \beta_0) \ge 1 - \xi_i \quad \text{and} \quad (3)$$

$$\xi_i \ge 0, i = 1, \dots, N$$

In equation (3), y_i is the ith element of the relabeled⁴ version of the output *Y*, x_i is the ith element of the initial matrix of predictor *X*, β is the vector of coefficients, β_0 a constant (i.e. intercept) and $\xi_{i \in \{1,...,N\}}$ are parameters quantifying the degree of non separability of the elements in the dataset. Geometrically speaking, solving this problem consists in determining the hyperplane such as the estimated values $\langle \beta, \Phi(x_i) \rangle + \beta_0$ don't deviate from the output values y_i . The aforementioned mapping from the initial low dimensional space to a higher dimensional space is done by so-called kernel functions $k(x_i, x_j)$ expressed as the inner product of the transform function Φ i.e. $k(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$. There are several types of kernel functions: linear $x_i \cdot x_j$, d-degree polynomial $(\gamma x_i \cdot x_j + C)^d$, Gaussian radial basis functions (RBF) $exp(-\gamma ||x_i - x_j||^2)$ and sigmoid $tanh(\gamma x_i \cdot x_j + C)$. We have selected RBF kernels for our

² An odd is defined as the ratio of P(Y = 1|X = x) the probability of failing given the predictors *X* over P(Y = 0|X = x) = 1 - P(Y = 1|X = x) the probability of not failing given *X*.

 $^{^{3}}$ Since a probability is obtained, it is still necessary to define a threshold to classify the outcome as 1 or 0. A method to identify the best threshold is given in Section 4.1.

⁴ While the initial $y_i \in \{0,1\}$, the relabeled $y_i \in \{-1,+1\}$

analysis because they offer the best trade-off in terms of computing cost, stability and performance.

In our case, C-SVM with Gaussian kernels can be tuned by 2 hyperparameters:

- 1. C is a "cost" (i.e. regularization) parameter controlling over fitting: the larger the C, the higher the penalization of the error. It makes a compromise between the complexity of the model and the respect of the constraints in equation (3).
- 2. $\gamma = \frac{1}{2\sigma^2}$ is the scaling constant (aka kernel bandwidth parameter in non-parametric statistics) controlling the shape of the Gaussian kernel: the higher the γ , the smaller the standard deviation of the Gaussian.

3.2.3. Classification trees

A classification tree is another nonlinear non-parametric statistical technique consisting in a hierarchy of nodes obtained by recursive partitioning of the initial dataset. Each child node is characterized by a subset of its parent node⁵ and is obtained by splitting the parent subset over a unique predictor, according to a threshold (continuous predictor) or partition over its levels (categorical predictor). Popularized by Breiman, Friedman, Stone and Olshen (1984), CART (Classification and Regression Tree) is the most popular implementation algorithm for classification trees and requires three elements:

- 1. a criterion to select the best dichotomic split at each node by minimizing a measure of error, typically the Gini index or a measure of information entropy
- 2. a stopping rule to decide whether a node is final becoming a "leaf" of the tree – or whether the splitting process should continue
- 3. a decision rule to assign each leaf to a class (i.e. outcome) of the output *Y*.

The tree is progressively grown in a recursive fashion by dichotomic splits at each node until all leaves have been generated. Each leaf corresponds to one of the disjoint partitions of the initial dataset and is characterized by a simple model that differs from leaf to leaf. The full tree being often prone to overfitting, it is possible to "prune" it and obtain a smaller tree with less leaves but better performance. The mathematical formulation of a classification tree is relatively simple:

$$\hat{f}_{\theta}(X) = \sum_{m=1}^{J} \delta_m I\{X \in R_m\}$$
(4)

where J is the number of leaves of the tree, $I\{.\}$ the indicator function and δ_m the value of the class (i.e. 0 or 1) assigned to the m^{th} leaf corresponding to the subregion R_m of the 11dimensional space of predictors. It should be noted that the variable names in Figure 2 and Figure 3 are ordered in a different manner than in Table 1.



Figure 2 - Tree fitted on the case study (renamed variables)

Trees are particularly flexible since they accept indistinctly continuous, ordinal or binary predictors. They are also very easy to interpret thanks to the visualization of the tree structure (Figure 2). Last but not least, calculations on trees are particularly fast.

However, they are characterized by low bias and high variance: the addition of an outlier or a new observation in the dataset may dramatically modify the thresholds for the dichotomic split and lead to trees with very different classification results. A solution to this instability consists in "averaging" the predictions from a set of trees: this is the idea behind random forests and gradient boosted trees. As a consequence, although a single tree is a relatively weak binary classifier, it is actually a very important statistical technique as it constitutes the basis of more sophisticated models.

The choice of the splitting criterion being not a tuning parameter *per se* but rather a methodological choice, the performance of classification trees can be adjusted by 2 hyperparameters:

- 1. The number of leaves in the tree, which is related to the depth of the tree and the degree of overfitting.
- 2. The cost complexity parameter C_p that defines the minimum benefit to be obtained in terms of model fit before a split should be attempted. It is notably used to prune the fully-grown tree.

3.2.4. Random forests

Formalized by Breiman (2001), random forests is an ensemble model constructed by combining a large number of bootstrapped trees after random sampling with

⁵ The first "root" node of the tree corresponds to the full initial dataset.

replacement amongst the N observations of the training dataset (X, Y) and also after random sampling amongst the p predictors X at each node. The class assignment is made by the majority vote on the class membership of the output Y (classification case). By averaging from a large number of uncorrelated, unbiased but high-variance single classification trees, the variance is reduced and the prediction accuracy is improved. The mathematical formulation of random forests is less simple because of the combination of single trees.

Random forests are not prone to overfitting (Hastie et al., 2009) and are also robust to outliers, noise, unbalanced datasets and missing data. Fast to compute, they provide estimates of correlations between predictors, the level of prediction accuracy and an assessment of the importance of each variable (Figure 3).



Figure 3 – Relative importance of the predictors

Random forests accept 3 main hyperparameters:

- 1. The number of single trees to be averaged into the random forest. The higher the number of trees, the higher the accuracy and the computing cost.
- 2. The number of predictors randomly sampled at each split.
- 3. The minimum size (i.e. number of elements) in the terminal nodes, or equivalently the maximum number of leaves in each of the individual trees.

3.2.5. Gradient boosted trees

Like Random forests, Gradient Boosted Tree (GBT) is an ensemble method based on combining a large number of single (classification) trees to form a stronger model. Contrary to random forests though, each individual tree in a GBT is weighted according to its prediction accuracy; a shrinkage parameter $0 < \nu < 1$ can also be defined to

penalize the contribution of each tree when it is added to the GBT. Developed by Friedman (2001), boosted trees can be formulated mathematically as:

$$\hat{f}_{\theta}(X) = \sum_{m=1}^{M} w_m \sum_{j=1}^{J_m} \delta_{jm} I\{x \in R_{jm}\}$$
(5)

where *M* is the number of trees while the weights w_m and the coefficients δ_{jm} are estimated by iterative procedures and are functions of the shrinkage coefficient v.

Boosted trees can quantify the relative importance of the predictors as well as their nonlinear marginal influence (aka partial dependence) on the output *Y*. We showed in equation (2) that the coefficients β have a similar role in the logistic regression, although they were constrained to have a linear marginal influence.

Gradient Boosted Trees can be tuned by 3 hyperparameters, some of which are common to the hyperparameters of single trees:

- 1. The number M of individual trees to combine in the ensemble model, equal to the number of boosting iterations. The higher, the more accurate and the computing cost of the model. If M is too high though, over fitting might occur, contrary to random forests.
- 2. The size $J_{m \in \{1,...,M\}}$ (i.e. the number of leaves) of each of the *M* constituent trees of the GBT.
- 3. The shrinkage parameter ν is penalizing each tree constituting a GBT. It is equivalent to the learning rate or the decay also encountered in neural network.

3.2.6. Neural networks

Neural networks are made of individual perceptrons whose output y_j can be written $y_j = f_j(\sum_i w_{j,i}x_{j,i})$ where $x_{j,i}$ are the inputs of the perceptron, $w_{j,i}$ its weights and f_j a socalled "activation function", typically the sigmoid $\sigma_s(x) =$ $1/(1 + e^{-sx})$. The perceptrons are organized in such a way that the output of a perceptron located upstream becomes the input of a perceptron downstream, forming *de facto* a net organized in three types of layers:

- 1. the input layer made of the *p* observed predictors,
- 2. the hidden layer(s) containing *M* non-observed perceptrons $Z_k = \sigma_s(w_{0,k} + \sum_{i=1}^{p} w_{i,k} x_i)$ computing the nonlinear features from linear combinations of the inputs
- 3. the output layer containing the probability of failure

In a neural network, the probability of each class of the binary output Y is therefore expressed as a complex nonlinear function of linear combination of the predictors:

$$P(Y = l \in \{0,1\}) = \frac{e^{\beta_{l,0} + \sum_{k=1}^{M} \beta_{l,k} \sigma_S(w_{0,k} + \sum_{i=1}^{P} w_{i,k} x_i)}}{\sum_{i=0}^{1} e^{\beta_{i,0} + \sum_{k=1}^{M} \beta_{i,k} \sigma_S(w_{0,k} + \sum_{i=1}^{P} w_{i,k} x_i)}}$$
(6)

Neural networks are very relevant to highly nonlinear problems and can produce very accurate results, despite being potentially subject to overfitting or non-convergence. However, they require a scaled dataset with no categorical predictors and a certain expertise in choosing the number of perceptrons and layers, the structure of the connections, the penalization (also called weight decay), amongst others. The two hyperparameters for neural networks are:

- 1. The decay v is often compared to a learning rate, in the sense that it will penalize the estimation of the weights $w_{i,i}$ of the neural network
- 2. The maximum number of iterations before convergence. The higher this number, the higher the probability for the neural network to reach a stable and accurate solution

Each of the aforementioned binary classifiers exhibit advantages and drawbacks that have been extensively documented in Machine Learning literature (Huang et al., 2003). The next section presents a comparison of their merits through an application to our case study.

4. RESULTS

This section presents the results of models' performance, based on the methodology developed in Section 3. After a description of the criteria retained for comparing the models, we present an overall ranking of the binary classifiers, followed by a more quantitative assessment of model's performance based on two criteria: prediction accuracy and the c-statistic.

4.1. Criteria for comparing models

To account for the different characteristics of the aforementioned binary classifiers, we defined a set of comparison criteria:

- 1. The accuracy of the model is a quantitative criterion measured by metrics such as the percentage of outcomes correctly predicted or the area under the Receiver Operating Characteristic (ROC) curve, a typical tool in the field of machine learning applied to binary classification (Fawcett, 2006) (Figure 4).
- 2. The interpretability of the model is defined more subjectively as the difficulty to understand and use the results of the model for a subsequent engineering analysis.
- 3. The easiness to fit the model is a second qualitative criterion indicating the level of efforts and skills to actually train the model (selection of the predictor, tuning of the hyperparameters, etc.).

4. The cost is a quantitative assessment of the computing time needed to train the model. For a fair comparison, the measures are acquired on the same computer under similar conditions for all the models.

We decided to include two qualitative comparison criteria because the performance of a binary classifier can't be reduced to quantitative metrics such as accuracy or computing cost. The complexity in training, understanding and interpreting a model indeed represents a large hidden cost that might strongly limit the performance of the model and even prevent its use in some situations (low maintainability, poor formal training, lack of statistical skills of the users, etc.).

4.2. Overall comparison of binary classifiers

The 6 binary classifiers are compared according to the aforementioned criteria, each assesses on a qualitative scale in order to respect confidentiality agreement (Table 3). Each binary classifier presents advantages and drawbacks for each of the criteria.

Not surprisingly, ensemble models based on classification trees (random forest, gradient boosted trees) as well as other strongly nonlinear models (neural networks and SVMs to a lower extent) are much more accurate than the linear logistic regression or the unstable weak classifier (single tree).

Regarding interpretability, logistic regression provides the coefficients of the model, which allows estimating the marginal effect that each predictor has on the output. Single trees give an interesting visual view on the problem, provided the tree is not too deep (number of leaves smaller than 20). Random forests can rank the predictors according to their importance. The other classifiers are more difficult to interpret because 1) their mathematical formulation is not as easy and/or 2) they don't provide directly a measure of the influence of the predictors.

The easiest training and fit is obtained with robust models with few and conceptually simple hyperparameters such as decision tree, logistic regression or random forest and boosted trees to a lower extent. On the contrary, complex and unstable techniques such as SVM and neural networks require expertise to be properly trained and fitted.

Unsurprisingly, the more sophisticated and the higher the number of hyperparameters, the more computing resources are necessary to fit the model. There is almost a direct relationship between the easiness to train a model and its cost.

4.3. Focus on prediction accuracy of the classifiers

Even though qualitative criteria are important, the prediction accuracy is often attributed a greater importance when ranking models, as it might appear as the most objective criterion: the higher the prediction accuracy, the more likely the model will predict future outcomes with success. In the case of binary classifiers, the prediction accuracy is the number of outcomes correctly predicted (i.e. the sum of true positives and true negatives) over the total number of observations in the dataset.

Nonetheless, the prediction accuracy varies according to hyperparameters of the model or according to the cut-off threshold selected to separate positive (Y = 1) and negative (Y = 0) outcomes. This variation in accuracy is obtained by computing the prediction accuracy over a range of hyperparameters or cut-offs, whose results are visualized through the so-called ROC curve. The ROC curve expresses True Positive Rate (TPR aka sensitivity of the model) in the Y-axis as a function of the False Positive Rate (FPR equal to 1-specificity) in the X-axis (Figure 4).



Figure 4. ROC curve comparing the classifiers' accuracy⁶.

There are two efficient ways to evaluate the performance of a binary classifier from the ROC graph:

- identify the point at the closest Euclidean distance from the top left corner of the ROC. This point corresponds to the highest TPR and the lowest FPR simultaneously, namely the highest prediction accuracy attainable by the model. This particular point has been retained as a common ground for comparing model accuracy, although Provost, Fawcett, and Kohavi (1998) debated over its robustness and relevance. To mitigate this effect, we generated Monte-Carlo simulations of 20 ROC by random sampling of training and test sets from the initial dataset, from which we extracted the worst, average and best prediction accuracy (Table 2). The averaged 20 simulations are presented in Figure 4 and allows a comparison between the 6 binary classifiers.
- 2. the Area Under the Receiver Operating Characteristic (ROC) curve (AUC), also called the c-statistic,

corresponds to the "probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance" (Fawett, 2006). The c-statistic measures the quality of the classification of the binary classifier over the full range of a parameter or threshold. For this reason, it is often described as more robust at quantifying the average performance of a classifier than the mere prediction accuracy.

We compared the binary classifiers by computing their average accuracies and the c-stastistic in percent (first value in each cell), as well as the minimum and maximum values (values in brackets) from the 20 Monte Carlo simulations (Table 2). To respect industrial confidentiality however, we provide data relatively to the average fit of the logistic regression model (marked in bold), as it is the simplest of the aforementioned binary classifiers. Since neural networks are known to be very sensitive to non-scaled datasets, we give the accuracy and AUC for the non-scaled (first line in each cell) and the scaled versions of the dataset (second line in each cell).

Table 2. Accuracy and c-statistic of the binary classifiers relatively to logistic regression.

Classifier	Relative	Relative c-
Classifici	accuracy	statistic
Logistic regression	100% [86-111]	100% [90-109]
Logistic regression	101% [88-111]	100% [91-106]
SVM	106% [25-128]	115% [108-122]
5 V IVI	105% [27-132]	115% [109-120]
Classification tracs	114% [82-131]	108% [98-116]
Classification frees	112% [80-136]	107% [100-116]
Pandom Forests	134% [131-136]	111% [103-118]
Kaldolli Polests	134% [131-136]	111% [101-122]
Cradient Poosted Trees	121% [102-132]	115% [104-127]
Gradient Boosted Trees	120% [99-131]	114% [105-120]
Naural natwork	115% [61-132]	115% [77-126]
incutat network	127% [119-132]	123% [115-129]

Several insights arise from Figure 4 and Table 2:

- The performance of the logistic regression is indeed the lowest on average, as measured by the prediction accuracy and the c-statistic. It is followed by classification trees, SVM, Gradient Boosted Trees, Neural Networks and random Forests, in that order.
- According to the partial ROC curve, some models are more accurate for some values of FPR and TPR. In absolute terms, neural networks are the most accurate for low to middle FPR while SVMs are more accurate for middle to high values of FPR.
- The variation in performance for different simulations of the same model is important, as measured by the range between the minimum and maximum values of

⁶ The TPR and FPR normally vary from 0 to 1 in a ROC curve. Figure 4 is only an extract with unscaled axes from the full ROC curve as it serves only as an illustration of the principle of ROC curves.

the accuracy and the AUC. For instance, SVMs have a good average performance (accuracy=106%, AUC=115%) but a change in the dataset can lead to very poor (25%) or excellent (132%) prediction accuracies.

- The variation in model performance can be large for one criterion and not for the other. The lower the variation, the more robust the method and thus the higher degree of confidence one can have on the quality of the output of a given model. Again, SVMs offer a good illustration of this effect, as the accuracy has a high variance compared to the AUC
- Except for 8 out of 24 cases, scaling the dataset improves the prediction accuracy of the c-statistic. It is particularly significant for neural networks, whose lowest performance becomes one of the highest amongst all models.

5. DISCUSSION AND CONCLUSION

First of all, the results appear promising compared to the state-of-the-art, although confidentiality agreement impeded us to provide absolute performance of the binary classifiers.

The overall comparison of the binary classifiers shows that the models are complementary. As often in statistical modelling, there is no "one size fits all" but rather models whose dissimilar characteristics make them more suitable to different objectives or users. On the one hand, the logistic regression will be more adapted to an infrequent user with less statistical skills and interested in quickly obtaining an approximate estimate from a simple and robust model. On the other end, neural networks might be a better choice for a well-defined objective where high and robust prediction accuracy is required (e.g. the integration into an optimization system). Business objectives will decide on the trade-offs between the conflicting criteria in Table 3, knowing that accuracy is often the criterion against which the other criteria - interpretability, computing cost, easiness to fit- have to be traded with. Nonetheless, ensemble models based on trees - namely random forests and boosted trees - seem to offer a proper overall compromise: they are robust, easy to train and fit, not too costly for the performance increase they allow while still yielding deep insights if interpreted correctly.

A quantitative ranking of the models is somewhat arbitrary as the performance might not increase for the accuracy and the AUC simultaneously. Moreover, some models are more performing for some zones of the ROC curve, meaning that different binary classifiers should be chosen according to the target values of FPR and TPR. Thus, it might be worthwhile to create an ensemble "meta-model" based on a combination of the 6 models, eventually applied selectively to right portions in the dataset. Variation in performance can be quite high and depends on two main factors, whose relative influence on the model robustness is challenging to assess:

- 1. The structure of the training and test sets randomly generated at each simulation. In such case, the absolute robustness of the models should be clearly questioned and the model should not be used, as it might not be possible to ensure the degree of accuracy of its predictions. SVM and to a lower extent single classification trees should thus be used carefully in our case study.
- 2. The internals of each method have some influence on the model performance: random generation of initial weights for neural networks, a local instead of a global minimum encountered by an optimization technique, etc. In such a case, the robustness of the model can be improved by tuning its hyperparameters. Nonetheless, this operation requires high statistical expertise and might not improve significantly the performance of a model

Scaling the initial dataset provides a better ground for comparing the models and almost always improves the model performance, should it be measured by the AUC or the prediction accuracy. This data transformation step is even necessary to ensure the relevance of neural networks, which finally ranks as the most performant in absolute terms. Thus, we recommend scaling the datasets whenever possible before fitting binary classifiers.

Next steps for future research can be formulated:

- The first step would consist in increasing the robustness of the performance assessment by generating more simulations (hundreds or even thousands) and taking quantiles or confidence intervals from the simulated ROC instead of the minimum and maximum values
- Improving the performance of each model might be a second step, done by better tuning of the hyperparameters and by adding more predictors, at the expense of a higher computing cost and probably for a marginal gain in performance.
- Compare the prediction accuracy of the statistical models with the manual engineering-based estimates done by seasoned maintenance engineers. This task would be time-consuming and uncertain, given the lack of structured data.

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NOMENCLATURE

- *N* number of observations in the sample
- *p* number of predictors in the model
- Y $N \times 1$ output vector to be predicted, containing the probability or the occurrence of failure
- $X N \times (p+1)$ matrix of predictors (incl. intercept)
- ε N × 1 vector of residuals of the model
- β (p+1) × 1 vector of model's coefficients
- f_{θ} actual function explaining *Y* according to *X*
- \hat{f}_{θ} estimate of the actual function

REFERENCES

- Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees*. Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software. ISBN 978-0-412-04841-8
- Caesarendra, W., Widodo, A., & Yang, B.-S. (2010) Application of relevance vector machine and logistic regression for machine degradation assessment. *Mechanical Systems and Signal Processing*, 24(4), pp. 1161-1171. doi:10.1016/j.ymssp.2009.10.011
- Chang, C. C., & Lin, C. J. (2011). LIBSVM: a library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2(3), 27.
- Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, vol. 27 (8), pp. 861-874. doi:10.1016/j.patrec.2005.10.010
- Friedman, J. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5): pp. 1189–1232. doi:10.1214/aos/1013203451
- Goebel, K., Saha, B., & Saxena, A. (2008). A Comparison of Three Data-Driven Techniques for Prognostics, *Proceedings of the 62nd Meeting of the Society For Machinery Failure Prevention Technology (MFPT)* (119-131), May 6-8, Virginia Beach, VA.
- Grogger, J. & Carson, R. (1991). Models for truncated counts. *Journal of Applied Econometrics*, 6(3), pp. 225-238. doi: 10.2307/2096628
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* New York: Springer Verlag
- Huang, J., Lu, J., & Ling, C.X. (2003). Comparing naive Bayes, decision trees, and svm with auc and accuracy. *ICDM '03: Proceedings of the Third IEEE International Conference on Data Mining*, November 19-22, Melbourne, FL.
- Jardine, A. K. S., Lin, D. & Banjevic, D. (2006). A review on machinery diagnostics and prognostics

implementingcondition-basedmaintenance.Mechanical System and Signal Processing, vol. 20, pp.1483-1510. doi:10.1016/j.ymssp.2005.09.012

- Jordan, W.E. (1972). Failure Modes, Effects, and Criticality Analyses. *Proceedings of the Annual Reliability and Maintainability Symposium* (30-37), January 25-27, San Francisco, CA.
- Kalbfleisch, J. D., & Prentice, R. L. (2011). *The statistical analysis of failure time data*. Hoboken, NJ: John Wiley & Sons, Inc.
- Kim, H-E., Tan, A C. C., Mathew, J., Kim, E Y. H., & Choi, B-K. (2008). Machine prognostics based on health state estimation using SVM . In Gao, J., Lee, J., Ma, L., & Mathew, J. (Eds.) Proceedings Third World Congress on Engineering Asset Management and Intelligent Maintenance Systems Conference (834-845). Beijing, China
- Lawless, J. F. (2003). Statistical Models and Methods for Lifetime Data (2nd ed.). Hoboken, NJ: John Wiley and Sons, Inc. ISBN 0471372153.
- Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics*, 34(1), pp. 1-14. doi: 10.1080/00401706.1992.10485228
- Meeker, W.Q., & Escobar, L.A. (1998). *Statistical Methods* for *Reliability Data*. Hoboken, NJ: John Wiley and Sons, Inc. ISBN: 978-0-471-14328-4
- Provost, F., Fawcett, T., & Kohavi, R. (1998). The case against accuracy estimation for comparing induction algorithms. In Shavlik, J. (Eds.), *Proceedings of ICML-*98 (445-453). San Francisco, CA: Morgan Kaufmann.
- Rafiee, J., Arvani, F., Harifi, A. & Sadeghi, M.H. (2007). Intelligent condition monitoring of a gearbox using artificial neural network. *Mechanical Systems and Signal Processing*, 21(4), pp. 1746-1754. doi:10.1016/j.ymssp.2006.08.005
- Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation, 1st International Conference on Prognostics and Health Management (PHM08) (1-9), October 6-9, Denver, CO.
- Vapnik, V. (1996). *The Nature of Statistical Learning Theory*, New York: Springer

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APPENDIX

Classifier	Accuracy	Interpretability	Easiness to train and fit the model	Computing affordability
Logistic regression	*	***	**	***
SVM	**	*	*	*
Classification trees	*	**	***	***
Random Forests	***	**	**	**
Gradient Boosted Trees	***	*	**	*
Neural network	***	*	*	*

Table 3. Overall qualitative comparison of binary classifiers according to four criteria.

The binary classifiers are ranked qualitatively according to four criteria, amongst which accuracy that is related to results in Table 2. The more asterisks, the better the classifier on the criterion. The qualitative ranking can be interpreted for two criteria:

• For "Interpretability": *** corresponds to a classifier directly returning regression coefficients, so that the results can be easily interpreted by non-specialists (i.e. coefficients of a multiple linear regression giving the marginal effect of the predictor). ** corresponds to either an easy visualization of the results (classification trees) or the classifier's ability to return the relative importance of the variables (random forests). * is given to "black-box" models for which engineering insights are difficult (gradient boosted trees) if not impossible to obtain (SVM, neural networks) from the results.

• For "Easiness to train and fit": *** corresponds to a classifier that can be used by anyone with normal engineering skills can manage with less than one days training. ** is awarded to classifiers requiring approximately 1-2 weeks of specialized training. * is given to models requiring professional expertise.

Unsupervised Kernel Regression Modeling Approach for RUL Prediction

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ABSTRACT

Recently, Prognostics and Health Management (PHM) has gained attention from the industrial world since it aims at increasing safety and reliability while reducing the maintenance cost by providing a useful prediction about the Remaining Useful Life (RUL) of critical components/system. In this paper, an Instance-Based Learning (IBL) approach is proposed for RUL prediction. Instances correspond to trajectories representing run-to-failure data of a component. These trajectories are modeled using Unsupervised Kernel Regression (UKR). A historical database is used to learn a UKR model for each training unit. These models fuse the run-tofailure data into a single feature that evolves over time and hence allow the construction of a library of instances. When unseen sensory data arrive, the learned UKR models are used to construct the test degradation trajectories. RUL is deduced by comparing the test degradation trajectory to the library of instance. Only the most similar train instances are kept for RUL prediction. The proposed approach was tested and compared to approaches that apply linear regression and PCA to model the library of instances. Results highlight the benefit of using UK compared to other approaches.

1. INTRODUCTION

Industrial systems are becoming more and more complex. Maintaining them is thus becoming costly and difficult. Prognostics and Health Management aims at reducing such maintenance costs while increasing systems security and reliability. In a PHM process, prognostic is a central activity where the common task is to predict the remaining life before failure of the examined equipment. As defined by the 2004 International Organization for Standardization (ISO, 2004), prognostics is an estimation of time to failure and risks of one or more existing or future failure modes. In general prognostic approaches can be classified into three classes: model-based, data-driven and hybrid approaches.

Model-based approaches study and model the degradation of the component by relying on the physical laws describing the damage propagation. This type of approaches gives accurate prognostics results. However, building such models for complex systems is a hard task especially in the absence of an adequate knowledge about the physical degradation phenomena.

Data-driven approaches, on the other hand, offer an appealing alternative to perform prognostics due to their ability to learn models from historical data. They are based on statistical and learning techniques and give the prediction output directly from the condition monitoring data. They offer a tradeoff between precision, complexity and implementation costs. Unlike model-based approaches which are application specific, data-driven approaches have a wider framework of applications. They can be applied on different systems as long as the assumptions related to the implemented approach are satisfied. However, the prediction outcome resulting from such approaches is less accurate.

Hybrid approaches are a combination of both data-driven and model-based approaches. The combined approach inherits the merits of both approaches while reducing the associated inconveniences. To increase the accuracy and the prediction performance, the physical model is studied and validated offline using model-based techniques and then models parameters are updated online using data-driven techniques.

As we do not have any prior knowledge about the physical degradation model of the monitored component, in this paper, we propose the use of a data-driven approach for RUL prediction. The approach is known under the name Instance Based Learning (IBL). The problem with this approach is to find an instance formalization that is able to estimate the RUL of a component while using the entire available sensory data.

There exist two types of instance formalizations: supervised

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and unsupervised formalizations. (Wang, Yu, Siegel, & Lee, 2008) for example used a supervised formalization of instances by applying linear regression. They proposed to learn a regression model of the damage by taking into account only the boundaries of the sensory data. (Mosallam, Medjaher, & Zerhouni, 2013) on the other hand, used an unsupervised formalization by applying principal component analysis.

We select the unsupervised formalization of instances and we propose the use of unsupervised kernel regression for this purpose. We compare the performance of the latter to both PCA and linear regression. Instances in our approach are thus obtained using unsupervised kernel regression. UKR allows modeling the latter without any assumptions about the components health status or the degradation model. The proposed method constructs a library of instances by fusing the run-tofailure data into a single feature that is faithful to the sensory data representing the damage propagation. Test instances are matched to the library of instances using a similarity measure and the RUL is estimated by using the end of life values of the retrieved best matches. This approach is compatible with any applications satisfying these assumptions:

- Run-to-failure data is available.
- Test components are assumed to go through the same degradation process as train components.
- Sensory data capture the health status evolution.
- Component level prognostics.

The remaining of this paper is organized as follows: section 2 details the proposed approach. Section 3 describes the experimental validation and the obtained results. Finally section 4 concludes the paper.

2. RUL PREDICTION APPROACH

The proposed approach predicts the remaining useful life of a new component based on already seen examples. That is learned instances.

IBL approaches for RUL prediction usually go through three main steps as depicted in Figure1; instance formalization, retrieval step and RUL prediction. The purpose of the instance formalization step is to construct a library of instances that characterize the health status evolution of components. At the retrieval step, a similarity test is conducted to retrieve the most similar instances that are present in the library and related to the problem instance. Once these instances are identified, the information present in them is then used for RUL prediction.

In our proposed approach, instances are formalized as degradation trajectories modeled using unsupervised kernel regression. The method is divided into two steps: an offline and an online step. Offline, a UKR model is learned from each train instance, where a train instance is an instance that goes



Figure 1. General IBL approach for RUL prediction.

through the whole degradation process. These learned models are used to fuse the multidimensional run-to-failure data into a single feature that depicts the evolution of the health status of the component. Hence, this modeling step enables the construction of a library of train instances that are faithful to the sensory data reflecting the degradation propagation. Online, each of the learned UKR models will be used to reconstruct a test degradation trajectory for the considered test unit. For a single test unit, all the reconstructed trajectories are compared to the train trajectories present in the library of instances. RUL is deduced by keeping only the train trajectories that are close to the test instance. The proposed approach is summarized in Figure 2 and will be further explained hereafter.



Figure 2. The general proposed approach. IBL approach for RUL prediction.

2.1. Instance Formalization

Instances are formalized as a one dimensional signal that is a faithful and compact representation of the multidimensional sensory data related to the degradation process. These degradation trajectories are modeled using unsupervised kernel regression.

UKR is a recent approach that is used to obtain a faithful latent dimensional representation $X=(x_1,x_2,,x_N)$, [qxN] of the set of observed data (sensory data in our case) $Y=(y_1,y_2,,y_N)$, [pxN]. The method was proposed by Meinecke and Klanke as an unsupervised formulation of the Nadaraya-Watson estimator. The idea is to generalize the estimator to the unsupervised case of function learning (Meinicke, Klanke, Memisevic, & Ritter, 2005). In the supervised case the estimator realizes a continuous generalization of the functional relationship between two random variables X and Y as described in Eq.(1)

$$y = f(x) = \sum_{i=1}^{N} y_i \frac{K_H(x - x_i)}{\sum_j K_H(x - x_i)}$$
(1)

Where K_H is the kernel density.

As stated in (Memisevic, 2003), the difference between the supervised and the unsupervised regression lies in the usage of the input variables. In the supervised case this becomes a problem of estimating a functional relationship of the input and the related output variable using samples of the latter. In the unsupervised case, the input variable space is considered missing and needs to be estimated together with the functional relationship by finding the sample set of outputs that gives the minimum reconstruction error. In order to derive the unsupervised counterpart of the estimator, (Meinicke et al., 2005) use the same functional form of the Nadaraya-Watson kernel regression estimator, but treat the missing input data as parameters. This set of parameters X=xi serves as a lower dimensional latent representation of the original dataset Y=yi. The UKR function becomes:

$$\begin{cases} b_i(x;X) = \frac{K(x-x_i)}{\sum_j K(x-x_i)} \\ y = f(x;X) = \sum_i^N y_i b_i(x;X) = Y b(x;X) \end{cases}$$
(2)

Where $b_i(x; X)$ contains the kernel-based latent basis function and f(x; X) is the UKR function.

The objective of unsupervised function as defined by Meincke et al. (2005) is to find a suitable realization of the mapping between the latent domain and the original data domain together with an associated latent representation. This can be reduced to a problem of finding a suitable latent mixture density p.

$$p(x;X) = \frac{1}{N} \sum_{i=1}^{N} K(x - x_i)$$
(3)

With that latent density model, the UKR function can be completely specified without any further parameters. After having defined the UKR model, the training phase of UKR consists in minimizing the reconstruction error, R, which is the error between the original observed data and the data points reconstructed from the latent variable vectors x_i

$$R(X) = \frac{1}{N} \sum_{i=1}^{N} ||y_i - f(x_i; X)||^2$$
(4)

The concept of UKR is an appropriate choice in our application since the output variable space to which we do not have access, as we do not have any prior information about the degradation evolution, is not required to perform the regres-



Figure 3. Learning how to formalize instances.

sion. The output of the regression model is a compact representation of the input data that keeps the resulting information loss at minimum.

As it can be seen from figure 3, from each training unit, a model is learned and saved in a library of models. This library is later used to formalize train and test instances. See figure 4.



Figure 4. Instance formalization. (a) For a training unit. (b) For a test units.

For a train instance, the corresponding UKR model is known and directly used to construct the degradation trajectory. As for a test instance, the corresponding model is not known but assumed to be one of the models presents in the library. In order to identify the right model, all the models of the library are used. This results in "n" - number of UKR models- test trajectories for a single test unit. At the retrieval step only the appropriate models are kept.

The obtained trajectories using UKR are further processed to produce a smoother output. Figure 5 presents the obtained trajectory after curve fitting.

2.2. Retrieval Step

In IBL, the retrieval step is of high importance. Retrieving unrelated instances will result in a large margin of prediction error. In order to obtain an estimation of the RUL of a given test instance, the train instances (instances with known End of Life values) similar to the test instance are retrieved. This is done by conducting a similarity test between test and train tra-



Figure 5. UKR degradation trajectory.

jectories. In most of the available IBL prognostic approaches, the historical data is not entirely used to set this similarity, it is either set by a vector of features characterizing the instance instead of of the actual instance data (Xue et al., 2008), or by using only the last measurements (Ramasso, Rombaut, & Zerhouni, 2013),(Zio, Di Maio, & Stasi, 2010).(Mosallam et al., 2013) and (Wang et al., 2008) took into consideration the whole historical data. However, with giving the same weight to all observations while it is known that late observations are of higher importance as failure of components occurs at late ages.

In this work, we use a similarity measure that considers the whole observation data with giving more weights to late ones. Figure 6 illustrates how to conduct this similarity test for a single test unit "p" when "n" train instances are available.



Figure 6. Retrieval step for a single test instance.

For each train instance, a single trajectory is constructed using the UKR model learned from that train instance. As for test instances, the testing unit consists of n test trajectories each constructed using one of the UKR models learned offline. As shown in Figure 6, each test trajectory is compared to its peer train trajectory that is the train trajectory constructed using the same UKR model. The sign +/- on the figure represents the computation of a similarity score between the two trajectories. This score is obtained by conducting a similarity measure as follows: The examined trajectories are divided into windows. Each window in the test trajectory is scanned throughout the entire train trajectory. The purpose of doing this is to find the trajectories with the highest similarity scores. The similarity between windows and thereby trajectories is based on the Euclidean distance, where late windows are given more importance since failure occurs at the late ages of life of the component. The final similarity score for each train trajectory is a value that is between 'zero' and 'one'. Zero indicating complete dissimilarity measure is formalized in algorithm 1 and illustrated in figure 7.



Figure 7. Proposed similarity measure.



Algorithm 1. Similarity measure algorithm.

By the end of the retrieve step, the most similar instances to the train instance are identified based on their similarity scores and kept aside for later use.

3. RUL PREDICTION

For a given test instance, RUL is predicted using the retrieved train instances. As described in figure 8, the library of instances contains instances with known end of life values. Once an online instance arrives, that is an instance with an unknown end of life value, a similarity test between instances is conducted using the approach described in this paper. RUL is then deduced using the EOLs of the best match instances.



Figure 8. Proposed similarity measure.

For each retrieved train instance, RUL is calculated as the difference between the end of life of the latter and the end of similarity. Eq.(5)

$$RUL(i) = EOL_i - EOSi \tag{5}$$

Where EOL_i is the end of life of the train instance i and EOS_i is the end of similarity which also indicates the current location on the train instance and is set by the similarity measure.

The predicted test RUL is obtained as either a simple average of RULs of best match instances, Eq. (6) or a weighted sum, where weights are obtained based on the similarity score of the best match instances, Eq. (7).

$$Mean predicted RUL = \frac{1}{k} \cdot \sum_{i=1}^{k} RUL(i)$$
(6)

$$W eighted sumpredicted RUL = \sum_{i=1}^{k} w(i).RUL(i) \quad (7)$$

where,

$$w(i) = \frac{SimScore(i)}{\sum_{i=1}^{k} SimScore(i)}$$

4. APPLICATION AND RESULTS

4.1. Data Representation

The challenge dataset of diagnostics and prognostics of machine faults from the first international conference of PHM (Saxena, Goebel, Simon, & Eklund, 2008) was used to evaluate and assess the performance of the proposed approach. This dataset simulates the damage propagation of aircraft gas turbine engines. It consists of 26 features which are multiple multivariate time series signals. Each time series represents a different engine from the same complex system. At the beginning, each engine is operating normally but ends up developing a fault prior to failure.

Among the available datasets, dataset 1 was used. This dataset is characterized by one operating condition and one fault mode. The training file is composed of 100 time series representing the damage propagation of 100 units. Each unit in this file goes through the whole degradation process. The test file is composed of 100 time series as well. However, these time series end up some time prior to failure. Hence, the objective is to predict the remaining useful life for each test unit. Among the 21 sensors, only 5 were used accordingly to (Ramasso et al., 2013),(Wang et al., 2008).

4.2. Evaluation Metric

To evaluate the performance of the proposed approach, the percentage of acceptable predictions is considered as an evaluation criteria.

A prediction is considered correct if its corresponding error, Eq. (9) falls with the range of acceptable errors (Ramasso et al., 2013), (Goebel & Bonissone, 2005). In this paper, the interval was set as I = [-10, 13]. The interval is asymmetric as early predictions i.e. predictions with positive errors, are preferable in prognostics and hence more tolerable compared to late ones. Figure 9 illustrates this interval.

The performance is then calculated as the percentage of the overall correct predictions.

$$Error = ActualRUL - PredictedRUL \tag{8}$$



Figure 9. Evaluation Metrics.

4.3. Results and Discussion

To estimate the remaining useful life of the test unit a UKR model was learned from each unit in the training file. The entire 100 units of the test file were used for testing. It should be noted here that test trajectories have different lengths. That is each test unit has a different prediction horizon.

Throughout the whole testing, the same set of parameters of the similarity measure was used, the size of windows was set to 30, the overlap to 15, λ was set to 1 and the threshold to

0.8. this set of parameters is user-defined and determine how strict is the similarity measure.

Figure 10 shows the predicted and real RUL values for the 100 test unit, using UKR with a simple average of best match RULs.



Figure 10. Actual and predicted RUL values for the test units.

The performance of our approach based on UKR was compared to PCA and linear regression. To do this, the UKR modeling step in the general approach, Figure 2, was replaced by PCA and linear regression.

As a first alternative to UKR, and for comparison reasons, PCA was used to fuse the sensory data into a one dimensional signal. This step was repeated offline and online. The obtained fitted online signal was compared to the library of instances constructed using PCA and RUL was calculated as described in section 2.3.

The second alternative was to model the degradation trajectories using linear regression. As proposed by (Wang et al., 2008) a regression model was trained offline by considering two states of the component; healthy and faulty. A component is considered healthy at the beginning of its life and faulty at the end of its life. Only sensory data representing the healthy and faulty states were used to train the model. The regression model was used both offline and online to fuse the sensory data. The fitted online trajectory was compared as well to the library of instances following the same approach described in this paper.

The performance of UKR was compared to PCA, since in this work UKR was used as dimension reduction tool and PCA is the most widely used and understood dimension reduction tool. Linear regression on the other hand was used by (Wang et al., 2008) for the same datasets and proved to be efficient for damage modeling on this dataset.

Results obtained using UKR based modeling approach, PCA and linear regression are shown in figures 11 and 12. Fig-

ure 11 depicts the obtained results using a simple average of RULs of best match instances while figure 12 depicts the obtained results using a weighted sum of the latter. Both methods had almost equal performance with slight preference of the weighted sum method.

Figure 13 depicts the performance difference between UKR linear regression and PCA according to the selected number of neighbors. The graph shows better performance of UKR.



Figure 11. Obtained results using simple average of best match RULS.



Figure 12. Obtained results using a weighted sum of best matches RULs.

The results show clearly higher performance of UKR based modeling approach compared to both PCA and linear regression modeling. This superior performance can be explained by the following main two reasons; absence of any type of modeling while using PCA, and using only portions of the training data to train the regression model while applying linear regression.



Figure 13. Performance difference between UKR, PCA and linear regression.

The approach is built on instance based learning where the similarity between train and test instances is of high importance. In the absence of any learned model, that is applied to both train and test instances as it is the case for PCA, finding and detecting such a similarity is rare (not always an option) since the instances were not modeled in the same way. This is why PCA had the worst performance compared to linear regression and UKR.As for linear regression, although a unique model was used for both test and train instances the model was learned using only a portion of the training data while neglecting the rest. This slightly affected the performance of the linear regression leading to worse performance than the proposed UKR-based approach for higher number of neighbors. As it can be seen from figures 8 and 9, changing the number of neighbors affects the performance of the prediction. The prediction performance for both approaches varies from 42% to 50% for the linear regression approach and from 38% to 57% for the UKR approach. The best prediction performance value using the linear regression approach is 50% and it is obtained by considering 9 neighbors while the best prediction performance for the UKR approach is 57% obtained using 15 neighbors. Comparing the best prediction performances of both approaches UKR seems to be better as it gives the highest overall performance.

5. CONCLUSION

This paper presented a prognostic approach for RUL prediction based on instance based learning and unsupervised kernel regression. UKR was used to model the degradation trajectories without any prior knowledge about the health state of the component. Online, the piece of trajectory constructed using the UKR models learned offline, is compared to a library of degradation trajectories. RUL is then estimated directly using the retrieved best match trajectories.

The approach was demonstrated on the challenge dataset of diagnostics and prognostics of machine faults. Results showed better performance of UKR modeling compared to PCA. As for linear regression, the performance difference is in favor of UKR for higher number of neighbors. Our future work will focus on further enhancing the instance formalization and the

similarity measure by adding to the temporal aspect of trajectories a frequency aspect and considering the frequency difference when setting the similarity score.

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REFERENCES

- Goebel, K., & Bonissone, P. (2005). Prognostic information fusion for constant load systems. In *Information fusion*, 2005 8th international conference on (Vol. 2, pp. 9– pp).
- ISO. (2004). Condition monitoring and diagnostics of machines, prognostics part 1: General guidelines (Vol. ISO/IEC Directives Part 2; Tech. Rep. No. ISO13381-1). International Organization for Standardization.
- Meinicke, P., Klanke, S., Memisevic, R., & Ritter, H. (2005). Principal surfaces from unsupervised kernel regression. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 27(9), 1379–1391.
- Memisevic, R. (2003). Unsupervised kernel regression for nonlinear dimensionality reduction. Unpublished doctoral dissertation, University of Bielefeld.
- Mosallam, A., Medjaher, K., & Zerhouni, N. (2013). Bayesian approach for remaining useful life prediction. *Chemical Engineering Transactions*, *33*, 139–144.
- Ramasso, E., Rombaut, M., & Zerhouni, N. (2013). Joint prediction of continuous and discrete states in time-series based on belief functions. *Cybernetics, IEEE Transactions on*, 43(1), 37–50.
- Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage propagation modeling for aircraft engine runto-failure simulation. In *Prognostics and health management*, 2008. phm 2008. international conference on (pp. 1–9).
- Wang, T., Yu, J., Siegel, D., & Lee, J. (2008). A similaritybased prognostics approach for remaining useful life estimation of engineered systems. In *Prognostics and health management, 2008. phm 2008. international conference on* (pp. 1–6).
- Xue, F., Bonissone, P., Varma, A., Yan, W., Eklund, N., & Goebel, K. (2008). An instance-based method for remaining useful life estimation for aircraft engines. *Journal of Failure Analysis and Prevention*, 8(2), 199– 206.
- Zio, E., Di Maio, F., & Stasi, M. (2010). A data-driven approach for predicting failure scenarios in nuclear systems. *Annals of Nuclear Energy*, 37(4), 482–491.

A Certifiable Approach towards Integrated Solution for Aircraft Readiness Management

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ABSTRACT

Aircraft readiness management plays pivotal role for aviation authorities to enhance mission availability, reliability and reduce maintenance cost. This has been the focus area of the industry for many years now. This paper focuses on developing an approach for maximizing the aircraft readiness based on the Aircraft Health Assessment and a novel approach for Maintenance Planning. An integrated solution using results from Prognostic Health Management (PHM) functions has been proposed. The concept is based on the condition based mission planning, operational risk assessment, maintenance planning and supply chain management. Also an insight is provided into the systematic approach to derive maintenance strategy leading towards certification. Although, the solution can be used for both commercial and military aviation, the focus in this paper is on implementation for military platforms. Details on implementation are discussed in brief and the results of this implementation on some hypothetical scenarios are presented. The results outline the effectiveness of the approaches in improving the aircraft readiness.

1. INTRODUCTION

Aircraft Readiness is a related measure of the availability and is a metric predominantly used for military aviation. Readiness includes operational downtime, free time and storage time. Aircraft Readiness covers a broader perspective than just availability of an aircraft, a complete availability of the operational systems with the supporting staff, resources and infrastructure necessary for the operations is a measure of the readiness. Overall readiness of an air vehicle is a joint product of capability assessment of planned missions based on present and future health of the vehicle and efficient maintenance planning considering logistic delay and other constraints related to supply chain. The Aircraft Readiness Management process can be subdivided into Maintenance Planning & Management, Resource Planning & management & Supply Chain.

The effective management of operations of aircraft across fleet, squadron and enterprise levels for an organization highly depends upon the availability of a matured Operation Support System. The Operation Support System, being core off-board ISHM module, generally provides ground support services through Mission Planning and Readiness Management of air vehicle.

Most of the air forces or airlines use disjoint tools for the sub-processes. This may lead to non-feasible mission plans, more maintenance time and introduces delays and operational overheads in identifying the suitable aircraft with the planned configuration. ISHM enables to provide integrated solution of these functions for efficient and cost effective readiness management.

Intelligent maintenance planner has an optimization model for appropriate clustering of maintenance tasks into maintenance events. This model, which synchronizes with resource planning and mission planning, enhances mission availability, fleet maintainability and operational cost saving. Intelligent maintenance planner augments the conventional Reliability Centered Maintenance (RCM) process (Preventive, Reactive, etc) with Condition Based Maintenance (CBM) to generate an optimized maintenance plan.

The novelty of this work includes method to create maintenance database from certifiable RCM decision logic, handling strategic importance of planned missions based on mission types, providing flexibility in selection of optimization modes (availability alone and availability along with cost). This also includes a simplified approach for accommodating resource constraints in order to provide

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an integrated solution. Simulation results of the solution integrated in ISHM Simulation Framework of Airbus Defence & Space illustrate the convincing performance of the algorithm and help in taking decision on functional architecture of off-board ISHM (Mathias Buderath, Adhikari P. P., 2012).

2. CONCEPT OF INTEGRATED SOLUTION OF READINESS MANAGEMENT

Planning for aircraft readiness generally is done in two phases, namely Long-term, Short-term. However, some operator prefers to implement also "Medium Term" (Muchiri Anthony K., 2002). In order to synchronize aircraft utilization and aircraft maintenance, a close relationship is maintained between air force head quarter and squadron for military operation; the Commercial Planning Department and Maintenance Planning & Support Departments for civil aviation. Long term planning, input for which is driven by Commercial Planning Department (for civil) or Air force Headquarter (for military), consists of the following functions:

- Flying Hours Programs (FHP)
- Aircraft Utilization Scenario
- Maintenance Scenario
- Resource Requirement Scenario

Flying Hours Programs (FHP) by Air force Headquarter determines the number of total yearly flying hours in order to ensure combat readiness and training requirement of Air Force (Philip Y Cho, 2011). Each squadron specifies daily sortie requirements and assigns to each aircraft for complete

year and this results to generate Aircraft Utilization Scenario. Preventive maintenance requirements with different frequencies are identified to predict maintenance scenario for each aircraft based on predicted usage for complete year. Then resource requirement for preventive maintenance scenario are identified date-wise for complete year.

Readiness management is a short term planning (1-3 months) of maintenance events and resources required along with associated managements based on health assessment which analyzes results from diagnostics, prognostics, inspections and assesses operational capability of aircraft for planned mission. Mission Planner receives information from Readiness management on readily available aircrafts for operational planning.

Reliability Centered Maintenance (RCM) provides maintenance strategy mapping maintenance type and redesign decision with each fault and PM task details (recommended schedule, Max FH, cycles, calendar date, etc) to Readiness Management. RCM is a well-structured, logical decision process used to identify the policies needed to manage failure modes that could cause the functional failure of any physical item in a given operating scenario.

3. FRAMEWORK TO DERIVE MAINTENANCE STRATEGY

There are at least six key factors required for maintenance to achieve its purpose of optimizing operating performance. These are to reduce operating risk, avoid aircraft failures, provide reliable equipment, achieve least operating costs, eliminate defects in operational aircraft and maximize availability. These purposes are determined by three KPIs: enhancement in mission availability, reliability and



Figure 1. Functional Block Diagram of Aircraft Readiness Management

reduction of maintenance cost. Suitable maintenance strategies are selected during design stage to provide the required values of the KPIs. However, maintenance strategy may get changed based on periodic evaluation of maintenance effectiveness and risk assessment during operation phase.

Maintenance Strategy aims to map all fault modes at individual and LRU levels to different maintenance categories: PM (S-Servicing, L-Lubrication, OC-Scheduled On-condition, HT-Hard Time and FF-Failure Finding Inspection), CBM, Run-to-Fail and other actions consisting of redesign, change in operation or maintenance procedure or restriction in operation. Optimized maintenance strategy is also derived at component/LRU level.

Maintenance credits are acquired when an ISHM system can replace the existing industry standard maintenance for a given component or complete aircraft system and this enhances availability, maintainability and mission capabilities of aircraft. To reach this level, evolution of ISHM development has to pass through effective process for technology maturation, development, verification, validation, qualification and finally certification.

After determination of the potential functionality and benefits of ISHM, technology maturation efforts are initiated. The maturation efforts are often performed through technology development guided by appropriate



roadmaps. Efforts are allocated to RCM analysis, design and analysis of algorithm for diagnostics, prognostics, sensor selection and other enablers related to off-board ISHM. This also includes enhancing the performance of ISHM in terms of increased accuracy, reduced weight, improved reliability, advanced communication and efficient data transfer. Technology gaps and risks are identified and efforts are allocated to fill the gaps and to mitigate the risks. During the maturation phase, the potential benefits and credits of ISHM are re-assessed and validation evidence is gathered through component rigs, integrated simulation framework, etc. The Figure 3 details the activities during concept refinement and technology development phases.

RCM analysis is the foundation to establish a framework for candidate selection. The Figure 2 depicts the logic for deciding maintenance strategy for a LRU. The proposed decision logic is based on existing guidelines: SAE JA1011, SAE JA1012, NAVAIR 00-25-403 and ATA MSG-3 with suitable modification. After fault consequence check, maintenance options for each fault type of a LRU are short listed based on technical feasibility only. Cost effectiveness and risk are computed for each selected option of the fault type. Best maintenance option or combinations of options are selected for LRU by solving optimization problem which maximizes availability, ROI of selected option and minimizes risk at the LRU level.

Technical & Risk Feasibility criteria for CBM
Is failure mode observable through condition monitoring?
Are State-of-the-art diagnostics & prognostics methods for failures available?
Are already available sensors support for condition monitoring?
Is installation of additional sensors feasible?
Are KPIs related to diagnostics and prognostics acceptable?
Does the task reduce the risk to an acceptable level?
Is maintenance credit justification in place?
Common Technical & Risk Feasibility criteria for any PM task (except scheduled on-condition)
Failure rate pattern type is of Bathtub or Traditional Wear-out
Is any PM task physically capable of being performed?
Does the task reduce the risk to an acceptable level?
 Technical and risk feasibility criteria are determined for each maintenance type
* Risk assessment is done using Hazard Risk Table

Figure 2. RCM Decision Logic for Maintenance Strategy



Figure 3. Guideline for technology development & maturation

4. MAINTENANCE PLANNING MECHANIZATION

Operations in commercial airline are more cost sensitive and hence it is no surprise that major focus of the work on maintenance planner has been on airline scheduling. Significant differences in the military and civil flight operations make most of the existing work not directly applicable to military aviation, but can be a good starting point. The basic difference in civil and military aviation is that the civil aviation is highly focused on route selection and assignments with profitability and cost savings being the major goal. On the other hand, the goal for military aviation is a high level of combat readiness with cost being relatively less significant factor. Also, since the fighter squadrons are usually fixed at a given location, readiness does not involve any decisions regarding routes. Hence the objective here is to define a maintenance schedule that will minimize the downtime thereby ensuring most effective utilization of the system with applicable constraints at the lowest possible costs. In other words enhancing the availability leading to combat readiness is achieved through advanced maintenance planning and management.

Maintenance-scheduling is not limited to aviation industry and the benefits are evident in various industries and substantial effort has been put into this over the last few years by various researchers, prominent among them are : power plants (Canto, 2008; Doyle, 2004; Damien et al., 2007); aircrafts and -engines (Almgren et al., 2008; Sarac et al., 2006); production planning (Panagiotidou and Tagaras, 2007). Almgren et al. (2008) presents mathematical models for finding optimal opportunistic maintenance schedules for systems, in which components are assigned maximum replacement intervals. The work is extended for complete aircraft having heterogeneous maintenance types (Run-tofail, Preventive, Condition Based Maintenance) along with the unique features as mentioned in the introduction.

The following figure summarizes key steps for maintenance planning.





4.1. Mathematical models for optimization

The proposed Maintenance Planner supports the following two modes of optimizations

- Availability Optimization
- Availability & Cost Optimization

Let us consider there are 'N' maintenance tasks and a finite maintenance time horizon (in terms of day/slot) is discretised into 'T' time steps. The optimization problem for all three modes can be represented as following.

Minimize (X,Z):
$$\sum_{t=1}^{T} \left(\sum_{i=1}^{i=N} C_{it} X_{it} + D_{t} Z_{t} \right)$$
(1)

Subjected to: The constraints related to due dates of maintenance, associated thresholds, minimum gap between two consecutive maintenances, exclusivity of tasks and resource availability, etc are mentioned bellow.

Where,

C _{it}	Weight factor of each design variable in terms of
	maintenance cost or over maintenance time/effort
	related to maintenance task 'i' at day/slot 't'
D _t	Weight factor of each design variable in terms of
	unavailability and or maintenance site cost related
	to possible maintenance event starting at day/slot 't'
X it	Sets to '1' if maintenance task 'i' is requested at
	day/slot 't', otherwise it sets to '0'
Zt	Sets to '1' if the resultant maintenance event for a/c
	occurs starts at day/slot 't', otherwise it sets to '0'

The following table defines objective parameters (' C_{it} ' & (D_t) in three different modes.

Optimization	C_{it}	D_t
Mode		
Availability Optimization	w1*(Over maintenance Time) : for each task (<i>i</i>) & each day/slot (<i>t</i>) within maintenance horizon	w2*(Mission Unavailability) : for probable maintenance event starting at day/slot (<i>t</i>) within maintenance horizon
Availability & Cost Optimization	w1*(Individual Maintenance Cost) + w2*(Over maintenance Cost) : for each task (<i>i</i>) & each day/slot (<i>t</i>) within maintenance horizon	w3*(Cost of Site) + w4*(Mission Unavailability) : for probable maintenance event starting at day/slot (t) within maintenance horizon

Table 1. Definition of Weight factors

Constraints:

If there is no resource constraint, each component is replaced / repaired on or before due date and maintenance schedule falls within opportunistic maintenance threshold and maintenance threshold.

$$\sum_{t=t0}^{tf} X_{it} \ge 1, \quad i \in \{1, 2, \dots, N\}$$
(2)

Where, $t0 = (t_{md}^{i} - t_{mth}^{i} - t_{omth}^{i})$, $tf = (t_{md}^{i} - t_{mth}^{i})$ and variables are defined here.

i t _{md}	Time when maintenance is due for task 'i'; This is calculated based on current and maximum FH, cycles and calendar date for preventive maintenance candidate. This is calculated from RUL from CBM candidate.
t_{omth}^{i}	Opportunistic maintenance threshold for task 'i'; Opportunistic maintenance threshold is maximum allowable window of maintenance schedule decision.
t ⁱ t _{mth}	Maintenance threshold for asset 'i'; Maintenance threshold is threshold time before expiry of RUL; before which maintenance has to be scheduled. This is set to zero for run-to-fail maintenance candidate.

For reactive maintenance of critical item, opportunistic maintenance threshold and maintenance threshold are zeros.

For reactive maintenance of non-critical item, opportunistic maintenance threshold = - Threshold, i.e. Next maintenance event will include this task. For only CBM candidate, maintenance threshold is non zero.

For preventive maintenance (Calendar based), gap between two maintenance dates scheduled should be such that number of days should be less than maximum numbers of days specified ('Ti') for the item. $1 \pm T_i$

$$\sum_{t=l+1}^{l+1} X_{it} \ge 1, \qquad l = 0, \dots, \quad T - Ti$$
(3)

If a maintenance event is scheduled, at least one maintenance task will be accomplished.

$$X_{it} < Z_t$$

 $i \in \{1, 2, \dots, N\} \& t \in \{1, 2, \dots, T\}$ (4)

For exclusives maintenance tasks, two sets can not be included in same maintenance event. \sum_{t}

$$_{t\in d}(X_{At}+X_{Bt})<1\tag{5}$$

Where.

$$d_q = \left[\left(t_{mdA}^{i=A} - t_{omth}^{i=A} \right) : t_{mdA}^{i=A} \right] \cap \left[\left(t_{mdB}^{i=B} - t_{omth}^{i=B} \right) : t_{mdB}^{i=B} \right]$$

'A' and 'B' are selected from two exclusive sets of maintenance tasks.

$$d = (d_1 \cup d_2 \cup \dots \cup d_q)$$

Where, 'd' represents the set of days where maintenance tasks 'A' & 'B' may get scheduled together in same maintenance event, 'q' is the maximum number of combinations of maintenance instances of 'A' and 'B' during complete maintenance horizon.

A/C has to be mandatorily available for selected days. Cost of maintenance event is set to very high on these days $(d_{1,2,..,n}).$

$$D_{t_{\ell(d_{1,2},n)}} \cong 10^{+10} \tag{6}$$

Special Constraints related to resource unavailability:

If there is resource constraint for a critical item, due date (t_{mdr}) of maintenance is postponed to earliest date when resource is available and opportunistic maintenance threshold and maintenance threshold are set to zeros. A/C will be down until maintenance of the critical items.

$$X_{it_{mdr}} = 1, \quad i \in \{1, 2, \dots, Nr\}$$
 (7)

If there is resource constraint for a non-critical item, due date of maintenance can be shifted to the earliest date when resource is available and opportunistic maintenance threshold is of negative value, i.e. next maintenance event shall include this task.

$$\sum_{t=t0}^{y} X_{it} \ge 1, \qquad i \in \{1, 2, \dots, Nncr\}$$
(8)

Where, $t0 = (t_{md}^{i} - t_{mth}^{i} - t_{omth}^{i})$, $tf = (t_{md}^{i} - t_{mth}^{i})$ and '*Nncr*' is number of non-critical tasks with resource constraint.

No maintenance event can be scheduled if common resources like infrastructure are not available in a set of days $(d_{1,2,..n})$.

$$Z_{t \in (d_{1,2..n})} = 0$$
 (9)

 ${}^{\prime}X_{it}$ & ${}^{\prime}Z_t$ are binary variables. Length of maintenance horizon is ${}^{\prime}T'$ and ${}^{\prime}N'$ is the maximum number of maintenance tasks to be scheduled within this horizon.

$$X_{it}, Z_{t} \in \{0, 1\},\ i \in \{1, 2, \dots, N\} \& t \in \{1, 2, \dots, T\}$$
(10)

The optimization problem is solved by Binary Integer programming.

Instead of enhancing more number of constraints due to resources, the solution is simplified by recalculating due date of maintenance requests and opportunistic maintenance threshold. Towards this end, Maintenance planner projects allocation of resources based on maintenance requests, task priority, predicted usage considering missions planned, available resources as updated by resource planner. Figure 5 depicts the interactions between maintenance planner and resource planner along with sequence numbers.

4.2. Availability model

Unavailability of mission due to A/C down for maintenance event, which starts at particular day/slot, depends on the following factors:

- Probable coincidence of maintenance schedule with mission schedule
- Type of mission planned and this is driven by strategic importance factor
- Duration of possible maintenance event consisting of maximum number of maintenance tasks

The aircraft down time for probable maintenance event starting at day / slot 'd' considering importance factor of missions affected is:

$$Ua(d) = \sum_{i=1}^{Mt} \sum_{j=1}^{Dd} Fm(i, j) * Cm((i, j) * Dm(i, j)$$
(11)

Where,

Fm(i,j)	Mission of mission type 'i' is scheduled or not scheduled at day/slot 'j'	
Cm(i,j)	Importance factor for mission type 'i' scheduled at day/slot 'j'	
Dm(i,j)	Duration of mission type 'i' scheduled at day/slot 'j'	
Mt	Maximum number of mission types	
Dd	Maximum number of days/slots required by maintenance event.	



Figure 5. Interaction between Maintenance Planner & Resource Planner

Re-plan r

Importance factors for different mission types are configurable. The following table shows an example of gradation of importance of different mission types.

Mission Type (code)	Importance
	Grade [Level]
Fighter Bomber	Very High [5]
Suppression of Enemy Air Defence	High [4]
Maritime Air Operations	Medium [3]
Reconnaissance mission	Low [2]
Surveillance Mission	Very Low [1]
No Mission	No impact [0]

Table 2: Example of Mission Importance Grade

In case of availability & cost optimization mode which may be applicable for civil operation, the aircraft downtime can be converted to cost incurred due to outage of aircraft operation. This contributes common maintenance cost related to maintenance event.

4.3. Model for Aircraft over maintenance

Due to clustering of maintenance tasks for batch maintenance of aircraft, some equipment may undergo maintenance ahead of their scheduled maintenance time. This is referred to as 'over maintenance'. Over maintenance incurs additional cost to operation and support activities.

Over maintenance factor for maintenance task 'i' at day '(*d*-*j*)' can be defined as:

 $Om(i, d-j) = Fo(i) * Hop*j \quad for j = 0 \text{ to } t^{i}_{omth} \quad (12)$

Where,		
d	Maintenance due date for task 'i'	
Fo(i)	Over maintenance effort per hour for task 'i'	
Нор	Average operating hour per day	
t ⁱ _{omth}	Opportunistic maintenance threshold for maintenance task <i>i</i> ?	

In case of availability & cost optimization mode, this over maintenance factor can be converted to over maintenance cost after multiplying with appropriate cost factor and this contribute cost related to each maintenance task.

4.4. Cost Model

In Availability and Cost Optimization mode, objective function for scheduling maintenance events represents total cost to execute maintenance events during complete maintenance horizon and this cost aspects are attributed due to the following factors

- Cost related to each maintenance task
 - The direct maintenance cost
 - Over maintenance cost attributed due to shifting of maintenance task from due date
- Common maintenance cost related to a maintenance event
 - Cost of site/infrastructure
 - Representative cost of unavailability of mission due to A/C down for maintenance



Figure 6. Cost of Individual Maintenance Task

Objective of maintenance optimisation is to reduce maintenance cost and to enhance availability. First type of cost is directly related with maintenance cost and second type of cost is mainly related with availability.

The direct maintenance cost related to each individual maintenance task has the following cost components:

- Material
- Labour
- Test
- Ground support equipment

Corresponding cost equations are given in detail in Table 3.1 of NAVAIR 00-25-403.

Common maintenance cost related to a maintenance event is attributed by the following factors

- Cost of site/infrastructure
- Representative cost of unavailability of mission due to A/C down for maintenance

Cost of site/infrastructure depends upon demand and availability. Even if there is no real cost related to site/infrastructure, representative cost figure based on site availability brings intelligence in optimization.



Figure 7. Resource Planner Block Diagram

5. RESOURCE PLANNING

Mission effectiveness is highly dependent on efficient maintenance which in turn is dependent upon reliable and prompt logistical support. Regardless of the cost it is important to have the item readily available to support the efforts of the mechanics in a timely manner. Resource control function (Figure 7) calculates resource demand based on long term maintenance scenario, historical data. Validity check module generates resource constraints and validates maintenance plan based on request from maintenance planner. Resource Management function manages purchase process, tracks availability and delivery, avoiding excess inventory and captures feedback to refine continuously important thresholds like lead times, etc.

6. CONDITION BASED MISSION PLANNING

The condition based Mission Planner developed has an additional feature of providing warning to user for replanning in addition to the conventional features like entry of mission plan through digital map, replay of mission with aircraft model in loop, creation of database for mission plan & flying program. Re-planning intelligence of Mission Planner is driven by performance evaluation (level 1&2), mission and segment capability computed by ORA and approved maintenance planned.

Initially the performance parameters of aircraft related to estimated trajectory as per mission plan are computed. If estimated performance exceeds the specified performance limits of aircraft, user is instructed in term of warning to reschedule the mission plan. Mission Planner warns the user to reschedule the mission plan if approved maintenance plan conflicts with mission plan. Applicability of mission segments of a particular aircraft is checked with respect to operational capabilities of the aircraft for the segment, computed by ORA. It checks whether operational capability for that segment is less than mission critical threshold. If operational capability does not support the particular mission segment for an aircraft, it instructs in term of warning to re-plan the particular segment of the Mission.

7. RESULTS & DISCUSSION

For simplicity, it is assumed that electrical and hydraulic system represents complete aircraft and a representative use case is defined to validate maintenance strategy and planning algorithm. Failure Mode Effect and Criticality Analysis (FMECA) are carried out for selected components which are run through the candidate selection logic to define maintenance type for each fault.

Figure 8 represents different units of maintenance scheduling. A maintenance task is considered as lowest unit of maintenance to be scheduled. Task steps (TS) will be considered in the description of each maintenance task. Maintenance events are scheduled by clustering a number of maintenance tasks using optimization. Maintenance Plan for an A/C is scheduling of all maintenance event during complete A/C maintenance horizon. Final Maintenance Plan is derived after merging individual maintenance plan for a fleet of A/Cs.



Figure 8. Definition of different unit of maintenance planning for a use case

A scenario is defined with maintenance tasks with asset ids within 100-116 (which are arbitrary). Database tables (~20) are populated with synthetic data related to faults, maintenance task details, resources required, cost details, etc aligning with the use case and mapping with OSA-CBM data structure. Figure 9 depicts the maintenance plan computed by the tool developed. Individual maintenance requests are represented by different red colored symbols whereas the blue line with blue symbols represents beginning of a maintenance event with respective tasks having maintenance event spread across the shaded zone. Maintenance plan is created in Maintenance benefit mode where only PM and RTF maintenance types are considered and the same is created in maintenance credit mode having all possible maintenance types including CBM. The generated maintenance plan for the defined hypothetical scenario leads to the following observations. Availability enhancement is 19% more in maintenance credit mode compared to maintenance benefit mode. This indicates the benefit of CBM compared to PM. Availability enhancement due to optimization is 64% in maintenance credit mode.

Selection of optimum value of opportunistic maintenance threshold is done based on fact that availability increases with increase of the threshold but cost saving initially increases but starts reducing after some value of the threshold due to over maintenance cost. With this consideration, user may decide opportunistic maintenance threshold as 8 days as per Figure 10 for this specific scenario.

Maintenance Planner ensures A/C to be more available for strategically more important mission. The priorities of missions are assumed as mentioned in the Table 2. A maintenance plan is already scheduled on a particular date, if a strategically more important mission is suddenly scheduled on the same date, maintenance planner will ensure to enhance probability to accomplish the mission and reschedule maintenance date. The Figure 9 (scheduling of maintenance event 3) depicts the same results.



Figure 9. Maintenance Plan: First tab of Maintenance Planner

Maintenance Planer provides feature to input selected dates on which A/C availability is mandatory. Maintenance Planner will also ensure availability of the A/C on the selected dates and shift maintenance to adjacent dates date based on only availability or both availability & cost optimization as per selection of optimization mode.



Figure 10. Selection optimum value of opportunistic maintenance threshold

Maintenance planner avoids scheduling the maintenance event on a particular day if logistic resources or required infrastructure is not available on the desired day. Shifting of maintenance date is based on criticality of item, priority, earliest date having appropriate amount of resource types available and optimum value of cost & availability. Relevant resource constraints are also tested and provide satisfactory results.

8. CONCLUSION

An integrated solution of aircraft readiness management based on ISHM has been presented. A logical approach has been proposed to provide framework for maintenance strategy based on certification guideline and optimization model for maintenance planning which efficiently handles important factors, resource constraints and flexible means of selecting optimization mode based on available data. The proposed approach reduces the complexity of the problem, but the solutions found may not always be the optimal solution. If optimization iterations can be done in single stage, that is, schedule of task steps in maintenance events is also part of main optimization model; the solution may be optimal. The results have been shown for one hypothetical scenario; more realistic data along with a Monte Carlo simulation would be more accurate. The present concept can be extended to finite time horizon optimization of maintenance and replacement models for multi-unit system having both deterministic and stochastic parts.

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NOMENCLATURE

- A/C Aircraft
- BIT Built-In Test
- CBM Condition Based Maintenance
- FF Failure Finding (inspection)
- FH Flying Hour
- FHP Flying Hours Program
- FMECA Failure Mode, Effects and Criticality Analysis
- HRT Hazard Risk Table
- HT Hard Time (task)
- ISHM Integrated System Health Monitoring
- IVHM Integrated Vehicle Heath Monitoring
- KPIKey Performance IndicatorLLubrication
- LRU Line Replaceable Unit
- OC On-Condition (maintenance)
- ORA Operational Risk Assessment
- OSA Open System Architecture
- PHM Prognostic Health Management
- PM Preventive Maintenance
- RCM Reliability Centered Maintenance
- ROI Return on Investment
- RUL Remaining Useful Life
- RTF Run-to-Fail (maintenance)
- S Servicing
- SHM Structural Health Monitoring
- TS Task Step

REFERENCES

- Almgren, T., Andréasson, N., Anevski, D., Patriksson, M., Strömberg, A.-B., & Svensson J. (2008). *Optimization of opportunistic replacement activities: A case study in the aircraft industry*. Preprint 2008:45, Dept. of Mathematical Sciences, Chalmers Univ. of Tech. and Univ. of Gothenburg, Göteborg Sweden.
- Andréasson, N. (2004). Optimization of opportunistic replacement activities in deterministic and stochastic multi-component systems. Licentiate thesis, Dept. of Mathematics, Chalmers Univ. of Tech. and Univ. of Gothenburg, Göteborg, Sweden.
- ATA MSG-3 (1993). Operator/Manufacturer Scheduled Maintenance Development. Maintenance Steering Group – 3, Task Force Air Transport Association of America.
- Canto, S. P. (2008). Application of Benders' decomposition to power plant preventive maintenance scheduling. *European Journal of Operational Research*, Vol. 184, pp. 759–777.

- Damien, P., Galenko, A., Popova, E., & Hanson, T. (2007). Bayesian semi parametric analysis for a single item maintenance optimization. *European Journal of Operational Research*, Vol.182, pp. 794–805.
- Doyle, E. K. (2004). On the application of stochastic models in nuclear power plant maintenance. *European Journal of Operational Research*, Vol. 154, pp. 673–690.
- Fatih Camci, G. Scott Valentine & Kelly Navarra (2006). Methodologies for Integration of PHM Systems with Maintenance Data. *IEEEAC* paper #1191, Version 1.
- Matthias Buderath & Adhikari P. P. (2012). Simulation Framework and Certification Guidance for Condition Monitoring and Prognostic Health Management. European Conference of Prognostics and Health Management Society 2012.
- Mike Sondalini. *How to Change RCM2 to Get Really Useful Maintenance Strategy*. Lifetime Reliability Solution.
- Muchiri Anthony K. (2002). Maintenance Planning optimisation for the Boeing 737 Next Generation. DELFT Aerospace, Master Thesis.
- NAVAIR 00–25–403 (2005). Guidelines for the Naval Aviation Reliability Centred Maintenance Process. Director of Commander, Naval Air System Command.
- Philip Y Cho (2011). *Optimal Scheduling of Fighter Aircraft Maintenance*. Massachusetts Institute of Technology, June 2011.
- Sarac, A., Batta, R., & Rump, C.M. (2006). A branch-andprice approach for operational aircraft maintenance routing. *European Journal of Operational Research*, Vol. 175, pp. 1850–1869.
- SAE JA1011 (2009). Evaluation Criteria for Reliability-Centred Maintenance (RCM) Processes. issued in 1999, revised in 2009.
- SAE JA1012 (2011). A Guide to the Reliability-Centred Maintenance (RCM) Standard. Issued in January 2002, revised in 2011.

BIOGRAPHIES



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Operational Metrics to Assess Performances of a Prognosis Function. Application to Lubricant of a Turbofan Engine Over-Consumption Prognosis.

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ABSTRACT

In the aeronautical field, one of the major concerns is the availability of systems. To ensure availability, Prognosis and Health Management algorithms are developed. The aim of these algorithms is twofold. The first one is to detect and locate degradation premise of "no go" condition occurrence. The second one is to predict the health state of the system at a given time horizon. Before introducing PHM algorithms in operation, it is necessary to assess their performances. This is accomplished thank to a "maturation" phase. This phase consists in defining the performance metrics from an operational relevance point of view, in estimating this performance indicator and finally in proposing improvements to meet the airline companies requirements. We consider that the maturation of the detection function has already been completed and that we are interested in the maturation of the prognosis function. This paper deals with the performance assessment of a prognosis function using two operational metrics. A performance estimation procedure is developed. It is applied to the prognosis of turbofan engine lubricant over-consumption.

The considered prognosis function is the probability to cross "no go" condition threshold at a given time horizon. This prediction is made thanks to an indicator of the health state of the system. Then it is compared with a threshold in order to trigger an alarm and give rise to a removal if necessary. Within this framework, we have defined two operational metrics for assessing the performance of this prognosis function. These metrics are the "ratio of justified removals" (P(Alarm|Crossing)) and the "ratio of not justified removals" (P(No-crossing|Alarm)). These metrics require the availability of observed lubricant over-consumption to compare the prediction results to the observed values. In the absence of lubricant over-consumption values in operation, a way is to simulate values.

This communication describes the procedure to estimate the performance of the prognosis function and presents the obtained results. The performances estimations trigger improvements. It appears that we have to enhance the precision of the considered health indicator before continuing to assess the performance of the considered prognosis function.

1. INTRODUCTION

With the context of air traffic growth, the availability of systems is a major challenge for airlines. To minimize non-programmed downtime, "no go" condition occurrence, impacting the decision of aircraft take-off, are subject to monitoring.

PHM systems have been developed by Safran Snecma. The introduction of these PHM systems in operation can be carried out only after having reached a certain maturity level. The required maturity level before operation is based on performance requirements. To achieve this level and thus meet the requirements, a maturation procedure (hmad, 2012) is applied to these PHM systems.

The maturation process has already applied to detection functions. It allowed defining performance indicators that meet the operational airlines needs. In this paper, we focus

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on the maturation of the prognosis function applied to the monitoring of the lubrication system.

The originality of this paper is to work on actual airline operating concerns and to propose solutions from an operational relevance point of view.

This communication is organized as follows: as a first step, the Engine Oil Consumption algorithm (EOC) that monitors the lubrication system is described. The considered prognosis function developed by Safran is presented next. In order to estimate the performance of this function, the prognosis performance indicators or metrics are defined in section 4. Their estimation requires the presence of degradations, which were simulated based on gamma process as discussed in section 5. Experimental results in the context of the prognosis of lubricant over-consumption are reported in section 6. To conclude this paper we summarize the main concerns and present possible opportunities.

2. ENGINE OIL CONSUMPTION PHM ALGORITHM

The EOC PHM algorithm allows monitoring of the lubricant consumption in automatic way in order to early detect any abnormal consumptions (Demaison, 2010). This represents a major challenge because deterioration of the lubrication system has non-negligible consequences on the execution of the turbojet engine.

Estimated lubricant consumption represents the indicator of the health status of the lubrication system. This indicator is used by the detection and prognosis functions in order to detect and prevent abnormal consumptions.

EOC PHM algorithm principle is based on the monitoring of the lubricant level evolution in the tank. It estimates the consumption at iso-condition on several flights, assuming a normalized operating environment. This estimator allows a better estimation of the lubricant consumption compared with a simple average consumption estimator calculated at each engine maintenance.

Lubricant levels in the tank after landing of a flight and before take-off of the next flight are measured to detect any lubricant filling performed by the maintenance service between successive flights. Once the fillings are detected and quantified, they are used to correct lubricant levels. This correction consists in subtracting the amount of estimated lubricant for each filling to the measured lubricant levels. After this correction, consumption estimation consists in determining the slope of the regression line of lubricant levels sampled on several flights.

The available data represent flight cycles (take-off, cruise, landing) on ten engines from five aircraft. No abnormal consumption has been observed during the operation. All of the estimated lubricant consumption represents normal consumptions. These nominal consumptions are distributed around an average value of 0.18 l/h or 0.2 l/h depending on

the engines. Figure 1 represents the estimated lubricant consumption on two engines from different aircraft.

Two consumption limits are considered in the maintenance manual:

- abnormal consumption: 0.38 l/h
- strongly drifted consumption: 0.76 l/h.



Figure 1. Example of estimated lubricant consumptions.

EOC PHM algorithm allows guaranteeing the health status of the lubrication system by monitoring the different possible causes of abnormal consumption. Experience shows that abnormal consumption can evolve suddenly or gradually up to cross the abnormal consumption (0.38 l/h) and the strongly drifted consumption thresholds (0.76 l/h).

According to experts, the gradual evolution of consumption translates into an increase in lubricant consumption of about 0.1 l/h per month and represents 90% of abnormal consumption cases. So we will focus on such evolution even if it has not been yet observed on collected data.

3. PROGNOSIS FUNCTION PRINCIPLE

The considered prognosis function consists in predicting the probability that the indicator of the health status cross a failure threshold at a given operational time horizon.

In operation, the prognosis function is triggered after the detection of a degradation premise. Detection takes place when the health indicator crosses a detection threshold (figure 2). From this moment noted " t_d ", the prognosis is initiated.



Figure 2. Illustration of the prognosis function initiation.

The prognosis function aims to estimate the probability to cross a failure threshold at a time horizon H based on a history of size T. The crossing probability estimation from t_d is performed by comparing the slope of the health indicator with the necessary slope (critical slope) to cross the failure threshold at $t_d + H$.

The health indicator slope is estimated using a linear regression on a window of size T. Then, the critical slope to cross the threshold at $t_d + H$ is determined from the point at instant t_d , intercept the value regression at this time, and point at instant $t_d + H$, intercept the failure threshold as shown by figure 3.

Under the hypothesis that these two slopes are normal random variables of unknown variance: these two slopes are compared using a Student test. The result of the test allows estimating the probability that the slope of the health indicator is lower or higher than the critical slope. This is equivalent to the probability that the health indicator crosses the failure threshold at time horizon H.



Figure 3.Illustration of the prognosis function principle.

The prognosis function input is composed of observations of the health indicator and its output is the estimated crossing probability. The prognosis function parameters are:

- the observations history size: T,
- the prognosis horizon size: H,
- the failure threshold,
- the consumption samples within the window.

In the abnormal consumptions prognosis case, the health indicator is the lubricant consumption estimated by EOC PHM algorithm over several flights. As the prognosis is initiated after having crossed the detection threshold, the observations history size, T, is 1 month of operation: 100 flights (taking into account the number of days on a calendar month). When detection occurs before, the observations history size is equal to the available number of flights until detection. The prognosis horizon, H, is set at 20 flights, 4 operating days in this case. The failure threshold is set to 0.38 l/h which corresponds to the abnormal consumption threshold from the maintenance manual. The objective is to estimate the performances of this prognosis function and compare it to the airline company's expectations. To do this, some performance metrics are needed. The next section focuses on the prognosis performance indicators or metrics.

4. PROGNOSIS PERFORMANCE INDICATORS OR METRICS

According to (Jardine, 2006), regardless of the application domain, there are mainly two prognosis metrics or indicators. The first consists in predicting the remaining time before the failure of a component or system knowing the past and present operating conditions. This metric is commonly named Remaining Useful Life (RUL). The second metric consists in predicting the probability that a component or system operates without failure during a given horizon knowing the past and present operating conditions (crossing probability).

In (Dragomir, 2008), the author states that it is important to differentiate prognosis metrics (or indicators) and prognosis performance metrics (or indicators).

These prognosis metrics define the nature of the realized prognosis:

- "deterministic" prognosis for remaining useful life (RUL)
- "probabilistic" prognosis for the crossing probability.

The performances indicators of a prognosis function depend on the nature of the realized prognosis. That is why two classes of prognosis performance metrics are encountered in the literature. The first class is related to "deterministic" prognosis approach (RUL). This class is discussed a lot in the literature (Si, 2011) (Sikorska, 2011). The second class is related to "probabilistic" prognosis metrics (crossing probability) and is little represented in the literature.

In the literature, prognosis performance metrics based on the RUL are numerous. (Saxena, 2008) has developed a state of the art of these metrics from different domains medicine, finance. automobile. (meteorology, Several metrics aeronautics...). are discussed in (Vachtsevanos, 2006) and (Saxena, 2009). Traditional metrics such as bias, deviation, mean squared error... may be used. Other less conventional are also used as accuracy, precision and timeliness...

Prognosis performance metrics associated with the "probabilistic" prognosis are less numerous and come mainly from the meteorological field where this kind of prognosis is frequently used. The first idea to evaluate the performance of any prediction function is to estimate the prediction error and the mean squared error of the difference between predictions and observations is generally considered. A similar metric exists within the "probabilistic" prognosis framework. This metric is named Brier Score (BS) (Brier, 1950).

The Brier score represents the mean squared error of the "probabilistic" prognosis:

$$BS = \frac{1}{N} \sum_{i=1}^{N} (p_i - o_i)^2$$
(1)

with :

N: the number of predictions,

 p_i : the crossing probability with threshold S, estimated at time t_p and for a given horizon H. $pi=P(X(t_p+H)>S/t=t_p)$ o_i : the observed probability which is equal to 1 if there is a

crossing and 0 otherwise.

The Brier score is between 0 and 1, the perfect score being 0.

According to (Candille, 2005) "probabilistic" prognosis functions must meet two criteria:

- **reliability** indicates to what extent the predicted probabilities are consistent with observations (crossings threshold). If the frequency of threshold crossing is larger or smaller than predictions, predictions are, respectively, underestimated or overestimated,
- **resolution** allows to assess the capacity of a prognosis function to separate multiple events to predict. The resolution of a prognosis function is high when predictions distribution corresponds to the observations distribution.

Estimation of reliability and resolution of a prognosis function is possible through the Brier Score decomposition (Murphy, 1973). The latter can be decomposed into three components (BS = reliability - resolution + uncertainty):

$$BS = \frac{1}{N} \sum_{k=1}^{T} n_k (p_k - \bar{o}_k)^2 - \frac{1}{N} \sum_{k=1}^{T} n_k (\bar{o}_k - \bar{o})^2 + \bar{o} (1 - \bar{o})$$
(2)

where a sample of *N* predictions is separated into *T* classes according to the predicted probabilities p_k (for example p_i belongs to: 0% - 5%; 5%-10%;...; 95%-100%). Each class contains n_k predicted probabilities (p_k). \bar{o}_k corresponds to the observed frequency of class *k* occurrence and \bar{o} corresponds to the average rate of positive samples over the whole data set.

The first two terms of BS have been defined previously. The third one is named uncertainty. The uncertainty allows quantifying the intrinsic variability of the observations. It is not used as a prognosis performance metric. It corresponds to the variance of a Bernoulli law of parameter \bar{o} .

It is possible to get an idea of the reliability using a reliability diagram (figure 4) which represents graphically the reliability of a prognosis function (Bröcker, 2007). This diagram consists in drawing (\bar{o}_k) observed frequencies of events (e.g. crossing threshold) on the basis of the predicted

probabilities p_k for these events. The resulting curve is compared to the diagonal of the diagram. The diagonal corresponds to predictions in perfect harmony with crossing observations. The points under (over) the diagonal indicate that predictions were overestimated (underestimated respectively).



Figure 4. Example of reliability diagram.

It is possible to have an idea of the prognosis function resolution using a ROC curve (Ebert, 2013). To do this, the prognosis should be reduced to a decision problem based on the estimated crossing probability. This implies that there is a decision rule that allows classifying the estimated probabilities in two classes (crossing or no crossing). The ROC curve allows characterizing the ability of a prognosis function to differentiate two categories of events which is also the objective of the resolution. Better the performance of the ROC curved, better the resolution of the prognosis function.

In the aeronautical field, prognosis performance indicators have to meet operational requirements defined by the airlines. They are different from those found in the literature. In this work, two operational metrics to assess performances of a prognosis function are used:

- the ratio of not justified removals which estimates P(No-crossing|Alarm): this metric focuses on the number of times where the prognosis function fails when it announces a crossing (leading to a removal),
- the ratio of justified removals which estimates P(Alarm|Crossing): this metric is equivalent to the proportion of good detection in the context of the prognosis. It corresponds to the success probability of the prognosis function.

These prognosis performance metrics are based on:

- triggering an alarm. In our case, an alarm is triggered when the estimated crossing probability is greater than 0.8 which gives rise to a removal.
- the availability of the sampled health indicator until crossing the failure threshold.

It appears that the assessment of prognosis performance is based on the availability of observations up to failure or exceeding the critical threshold.

Such data are not (or rarely) available in the aeronautical field. The available data represent cases without degradation. Therefore, the application of the presented metrics is not possible.

To compensate the lack of data with degradation, it is possible to simulate health indicator series up to failure or up to a threshold corresponding to a degree of critical degradation. The simulation is based on a degradation model that represents the effect of the deterioration mechanism or degradation of a component or a system on the health indicator. Degradation models are discussed in the next section.

5. DEGRADATION MODELS

The term "degradation" describes the irreversible evolution of one or several characteristics of a component related to time, the operating time or an external cause. This evolution can be sudden or gradual, and its outcome is failure (if the degradation is not stabilized over time).

In this paper, we focus on gradual evolution of continuous degradation since they represent 90% of the abnormal consumption causes.

The objective of degradation models is to characterize the health indicator evolution from a given system or component in modeling the evolution of its degradation to the failure or trespassing of a critical threshold affecting the performance.

Gradual degradation modeling considers several possible states of the studied system or component. Different states range from nominal operating condition to failure through intermediate states that do not affect critically the system performance.

Two continuous degradation models are frequently used (Nikulin, 2010): the Gamma process and the Wiener process with a positive trend. They represent the evolution of increasing deterioration or increasing on average respectively. They belong to the class of Levy processes which are stochastic processes with independent increments.

In the case of Wiener process, the probability of decreasing degradation on a time interval is not zero, which can be a drawback for some modeled systems.

On the other hand, the Gamma process is monotone increasing and allows modeling degradation mechanisms that are inherently slow, continuous and increasing with independent increments.

Degradations, in our case, have a gradual evolution which is growing and monotonous. It reflects the fact that the health state of the system cannot improve over time. The Gamma process has therefore been chosen to characterize this evolution.

The Gamma process is a continuous state space and increments are positive and independent. It presents other very interesting features:

- it is possible to formulate a hypothesis about its average trend (e.g. using expert opinions or human knowledge),
- increments can be stationary or not. In the case of stationary increments, it is a homogenous Gamma process.

Non-stationary increments can model nonlinear degradation evolution. This feature of the Gamma process is a benefit that justifies his frequent use (Van Noortwijk, 2009).

The Gamma process consists of a form parameter (v(t)) and a scale parameter (u). So, $(Xt)_{t \ge 0}$ is a Gamma process if:

- $X_0 = 0$
- $(X_t)_{t\geq 0}$ is a stochastic process with independent increments
- For $0 \le h \le t$, the law of increment $(X_t X_h)$ follows a Gamma distribution : $\Gamma(v(t) - v(h); u)$

The density of the gamma distribution $\Gamma(v(t), u)$ is defined by:

$$f_{X_t}(x) = \frac{u^{v(t)}}{\Gamma(v(t))} x^{v(t)-1} e^{-ux} I_{(0,\infty)}(x)$$
(3)

With:

$$I_{A}(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{otherwise} \end{cases}$$
$$\Gamma(a) = \int_{0}^{\infty} z^{a-1} e^{-z} dz \text{ (Gamma function)}$$

It can be shown that:

$$E(X_t) = \frac{v(t)}{u}$$
(4)

$$Var(X_t) = \frac{\nu(t)}{u^2}$$
(5)

- (X_t)_{t≥0} is a process whose trajectories are almost surely increasing,
- $(X_t)_{t\geq 0}$ is a Markov process,
- The trajectories of X admit a countable infinity of jumps in any time interval,
- If *S* is the failure threshold and $T = inf(t > 0 : X_t \ge S)$ we have :

$$P(T > t) = P(X_t < S) = \int_0^S \frac{u^{v(t)}}{\Gamma(v(t))} x^{v(t)-1} e^{-ux} dx$$
(6)

The homogenous Gamma process is a special case of the Gamma process when the shape parameter v(t) = ct with c>0.

The non-homogeneous three-parameter Gamma process is a special case of the non-homogeneous Gamma process with an exponent on time (Van Noortwijk, 2009). The shape parameter has the following form $v(t) = ct^b$ (with b and c strictly positive real).

It is possible to obtain various degradation evolution shapes depending on the value of b (figure 5):

- If b = 1, the Gamma process is a homogeneous process. The process increments are stationary. The evolution of the degradation is linear.
- If b < 1, the Gamma process is a non-homogeneous process and the evolution of the degradation has a logarithmic shape.
- If b > 1, the Gamma process is a non-homogeneous process and the evolution of the degradation has a parabolic shape.



Figure 5. Example of Gamma processes evolution for b = 1; b > 1 and b < 1 in the relationship $v(t) = ct^{b}$.

The parameter estimation of the Gamma process can be realized using the moment's method or the maximum likelihood method (Roussignol, 2009).

For given parameters, it is possible to generate evolution trajectories (paths). When the parameters of the Gamma process are known, the method to generate a trajectory of the Gamma process settings $v(t) = ct^b$ and u consisting of n observations is the following:

- generate *n* observations time *t_i*
- simulate the realization of *n*-1 increments with

$$\Delta X_i = X_{t_i} - X_{t_{i-1}} \sim \Gamma(\nu(t_i) - \nu(t_{i-1}); u) \quad i = 1...n$$

• build the trajectory $x_0 = 0$ et $x_n = \sum_{i=1}^n \Delta x_i$.

If degradation data are not available, a common procedure is to choose the Gamma process parameters in order to fit experts' statements. They generally give information about the trend, the variance and the shape of degradation curve. The degradation shape corresponds to the acceleration of the degradation process with time.

Based on such degradation model, the next section is dedicated to prognosis performance metrics estimator.

6. PROGNOSIS PERFORMANCE METRICS ESTIMATOR

This section describes the estimation method of the prognosis performance metrics (P(No-crossing|Alarm) and

P(Alarm|Crossing)) in the case of EOC PHM algorithm. First of all, it is necessary to describe the data available for their estimate. The considered data are:

Estimated lubricant consumption values, noted $C_i(t)$, represent the health indicator produced by EOC PHM algorithm (c.f. figure 1).

Overconsumption, noted $SC_i(t)$, simulated using Gamma process chosen according to expert statements. A lubricant leak, in 90% cases, induced an increase in nominal consumption of 0.1 l/h/month with a standard deviation of 0.01 l/h at the end of a month. Figure 6 represents trajectories of the Gamma process generated from information provided by the experts. 500 trajectories have been generated for a linear evolution (b = 1) by an average of 0.1 l/h all 100 flights and a standard deviation of 0.01 l/h at flight no. 100.



Figure 6. Example of 500 overconsumption trajectories generated by simulation.

« Pseudo observed » trajectories, noted $PO_i(t)$, have been built by adding the simulated overconsumption and the estimated consumption to get a degradation evolution with the desired properties, $PO_i(t) = C_i(t) + SC_i(t)$. Figure 7 represents these trajectories for the data from the two previous figures,



Figure 7. Example of « pseudo observed » Trajectories.

« **Theoretical** » **trajectories**, $CTH_i(t)$, describe the relevant theoretical phenomenon. This translates into a linear evolution of the lubricant consumption which is considered constant during normal operation (≈ 0.2 l/h). These

trajectories correspond to the simulated overconsumption added to the average consumption (CM), $CTH_i(t) = CM + SCi(t)$. An example is given in figure 8.



Figure 8. Example of « theoretical » trajectories.

Using these data, the estimation of each prognosis performance metric procedure is described in the two following paragraphs.

6.1. P(NO CROSSING|ALARM)

The estimate of P(No-crossing|Alarm) is, from multiple paths, to determine the proportion of alarms triggered by the prognosis function while the real degradation indicator stays below the failure threshold in the considered time horizon (H). To do this, the procedure is:

For each "pseudo observed" trajectory:

- determine the instant (*t_d*) that initiate the prognosis function,
- apply the prognosis function to observations that belong in the interval [*t_d T*, *t_d*],
- estimate the probability that observations cross the failure threshold after time horizon *H* (at *t*_d + *H*),
- if the estimated crossing probability exceeds a limit set at 0.8, an alarm is triggered,
- in case of alarm, identify the "theoretical" path corresponding to the considered "pseudo observed" trajectory,
- check if the "theoretical" trajectory has crossed the failure threshold at instant t_d + H. Increment not justified crossing counter if this is not the case.

This procedure has been applied from the detection time t_d on each simulated trajectory. Once all trajectories are considered, the ratio of unjustified crossings that represents an empirical estimate of P(No-crossing|Alarm) has been determined. This allowed observing the evolution of this indicator over flights.

6.2. P(ALARM|CROSSING)

This indicator corresponds to the probability of good failure prognosis.

The estimation procedure is:

For each "theoretical" trajectory:

- determine the instant (*t_p*) which corresponds to the instant when the considered "theoretical" trajectory *CTH_i*(*t*)cross the failure threshold.
- apply the prognosis function to observations of the corresponding "pseudo observed" path within the time interval [t_p-H-T, t_p H] to estimate the probability that the trajectory crosses the failure threshold at time t_p.
- if the estimated crossing probability exceeds a limit of probability set at 0.8, an alarm is triggered and the justified crossing counter is increment.

For each trajectory, this procedure has been applied from the time t_p to the end of the observation time. This was repeated for all trajectories. Once all trajectories have been considered, the ratio of justified crossings that represents an empirical estimate of P(Alarm|Crossing) has been determined.

7. CASE STUDY: LUBRICANT OVER-CONSUMPTION PROGNOSIS

The methodology to evaluate the performance of the prognosis function has been applied to the EOC PHM algorithm. Results are presented on figure 9 and figure 10 for one engine on two different aircrafts.

Each figure is composed of three subfigures:

- 1. the first one represents the "pseudo observed" trajectories for one engine, the failure threshold (horizontal solid line), the detection threshold (horizontal dashed line) from which the prognosis is initiated, a threshold that indicates that 10% of "theoretical" paths have crossed the failure threshold (vertical dashed line on the left) and a second threshold indicating that 90% of "theoretical" paths have crossed the failure threshold (vertical dotted line on the right).
- 2. the second one represents the ratio of unjustified failure prognosis, P(No-crossing|Alarm), over flights and the 10% and 90% thresholds.
- 3. the third subfigure represents the ratio of justified failure prognosis, P(Alarm|Crossing), over flights and the 10% and 90% thresholds.

The unjustified crossings ratios are not null. They range from 6% (figure 10), which is acceptable, up to more than 40% (figure 9), which is not acceptable.

These unacceptable values are explained by the noisy nature of estimated consumption. Depending on the learning slope zone of the "pseudo observed" trajectories, the latter may be more or less pronounced which has a direct impact on the crossing probability. It happens that the slope of a trajectory is important and induces a crossing probability greater than 80%. However, as the estimated consumption falls sharply, the trajectory in question does not cross the failure threshold and therefore gives rise to an unjustified failure prognosis (unjustified removal).

Concerning the justified crossings proportions, they increase over flights to 100% once all paths are above the failure threshold. The noisy nature of the estimated consumptions has also a significant impact there. This is due to the fact that certain trajectories go below the failure threshold for a short time before crossing it again.

However, these non-acceptable performances in terms of P (No-Crossing|Alarm), deserve to be nuanced. It is less damaging to observe an unjustified alarm when the "theoretical" crossing probability is close to 90% than when it is approximately 10%. If the peak of the P(No-crossing|Alarm) curve is close to the flight at 90% threshold this is less damaging than if the peak is nearby the flight at 10% threshold. In terms of justified crossings ratios, P(Alarm|Crossing), deserve to be refined. It is less damaging than P(Alarm|Crossing) is low when the theoretical crossing probability is approximately 10% than when the theoretical crossing probability is approximately 90%. If a large value of the P(Alarm|Crossing) curve appear between flights at 10% and 90% this is less damaging than if this value does not appear until after the flight to 90%.

The accuracy of estimated consumption has a direct impact on the performance of the prognosis function. It is therefore necessary to improve the accuracy of estimated consumption in order to re-evaluate the performance. This is discussed in the next section.







Figure 10. Engine 1 aircraft 5, « pseudo observed » trajectories and associated prognosis performances.

7.1. Performance analysis and enhancement

Several proposals have been made to improve the performance of the prognosis function:

- First, as mentioned above, stabilization of the precision estimated consumption. It appears clearly that the fluctuation of the paths causes unjustified failure forecasts or fail to forecast failure,
- If this is not sufficient, the limit of probability, arbitrarily set to 0.8, which gives rise to an alarm and removal can be modified. Increasing this limit of probability is likely to diminish the number of unjustified crossing predictions,
- The tuning of the history window size (*T*) or the prognosis horizon size (*H*).

However, the impact of the two last proposals cannot be assessed until the accuracy of the estimated consumptions is not improved.

In this perspective, corrections of consumption have been realized taken into account some missing fills. These improvements are to acting on the extraction of lubricant levels to improve the final estimate of consumption. Inaccuracies remain however. They are explained by the omission of one or more fillings when some flights are missing.

These consumption estimates were used to estimate the performance of the prognosis function again. The estimation procedure remains unchanged. The results in figure 11Figure and figure 12 are presented in a similar way and on the same data as figure 9 and figure 10.

For engine 1 of aircraft 4 (figure 11), the results after changes appear poorer than before. This is again due to the estimated consumptions. It would appear that other fillings than those already corrected have been omitted. This explains the increases in consumption followed by decreases which are probably due to a subsequent detection of missing fills.



Figure 11. Engine 1 aircraft 4, « pseudo observed » trajectories and associated prognosis performances.

Conclusions are the same for engine 1 of aircraft 5 (figure 12) with not justified crossing ratio of 98% just before crossing the failure threshold. This is due to the fact that, due to noise, the trajectories are decreasing just before crossing the failure threshold. It follows that the majority of crossing probabilities estimated on the history window (T) prior to this phenomenon are greater than 80% resulting in a high proportion of unjustified crossings. It appears that results strongly depend of each engine and it is not easy to have a general conclusion.



Figure 12. Engine 1 aircraft 5, « pseudo observed » trajectories and associated prognosis performances.

8. CONCLUSION

In the aeronautical field, the formalization of PHM systems and their performance requirements are defined from an operational point of view. This often results that used performance indicators are different from those derived from the literature. The performance evaluation is to adapt indicators from the literature to industrial needs or to define new ones. The adaptation of these indicators is to ensure their relevance with regard to the expected performance requirements.

The performance of PHM systems requirements defined by operators are the ratio of unjustified failure prognosis, P(Nocrossing|Alarm), and the ratio of justified failure prognosis, P(Alarm|Crossing). The estimation of each of these probabilities procedure was undertaken by the prognosis process of lubricant overconsumption. The required data for their estimate are: the estimated consumptions, simulated overconsumption using Gamma process, "pseudo observed" trajectories and "theoretical" trajectories. This has allowed establishing a method to perform empirical estimation of the performance of the prognosis function.

The estimation of performance indicators and the analysis of the results have been illustrated by the maturation of the prognosis function in the case of EOC PHM algorithm.

Results show that:

- the accuracy of estimated consumptions have a direct and significant impact on the performance of the prognosis function,
- prognosis is very sensitive to the noise of the signal which it uses to make the prognosis.

Extraction of lubricant levels improved partially stabilized consumption estimate. This is not sufficient for the use of the prognosis function. We should continue in this direction in order to correct missing fills. Once these done, other optimizations may be considered:

- the limit of probability, arbitrarily set to 0.8, which gives rise to an alarm and a removal could be optimize,
- the size of the history window, T, and/or the prognosis horizon, H, could be tune in order to improve results .

Another possible improvement would be to change the prognosis method. This perspective is being studied. A second prognosis function using particle filtering has been developed. After maturation of the latter, the performance of the two prognosis methods (linear regression and particle filtering) will be compared.

NOMENCLATURE

- BS Brier Score
- *Ci(t)* estimated lubrication consumption values
- *CM* average consumption

CTHi(t) theoretical trajectories

- *EOC* engine Oil Consumption
- *H* prognosis horizon size

P(*Alarm*/ *Crossing*) ratio of justified removals

P(*No Crossing*/*Alarm*) ratio of not justified removals

- PHM Prognostics and Health Management
- *POi(t)* Pseudo Observed trajectories

ROC	Receiver	Operating	Characteristic
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- *RUL* Remaining Useful Life
- *S f*ailure threshold
- SCi(t) simulated overconsumption
- *T* observations history size
- *td* detection time (initiation of the prognosis function)
- *tp* theoretical path failure threshold crossing instant

REFERENCES

- Brier G.W. (1950). Verification of forecasts expressed in terms of probability. Mon. Wea. Rev., 78, pp 1-3.
- Bröcker J. et Smith L.A. (2007). Increasing the reliability of reliability diagrams. Wea. Forecasting, 22, pp 651-661.
- Candille G. et Talagrand O. (2005). Evaluation of probabilistic prediction systems for a scalar variable. Royal Meteorological Society, pp 1-20.
- Demaison F., Flandrois X., Massé J.R., Massot G., Hmad O. & Ricordeau J. (2011). Method and system for monitoring the level of oil contained in a tank of an aircraft engine. Patent # WO/2011/131892.
- Dragomir O.E., Gouriveau R. et Zerhouni, N. (2008). Adaptive neuro-fuzzy inference system for midterm prognostic error stabilization. International Journal of Computers, Communications and Control, pp 271-276.
- Ebert B. Forecast Verification Issues, Methods and FAQ. Last access 2013, url: http://www.bom.gov.au/bmrc/wefor/staff/eee/verif/verif web page.html.
- Hmad O., Grall-Maes E., Beauseroy P., Masse J.R. & Mathevet A. (2012). A Maturation Procedure for Prognosis and Health Monitoring Algorithms. PSAM11 & ESREL12 conference, June 25-29, Helsinki, Finland.
- Jardine A.K.S., Lin D. et Banjevic D. (2006). A review on machinery diagnostics and prognostics implementing condition based maintenance. Mechanical Systems and Signal Processing, 20, pp 1483-1510.
- Letot C. et Dehombreux P. (2009). Modèles de dégradation pour l'estimation de la fiabilité et de la durée de vie résiduelle : applications à la fissuration. Actes du 4ème congrès PENTOM, Autrans, France.
- Murphy A.H. (1973). A new vector partition of the probability score. J. Appl. Meteor., 12, pp 595-600.
- Nikulin M.S., Limnios N., Balakrishnan N., Kahle W. et Huber-Carol C. (2010). Advances in Degradation Modeling Applications to Reliability, Survival Analysis, and Finance. Birkhauser, Boston.
- Roussignol M. (2009). Gamma stochastic process and application to maintenance. Cours de l'université Paris Est – Marne la vallée.
- Saxena A., Celaya J., Balaban E., Goebel K., Saha B., Saha S. et Schwabacher M. (2008). Metrics for Evaluating Performance of Prognostics Techniques. 1st International Conference on Prognostics and Health Management, Denver, USA.

- Saxena A., Celaya J., Goebel K., Saha B. et Saha S. (2009). Evaluating Algorithm Performance Metrics Tailored for Prognostics. IEEE Aerospace Conference, Big Sky Montana, pp 1-13.
- Si X.S, Wang W., Hu C.H., Zhou D.H. (2011). Remaining useful life estimation – A review on the statistical data driven approaches. European Journal of Operational Research, Volume 213, Issue 1, pp 1-14. ISSN 0377-2217.
- Sikorska J.Z., Hodkiewicz M., Ma L. (2011). Prognostic modelling options for remaining useful life estimation by industry. Mechanical Systems and Signal Processing, Volume 25, Issue 5, pp 1803-1836. ISSN 0888-3270.
- Vachtsevanos G., Lewis F.L., Roemer M., Hess A. et Wu B. (2006). Intelligent Fault Diagnosis and Prognosis for Engineering Systems. First edition, John Wiley & Sons, Hoboken, New Jersey.
- Van Noortwijk J.M. (2009). A survey of the application of gamma processes in maintenance. Reliability Engineering and System Safety, 94(1), pp 2–21.

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Performance Evaluation for Fleet-based and Unit-based Prognostic Methods

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ABSTRACT

Within the last decade several new methods for prognostics have been developed and an overall understanding of the various issues involved in predictions for health management has significantly improved. However, it appears that there is still a lack of consensus on how prognostics is defined and what constitutes good performance for prognostics. This paper first differentiates prognostics from other prediction approaches before highlighting key attributes of performance for prediction methods. Then it argues that it is important to understand what factors affect the performance of a prognostic approach. Factors such as the application and end use of a prognostic output, the various methods to make predictions, purpose of performance evaluation, etc. are discussed. This paper presents a comprehensive view of various such aspects that dictate or should dictate what performance evaluation must be as far as prognostics is concerned. It is also discussed what should be used as baseline to assess performance and how to interpret commonly used comparisons of algorithm predictions to observed failure times. The primary goal of this paper is to present some arguments of how these issues can be addressed and to stimulate a discussion about meaningful evaluation of prognostic performance. These discussions are followed by a brief description of prognostics metrics proposed recently, their applicability, and limitations. This paper does not intend to suggest any metrics in particular rather highlights important aspects that must be covered by any performance evaluation method for prognostics.

1. INTRODUCTION

The demand for engineering systems with sophisticated functionality, high safety levels, low environmental footprint, and other requirements is accompanied by increasing cost to build and operate these systems. Besides increased manufacturing cost, it is the mitigation of operational disruptions caused when hardware or software break down that are driving up life-cycle cost and affecting operational availability. The malfunction of just a small part can seriously degrade the utility of a large portion of a complex system or cause it to seize performing its primary function altogether. To counteract that, operators and manufacturers are increasingly looking towards system health management as a mechanism to actively deal with changing performance characteristics of individual components. This is accomplished by assessing the state of health of the system components, estimating their remaining useful life, and by initiating mitigating action that will either prevent the breakdown, minimize downtime, avoid unscheduled maintenance, or result in similar results that minimize lifecycle cost of the system. At the core of system health management is Prognostics, the method by which remaining useful life of a component (or system) is estimated. The ability to predict future events, conditional on anticipated usage and environmental conditions, is the Achilles heel of System Health Management. It is therefore not surprising that considerable attention has been given to this technology in the last few years. Indeed, the term "prognostics" has been used by various practitioners in any context that has a predictive element, not all of which actually result in estimation of remaining life. In the first part of this paper, the different instantiations of life prediction are reviewed in the context of methods that are based on fleet-level and unitbased life prediction and the term "Prognostics" is clarified.

An indispensable element in maturing prognostics is the ability to measure the performance of a prognostic algorithm. Traditional metrics that are, for example, used for diagnostics do not capture the unique characteristics of prognostics. Since the discipline is still young, new metrics are emerging that each measure specific features of prognostics. The second

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part of this paper explores the most important metrics that have emerged. The paper also discusses general considerations when evaluating Prognostics. While assessing and ranking one method over another, it is important to pick metrics that evaluate the same components and do not, for example, penalize one algorithm (but not another) for poor quality of external inputs (such as noisy or missing data, inadequate domain models, etc.). Furthermore, the metrics should consider evaluating various aspects of a prediction that are useful towards decision making, such as time to prediction or confidence in prediction. Finally it is important to consider what the performance is being measured against. In online applications where it may not be possible to know the ground truth, it is difficult to measure accuracy aspects of performance because the failure has not yet happened (and hopefully will not happen when human life or costly assets are at stake) (Engel, Gilmartin, Bongort, & Hess, 2000). However, even in offline cases where ground truth is established through prior experiments, it may not be the plausible course of action to compare the predictions against one outcome (realization) of an, otherwise stochastic, process in light of several sources of uncertainties.

The paper concludes with a discussion of the path ahead for Prognostics. Specifically, the following issues are considered in detail:

- What does prediction performance mean in different application contexts?
- What are different components of algorithms that need to be evaluated and compared in prognostics applications?
- What are various assessment approaches that are currently used and how to interpret the results?
- What are lacking issues that need to be considered?

2. CONSIDERATIONS IN PERFORMANCE EVALUATION

2.1. Attributes of Prediction Performance – Correctness, Timeliness, and Confidence

The essence of a meaningful prediction lies in three key attributes that are important to achieve regardless of the prediction method used. These key attributes are - correctness (accuracy and precision), timeliness, and confidence in a prediction. It should be noted that attributes as defined here are not metrics themselves but a set of properties that define performance of a prediction algorithm. Suitable metrics can be defined to measure and quantify these attributes as discussed in latter sections.

Correctness: By definition performance evaluation refers to the notion of assessing correctness of a system output with respect to its desired specification. Prediction outputs are generally understood to be in the form of probability density functions due to inherent uncertainties involved. Hence the notion of correctness translates into accuracy and precision of the predicted distributions. Accuracy is a measure of deviation of a prediction output from measured, observed, or inferred ground truth. Specifically the prediction accuracy is a quantitative measure of error between the predicted end-oflife and the observed end-of-life of the monitored component/system. Several metrics can be used to define prediction accuracy such as but not limited to those listed in (Saxena, Celaya, Balaban, Goebel, Saha, Saha, & Schwabacher, 2008). Precision on the other hand is a measure of spread of a distribution. By definition (precision = [standard deviation]⁻¹) narrower distributions are considered more precise. When estimating a single point, ideal precision would be infinite if accuracy is 100%. However, it must be kept in mind that higher precision (or narrower distribution) is not always better. More than a decade ago Engel et al. (2000) explained the paradox in prognostics - "The more precise the remaining life estimate, the less probability that this estimate will be correct". Furthermore, it was analytically shown by (Sankararaman & Goebel, 2013) that the end-oflife point (or the RUL) is stochastic by nature. Therefore, a prognostics algorithm should estimate a probability distribution function and not just the observed single instance of a failure. However, the ideal value for precision of a predicted distribution would be to match the precision of ground truth distribution. In other words, arbitrarily narrow distributions could lead to risky decisions, just as arbitrarily wide distributions lead to larger ambiguity (or less confidence) in a prediction.

Timeliness: This refers to the time aspects related to availability and usability of predictions. It measures how quickly a prediction algorithm produces its outputs, in comparison to the failure effects that they are mitigating.

Prediction Horizon: The measure of how early, before the actual failure event, a prediction system produces a correct (w.r.t. specifications) prediction of end-of-life to be able to implement an actionable decision and response as part of the health management activity. For prognostics it is measured as Prognostic Horizon or Prognostic Distance at the time a prediction is made (Johnson, Gormley, Kessler, Mott, Patterson-Hine, Reichard, & Scandura Jr, 2011; Saxena, Celaya, Saha, Saha, & Goebel, 2010).

Prediction Response Time: The measure of how quickly the prognostic function produces a correct output, from a given set of system measurements. It includes the time it takes for an algorithm to converge to a reasonable performance level.



Figure 1. Correctness and timeliness attributes of prediction performance.

Confidence: It is a measure of trust (or conversely, the measure of uncertainty) in a prediction method's output. It is generally viewed in several related but different contexts. In predicting end-of-life for a unit confidence is expressed as probability of failure at any given time computed from a given failure-time distribution. From a decision making point of view is it is expressed through precision of the predicted distribution, i.e. more precise distributions lead to higher confidence and less ambiguity for decision making (Engel et al., 2000). Similarly confidence is also associated to the notion of risk of failure with respect to the time an action is taken. In the broader context of validation confidence is expressed as trust in a prediction method based on stability of predictions over time through sensitivity and robustness measures (Guan, Jha, Liu, Saxena, Celaya, & Goebel, 2010; Johnson et al., 2011). These measures are evaluated with respect to factors that directly affect predictions such as data quality (amount of data, sampling rates, noise levels, etc.), model quality (granularity of models, correctness, adaptability, etc.), accuracy of priors, etc.

The three performance attributes as described above are the most important ones from prognostics point of view. There are several metrics that can be used to assess each of these attributes, however, the important message here is that prognostic performance evaluation must account for all three of these and which specific metrics are used depends on several other factors as discussed in further sections.

2.2. Type of Prediction Method

Within the Health Management (HM) community there are several different interpretations of what is meant by the term prognostics. Although all interpretations involve some type of predictions about system's health the basis for such predictions is very different. This paper acknowledges the significance of all prediction methods but at the same time considers *Prognostics* strictly as condition based prediction methods. It is argued that depending on the type of predictions the metrics to evaluate prediction performance should be slightly different. As discussed above in Section 2.1, at its core prediction performance is characterized by three attributes namely, *Correctness, Timeliness,* and *Confidence*, although the specific metrics that measure these could differ from each other in different cases.

A classification of various prediction methods was proposed in (Coble Jamie Baalis, 2010). While the author tried to classify these methods into well-defined categories, there is often a fuzzy boundary where a method may fall into one category or the other. Furthermore, it can be observed that in that classification one method follows naturally from another as one moves from predictions based on information from a fleet towards using information from a single specific unit. A brief definition for each is provided here for readability, but a more detailed description and some examples can be found in (Coble Jamie Baalis, 2010). Type-I or Reliability-based Prediction methods predict component failure time based on statistical models fit to lab testing data or historical failure data. These methods are not considered prognostic methods in a strict sense but are the basis for much of how the assets have been maintained traditionally. Predictions are expressed in terms of Mean-Life metrics such as Mean Time Between Failures (MTBF) and many other variations expressing observed failure rates (Saxena & Roemer, 2013). Theoretically speaking it is possible to make life predictions for a specific unit through models used in these methods and assess correctness based on actual end of life, the performance is likely to be within expectations only when predictions for a large number of similar units is aggregated. Therefore, aggregate error and precision based metrics are generally used. Notions of timeliness do not quite apply here as predictions can be made at any time as they are based on historical data already processed to build models. Furthermore, since these models are static and do not get updated with time, the prediction of end-of-life does not change irrespective of when in time that prediction is made. Therefore there is no notion of performance tracking as in prognostics. Confidence is usually expressed as probability of failure at any given time computed from failure-time distribution. These metrics are generally useful for operators, maintainers, designers, and policy regulators for gauging and optimizing operational performance at the fleet level. The key shortcoming of this approach is that it cannot take into account the effects of operational conditions that have a significant bearing on actual component life.

Type-II or Damage Accumulation-based Prediction - These models estimate the lifetime of an average component operating under a given set of usage conditions (stressors). The output of these models is a distribution of failure times due to stochastic nature of operating conditions. These models however do not rely on condition monitoring data to estimate the state of a specific system and the predictions are based on population models of failure of such systems. For performance evaluation, correctness can be measured using any of the accuracy and precision metrics drawing comparisons from the actual ground truth for a specific unit. Although predictions here tend to be more accurate than for Type-I methods, algorithms are best evaluated by aggregating performance from several units as they are still based on population models. However unlike Type-I methods, notions of timeliness become relevant here as predictions must be updated regularly to account for changes due to recent operational conditions. Therefore, most metrics for Type-III methods may be applicable with slight modifications to aggregate performance from several units. Confidence is generally expressed as probability of failure and precision based metrics, although concepts of robustness to data quality may be applicable.

Type-III or Condition-based Prediction or Prognostics -Prognostics is the prediction of remaining useful life of a specific component or system based on its usage history inferred from monitoring data and expected future load profile. Prognostics generally utilizes a degradation model that predicts the future states based on inputs about current system state and expected load levels (stressors) on the system. These domain specific models are generally adaptable and can be developed based on physics of failure or can be learned from run-to-failure data through data-driven methods. Since the predictions are made specifically for a given unit correctness is measured for that individual unit and aggregation over multiple units is not required. Due to the notion of runtime adaptation or learning, it is important to track the response time and consequently the prediction horizon every time a prediction is generated. Similarly the concept of online performance measurements is most relevant in these scenarios. Confidence is expressed through expressing uncertainties properly and computing probability of failure within acceptable error bounds.

Type-IV or Data Analytics-based Prediction or Predictive Analytics - Predictive analytics is a term that has surfaced recently and is often being used interchangeably with prognostics in the PHM contexts. While it does involve making predictions based on information gleaned from past usage history data, the nature of predictions itself is not exactly the same as that in prognostics. A key difference being prognostics generates a prediction over a continuous space and therefore provides exact values of RUL over a set of real values in \mathbb{R} . Predictive analytics is more suited towards making discretized predictions that may not be a real number but a range over \mathbb{R} or a qualitative set, such as [low, medium, high]. It is different from reliability based prediction in that here the predictions are based on trends observed in a multidimensional space that includes observations from a verity of non-homogenous and often unstructured data such as time sequences of complex operational patterns, sensor data, operator observations, environmental factors, geographical features, etc. just to name a few. Here the key problem to deal with is to mine information from large datasets and identify complex patterns that have been shown to lead towards anomalies of failures through collected history data. The approaches are mostly based on a datadriven (data-mining and machine learning) methods and are employed in situations where modeling the system behavior and its interaction with the external environment including human operators is often too complex to model. Correctness in such cases is measured through metrics used in pattern classification literature such as error rates (false positives and false negatives), Confidence in a prediction is expressed through similarity ranking metrics, or probability of failure occurring.

2.3. Purpose of Performance Evaluation

Relevance of a prediction is truly defined by the purpose it serves towards meeting overall system goals. In one application performance assessment could be used to optimize system operations at run-time, in another it could be used to optimize logistics chain to improve maintenance and repair efficiencies over a longer time horizon. Actions based on predictions range from fully autonomous to human controlled. Therefore, while it is important to measure prediction performance at the algorithmic level to assess technical quality (accuracy, uncertainty handling, performance improvement over time, convergence, etc.), from a practitioner's perspective it is equally important to design metrics that measure effectiveness of predictions towards improving system performance. A classification of metrics was proposed based on their relevance to various PHM stakeholders, which showed that not all metrics are relevant to all practitioners (Goebel Kai, Saxena, Saha, Saha, & Celava, 2011). Similarly, following hierarchy can be observed in performance metrics depending on the scope of the system within which prediction performance is measured defining the overall goal of performance evaluation.

Table 1. Hierarchy of prediction performance metrics based on scope and function.

System Scope	Goal	Metrics
Core algorithm level (software and logic)	Improve prediction algorithm performance	Algorithm performance metrics assessed during development
Implementation level (software and hardware)	Efficient design of PHM system	Computational performance metrics during system design
System level with prognostics outside the decision loop	Logistics planning	PHM effectiveness metrics at system/fleet level assessed over long periods
System level with prognostics in decision loop	Operational planning	PHM effectiveness metrics at decision control loop level assessed both at long and short terms

2.4. Sources of Errors in Prognostics

Irrespective of the overall approach taken (data-driven, model based or any combination thereof) any prognostic (condition based prediction) method consists of several components each of which must together perform well to achieve good prediction performance. As described in (Roychoudhury, Saxena, Celaya, & Goebel, 2013) a general prognostics method can be thought of being composed of at least four independent elements (data sources, domain models, implementation aspects, and a core prediction algorithm), each of which contributes to the overall prediction performance. For instance, given a choice of a particular algorithm, the performance will additionally depend on the quality of sensors (location, resolution, sampling rates, signal-to-noise ratio, etc.), method of signal processing (information loss, feature extraction, etc.), quality of degradation model, and the ability to accurately estimate future load profile.

Generally speaking a core prognostic algorithm itself consists of steps like state estimation, state propagation, future load and uncertainty estimation, failure threshold determination, etc. Therefore, a performance evaluation method must be cognizant of which factors are being evaluated so the performance can be attributed to the right elements and not necessarily generalized to the prognostic algorithm. For reference, some examples of core algorithms and corresponding sources of errors are described below.

- Model based filtering algorithm for prediction generally consists of state estimation step followed by state propagation for prediction of RUL. Degradation models are developed based on domain knowledge about the physics of failures. Magnitude of errors in models therefore depend on quality of domain expertise. While state propagation step is the only true predictive element in these algorithm, overall performance is also affected by quality of state estimation and the estimation of future loading on the system.
- Data-driven algorithms that were compared by (Goebel K., Saha, & Saxena, 2008) used a common preprocessing step to eliminate variability due to data preprocessing and uncertainties in state estimation while comparing prediction performance of several regression algorithms. Here the degradation models are learnt from available run-to-failure data and hence errors in models here depend on quality of information available from data and the choice of data models or mappings that describe relationships between sensor observations and system states, and operational conditions and fault growth rates.
- Other pure data-driven approaches used such as in PHM08 challenge used a variety of preprocessing steps. See for instance the methods used by (Coble J. B. & Hines, 2008; Wang & Lee, 2009). These approaches bypass an explicit state-estimation step and make predictions purely based on similarity computations. Here errors depend on choice of variables used for computing similarity, similarity measure itself, and the vector length to compute similarity, for example.

While it is arguable which factors should be included as part of prognostic algorithm and which as external to the algorithm, from a PHM system level viewpoint performance of the following must be evaluated at a minimum (1) correctness of state estimator (2) correctness of assumed future loading, operating, and environmental conditions; and (3) correctness of degradation (or fault propagation) model. A more detailed discussion on this is provided in Section 3.

Furthermore, in an operational context, performance of a prognostic method can only be evaluated through overall effectiveness observed together with the decision making control loop. For example, whether the overall failure rates have gone down due to implementing of a prognostics algorithm, or whether a system was able to optimize its operation to maintain safety and maximize mission goals based on prognostics. It is important to determine which factors should be included in performance assessment, which accordingly guides the choice of specific metrics. For example, from an operational view point one is interested in the performance of overall prognostics and health management (PHM) system, but at the low level the interest lies in identifying which algorithm performs better given the same set of inputs (measurement data quality, domain models, implementation hardware, etc.), which is the focus of this paper.

2.5. Offline vs. Online Performance

Offline performance measurement generally refers to testing prediction ability of an algorithm on a dataset where failure time is precisely known as that event has already taken place. Performance is assessed based on how well a predicted estimate matches the true outcome. This, however, has limited usefulness and does not fully help when an algorithm is implemented on a real system. It is often desirable to track prediction performance to ensure that appropriate and timely decisions can be taken to benefit from advanced warnings from predictions. Therefore, online metrics are designed to track algorithm performance in real-time and predict system's RUL while the actual EOL will not be known until it actually fails or may never be known if a repair action is executed based on predicted impending failure. In the absence of availability of true failure time it becomes challenging to assess how well an algorithm is predicting at runtime and most offline performance evaluation metrics are of little or no use. While, this is still an area of active research some attempts have been made. For instance, two main approaches have been suggested. A short term fixed-k step ahead state prediction is generated in addition to RUL predictions. These short term predictions can then be evaluated for correctness with only a k-step delay and not having to wait until the failure time. Consistently good values or convergence of the correctness metrics is taken as a measure of confidence in RUL prediction performance. Similarly, other metrics such as stability (less fluctuations from one prediction to the next) of short term predictions can be used to improve confidence and usability in a decision making loop.

3. WHAT SHOULD BE MEASURED?

Several metrics have been developed and currently used for assessing prognostic performance that also account for uncertainties in predictions. It is, however, rarely discussed how distributions of predicted RUL are to be interpreted, what they should be compared to for correctness, or how to actually make such comparisons. While the role of uncertainties in RUL predictions was discussed in (Celaya, Saxena, & Goebel, 2012; Sankararaman & Goebel, 2013) this section sheds some light on the contribution of uncertainties in RUL predictions to unravel the details of what comparisons are mathematically meaningful, and how to correctly interpret various types of comparisons within a performance evaluation task.

Existing methods for performance assessment can be broadly classified as being applicable to two types of situations: (1) where the RUL of a component/system is stochastically predicted using a prognostic algorithm, and the ground truth end-of-life (that is measured after failure) is compared against the algorithm prediction; and (2) where the RUL of a component/system is stochastically predicted using a prognostic algorithm, and this prediction is compared against an ensemble of end-of-life realizations available by running multiple nominally identical components to failure; sometimes, historical run-to-failure data sets are readily available in the literature for this purpose.

While the former requires the comparison of a probability distribution to a point value, the latter requires verifying whether the run-to-failure times are samples of the predicted probability distribution. Sometimes, in the latter case, the different run-to-failure times may be used to construct a probability distribution, and therefore, it is necessary to measure the extent of agreement between the run-to-failure probability distribution and the RUL distribution predicted by the prognostic algorithm. This section explores the scientific philosophy behind these two approaches for performance evaluation, and investigates the interpretation and relevance of such comparison.

To begin with, it is necessary to understand why the prediction of a prognostic algorithm is uncertain. Sankararaman and Goebel (2013) explain that, in conditionbased prognostics, all the uncertainty needs to be interpreted subjectively. In other words, the uncertainty is simply reflective of the analyst's knowledge and not related to true randomness. For example, the component/system is at a particular state at any time instant. Since this state cannot be estimated accurately, it is represented using a probability distribution. Similarly, though future loading conditions are expressed using probability distribution(s), only one realization (based on that probability distribution) would actually occur during the course of operation of the component/system. Similarly, the degradation model also predicts how the health deteriorates; though this model may be uncertain, this uncertainty is not related to physical randomness. A prognostic algorithm aims at processing all of these sources of uncertainty (state, loading conditions, and degradation model), and quantifies their combined effect by computing the uncertainty in the RUL. Thus, the uncertainty estimated by the prognostic algorithm is not (and should not be) related to true randomness, and is purely subjective in nature.

This raises the question: What is related to physical randomness? True randomness occurs while running multiple nominally identical components to failure. The material properties of these components exhibit true variability. The initial state of these components exhibits true variability. The loading conditions that these components are subjected to experience true variability. Therefore, the RUL distribution estimated by running multiple components to failure exhibits true variability. It is not really meaningful to compare this probability distribution against the probability distribution predicted by the prognostic algorithm, since the former reflects the presence of true variability (in properties and loading conditions) across multiple nominally identical components/systems, whereas the latter focuses on predicting the RUL of one particular component/system. This implies that comparing the stochastic prediction of a prognostic algorithm to historical run-to-failure data sets does not necessarily help in evaluating the performance of the algorithm, since the sources and interpretation of uncertainty underlying these two statistical distributions are completely different.

In other words, if prognostic algorithms are meant for condition-based RUL assessment, then they should predict the RUL of only the intended component/system, and hence, it is necessary to rely on the ground truth end-of-life of that particular component/system in order to evaluate algorithm performance.

The prediction of a prognostic algorithm depends on four factors:

- 1. Choice of degradation model and associated uncertainty
- 2. State estimate and associated uncertainty, at time of prediction
- 3. Assumed future loading conditions and associated uncertainty
- 4. Procedure by which the algorithm processes all the above three uncertainties, in order to compute the uncertainty in the RUL.

The first three of these four factors need to be both accurate and precise, in order to achieve the best possible performance, from the perspective of the prognostic algorithm. The fourth factor needs to be mathematically and statistically exact, without making any approximations and/or assumptions regarding the probability distribution type and parameters of the RUL.

Note that, at present, it is not possible to verify whether the first three factors accurate or check whether the predicted
uncertainty in the RUL is truly reflective of the combined effect of the different sources of uncertainty. It is necessary to directly evaluate the prediction of the prognostic algorithm by directly comparing against the ground truth RUL. The rest of this section explores how this goal can be accomplished, by analyzing what quantities can be measured, in order to evaluate prognostic algorithm performance.

3.1. Ideal, Hypothetical Scenario

Consider an engineering component/system and a particular time-instant at which the RUL needs to be predicted using a prognostic algorithm. The algorithm, first, estimates the state, in terms of a probability distribution. Assume that a degradation model is readily available. Further, the uncertainty regarding the future loading conditions is also assumed to be available.

Imagine a hypothetical scenario wherein it is possible to run the same component/system to failure multiple times. From one run to another, the properties of the component/system do not change because the same system is being used, and the initial state is also invariant. However, the loading experienced in each run is different from another run. It is unreasonable to assume that the prognostic algorithm would possess knowledge regarding the statistics of the actual future loading conditions; therefore, the assumed loading statistics may or may not be identical to the actual loading statistics. (This, in fact, is the major challenge in prognostics in comparison with several other disciplines, because future loading conditions need to be anticipated accurately, in order to predict failure.)

It is possible to test whether the observed run-to-failure times are actually realizations of the probability distribution predicted by the algorithm using statistical methods, and such a test will be indicative of the prognostic algorithm performance. Note that the prognostic algorithm is likely to overestimate the uncertainty because (1) while the true state estimate is point-valued, the algorithm only estimates a probability distribution; and (2) the degradation model adds additional uncertainty. However, (1) if these two factors are infinitely accurate and precise; (2) if the algorithm assumes loading conditions that are exactly similar to those observed in reality; and (3) if the algorithm accurately processes the different sources of uncertainty, then the probability distribution predicted by the algorithm will be exactly identical to the probability distribution of the observed runto-failure times.

Note that this evaluation jointly evaluates all of the aforementioned four factors, i.e., even if one factor were not accurate/correct, this would be reflected as a difference between the probability distributions corresponding to prediction and observation. However, as it can be seen from the description of the scenario, such evaluation is only hypothetical because it is not possible to fail the same component multiple times, while starting from the same timeinstant. Therefore, it is necessary to investigate other evaluation measures that are useful in practice.

3.2. Post End-of-Life: Point-Valued Evaluation

As mentioned at the beginning of this section, the most commonly preferred method of evaluation is to wait until the end-of-life is reached, and compare the actual run-to-failure time against the algorithm prediction. The accuracy and precision of the prediction can be estimated easily. However, such comparison is not only unfair, but, sometimes, it may lead to incorrect conclusions.

Unfairness: From the time of prediction until the time of failure, the algorithm assumes some uncertainty regarding the future loading and usage conditions. However, the observed ground truth is reflective of only one loading/usage condition, thereby implying that similar quantities are not compared.

Concluding poor performance for a good algorithm: The aforementioned unfairness can sometimes lead to concluding that a good algorithm is poor. Consider the case where an algorithm is provided future loading conditions that are completely different from the actual loading conditions. The algorithm may process the provided information accurately and compute the RUL. However, this prediction may be completely different from the observed RUL. This difference needs to be attributed only to the incorrectly assumed loading conditions and it is not reasonable to penalize the prognostic algorithm in this context.

Concluding good performance of a poor algorithm: Suppose that the prediction of the algorithm is extremely accurate and precise, with respect to the observed ground truth. Then, it cannot be inferred that the algorithm is performing well. For instance, if the true damage (expressed in terms of the states) had been overestimated, and if the degradation model depicts a slower degradation rate than reality, then, ground-truth-based evaluation may suggest that the algorithm is indeed performing well. It is generally understood that a good prognostic algorithm needs to accurately estimate the state, and if the state estimation is not accurate, then the algorithm is not penalized.

3.3. Post End-of-Life: Informed Evaluation

It is possible to eliminate the effect of not knowing the loading condition in advance, by waiting until failure. The actual loading/usage condition experienced by the component/system can be observed, and the prediction algorithm can be provided with this information. Therefore, the algorithm prediction can be "informed" with the actual loading condition, and the informed-prediction can be computed easily. Note that, at the time of prediction, this information would not be available to the algorithm. Therefore, this procedure is only to evaluate the algorithm performance, after eliminating the effect of unknown future loading conditions. All the other information provided to the algorithm need to be reflective of the information available to the algorithm at the time of prediction.

Similar to the traditional ground-truth-based evaluation, the informed prediction of the algorithm can be compared against the observed ground truth. Note that the former is uncertain because of uncertainty in the state estimate and the degradation model. The precision and accuracy of the prediction can be computed. It can be easily seen that this evaluation is stricter than the evaluation in Section 3.2, and this performance evaluation needs to be meet requirements. However, whether this evaluation is sufficient, is unclear at present. This is because, just as in Section 3.2, overestimate damage and underestimated degradation rates may compensate each other and lead to higher accuracy and precision.

3.4. Pre End-of-Life Evaluation

While the above described measures of evaluation focus on characterizing the effects of state estimates, future loading conditions, and degradation model, it is also necessary to check whether the algorithm is accurately processing the different sources of uncertainty. This is not related to accurately predicting the RUL, but is directly associated to the mathematical treatment of the various sources of uncertainty.

Some algorithms may average the effect of the different sources of uncertainty on the RUL, and arbitrarily calculate the variance of RUL using approximations and assumptions (Celaya et al., 2012). It is important not to underestimate or overestimate the underlying uncertainty and accurately calculate the probability distribution of RUL. The ideal approach to perform such calculation is the use of Monte Carlo simulation with a large number of samples; though this requires high computational power, this method can be used to check the performance of other algorithms that are suitable for online prediction. In other words, the probability distributions obtained using the specific algorithm and Monte Carlo simulation can be compared and any discrepancy can be quantified, in order to evaluate the performance of the algorithm, from the perspective of integrating the different sources of uncertainty.

3.5. Summary

The search of prognostic performance evaluation measures raises several important questions and concerns. There are four important critical factors that control the performance of prognostic algorithm, and it is not practically possible to individually evaluate the goodness of these factors. While testing the performance against observed ground truth seems to be the most widely used method, it is not only unfair but may lead to incorrect conclusions. The informed-prediction method eliminates the uncertainty regarding the future loading conditions, and quantifies the combined effect of state uncertainty and degradation model uncertainty on the RUL prediction. The fourth factor, i.e., whether all the sources of uncertainty are being processed and integrated accurately, can be verified by comparing the algorithm prediction against rigorous Monte Carlo simulation.

An important challenge is the inability to check whether the loading conditions assumed by the algorithm are reflective of what is expected in reality. Is it reasonable to penalize the algorithm for poor performance? Another issue is the ability to identify whether the adverse effect of two (or more) incorrectly estimated quantities jointly cancel out one another, and deceivingly suggest that the prediction is highly accurate and precise. Further research is necessary to address these issues and improve the state of the art techniques for prognostic performance evaluation.

4. STATE-OF-THE-ART ON PROGNOSTICS METRICS

Several performance metrics were proposed earlier that evaluate key attributes (correctness, timeliness, and confidence) of prognostic performance as described in Section 2.1). Specifically following four metrics were suggested –

Prediction horizon – quantifies how early a prediction algorithm can make reasonable predictions to allow maximum advance warning before an impending failure.

Alpha-lambda accuracy – specifies whether an algorithm's prediction error is within desired accuracy bounds (specified by α) at any given time (specified by λ).

Relative accuracy – quantifies the prediction error normalized by remaining component life at any given time.

Convergence – tracks the rate of improvement in prognostic algorithm's performance as time progresses.

As described in (Saxena et al., 2010) these metrics convey how prognostic performance evolves with time as end-of-life time approaches closer. These metrics also acknowledged that prognostics must account for uncertainties and that any prediction method should include a representation of uncertainties through abstractions such as, for instance, the probability distributions. These metrics are parameterized through several parameters α (accuracy modifier), β (confidence modifier), and λ (time window modifier), which must be derived as specifications for prognostics based on high level requirements. In their latter publications authors described and illustrated through an example how such a flowdown can be carried out to derive numerical specifications for these parameters (Saxena, Roychoudhury, Celaya, Saha, Saha, & Goebel, 2012). There have been other recent efforts that acknowledge the need to evaluate performance under uncertainty. Generally speaking individual efforts are driven by respective application needs, however, it appears that many research articles have been developing metrics without explicitly discussing the

interpretation of the quantities being compared, therefore largely ignoring the issues such as those discussed in Section 3.

In (Leao Bruno P, Gomes, & Yoneyama, 2011; Leao Bruno P. & Yoneyama, 2013) a Probability Integral Transform (PIT) based method is presented that evaluates whether an algorithm processes uncertainties adequately by comparing the statistics of predicted RUL distributions to a ground truth distribution obtained from several run-to-failure datasets. The advantage of this method is in that it allows comparisons of arbitrary (parametric or non-parametric) distribution types obtained from field data or experimentation to address the scenario described in Section 3.1. Since the statistical significance of the analysis depends on the number of run-tofailure test cases available, limits on values can be computed for a desired significance level to assert whether a particular algorithm processes the uncertainty (as observed through several examples) correctly in a statistical sense. Authors also proposed some graphical visualizations to express confidence bounds in such assertions. As a limitation, availability of statistically sufficient ground truth data and validity of aggregating the field data into a single histogram is always questionable for such approaches to work properly. As presented in some of the earlier works from the authors (Saxena et al., 2008; Saxena, Celaya, Saha, Saha, & Goebel, 2009b; Saxena et al., 2010) there has been a general tendency towards computing an aggregate metric score over performance of several units under test. However, in the context of condition based prognostics, where users are concerned with prognostic performance of an algorithm on specific use case, applying aggregation or averaging metrics may not be valid due to effects of different operational and loading conditions on the usage life of units included in a historical dataset.

Next, the various metrics proposed based on PIT do not address the timeliness attributes of performance as discussed in Section 2.1. In fact, unfortunately, it is still very common to find metrics that disregard the timeliness aspect of prognostic performance. In (Sharp, 2013) several averaging metrics are presented that can be considered an improvement over traditional error or variance based metrics, but suffer from same limitations that it is not technically correct to average predictions made at different times. Although, by means of a user defined weighting function this limitation is somewhat alleviated, but choosing an appropriate weighting function is another subjective proposition that makes these metrics non-standardized and difficult to implement. Metrics such as Weighted Error Bias (WEB), Weighted Prediction Spread (WPS), Confidence Interval Coverage (CIC), Confidence Convergence Horizon (CCH), and a weighted sum total of all to create a Total Score Metric (TSM) may not be as simple or intuitive as authors intended them to be.

While most of the above metrics were proposed primarily for offline evaluation of prognostic performance, there have been

other works that tackle specific challenges. Much of the recent literature either focuses on incorporating uncertainties or attempts to develop methods for online performance evaluation. Some of the recently published methods are summarized in Table 2. The aspect of online performance evaluation is mostly addressed by assessing performance on short term predictions of the system state (not necessarily the end-of-life). Correctness and consistency of these predictions over time is used to assert confidence in long term RUL predictions, where there cannot be an explicit evaluation of correctness and timeliness in the absence of end-of-life ground truth. Short term correctness is measured through usual accuracy and precision metrics, and consistency is generally measured by variance between successive predictions. There is no denying the fact that these are still conceptual challenges in evaluating prognostic performance and the research community continues to work towards finding a robust solution.

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REFERENCES

- Celaya, J., Saxena, A., & Goebel, K. (2012). Uncertainty Representation and Interpretation in Model-based Prognostics Algorithms Based on Kalman Filter Estimation. Paper presented at the Annual Conference of the Prognostics and Health Management Society (PHM12), Minneapolis, MN.
- Coble, J. B. (2010). Merging Data Sources to Predict Remaining Useful Life – An Automated Method to Identify Prognostic Parameters. PhD Dissertation, The University of Tennessee, Knoxville.
- Coble, J. B., & Hines, J. W. (2008). *Prognostic Algorithm Categorization with PHM Challenge Application*. Paper presented at the 1st International Conference on Prognostics and Health Management (PHM08), Denver, CO.
- Engel, S. J., Gilmartin, B. J., Bongort, K., & Hess, A. (2000). *Prognostics, the Real Issues Involved with Predicting Life Remaining.* Paper presented at the IEEE Aerospace Conference, Big Sky, MT.
- Goebel, K., Saha, B., & Saxena, A. (2008). A Comparison of Three Data-Driven Techniques for Prognostics. Paper presented at the 62nd Meeting of the Society For Machinery Failure Prevention Technology (MFPT), Virginia Beach, VA.
- Goebel, K., Saxena, A., Saha, S., Saha, B., & Celaya, J. (2011). Prognostic Performance Metrics. Machine Learning and Knowledge Discovery for Engineering Systems Health Management, 147.
- Guan, X., Jha, R., Liu, Y., Saxena, A., Celaya, J., & Goebel, K. (2010). Comparison of Two Probabilistic Fatigue

Damage Assessment Approaches Using Prognostic Performance Metrics. *International Journal of Prognostics and Health Management*, 2(1)(5), 11.

- Johnson, S. B., Gormley, T., Kessler, S., Mott, C., Patterson-Hine, A., Reichard, K., & Scandura Jr, P. (2011). *System health management: with aerospace applications:* John Wiley & Sons.
- Leao, B. P., Gomes, J. P., & Yoneyama, T. (2011). Improvements on the offline performance evaluation of fault prognostics methods. Paper presented at the Aerospace Conference, 2011 IEEE.
- Leao, B. P., & Yoneyama, T. (2013). *Performance Metrics in the Perspective of Prognosis Uncertainty*. Paper presented at the Annual Conference of the Prognostics and Health Management Society (PHM13), New Orleans, LA.
- Liu, S., & Sun, B. (2012). A Novel method for online prognostics performance evaluation. Paper presented at the Prognostics and System Health Management (PHM), 2012 IEEE Conference on.
- Olivares, B. E., Muñoz, M. A. C., & Orchard, M. E. (2013). Particle-Filtering-Based Prognosis Framework for Energy Storage Devices With a Statistical Characterization of State-of-Health Regeneration Phenomena. *IEEE Transactions on Instrumentation and Measurement*, 62(2), 13.
- Orchard, M. E., Tang, L., Goebel, K., & Vachtsevanos, G. (2009). A Novel RSPF Approach to Prediction of High-Risk, Low-Probability Failure Events. Paper presented at the Annual Conference of the Prognostics and Health Management Society (PHM09), San Diego, CA.
- Roychoudhury, I., Saxena, A., Celaya, J. R., & Goebel, K. (2013). Distilling the Verification Process for Prognostics Algorithms. Paper presented at the Annual Conference of the Prognostics and Health Management Society (PHM13), New Orleans, LA.
- Sankararaman, S., & Goebel, K. (2013, October 2013). Why is the Remaining Useful Life Prediction Uncertain? Paper presented at the Annual Conference of the Prognostics and Health Management Society, New Orleans, LA.
- Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., & Schwabacher, M. (2008). *Metrics for Evaluating Performance of Prognostics Techniques*. Paper presented at the 1st International Conference on Prognostics and Health Management (PHM08), Denver, CO.
- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2009a). *Evaluating Algorithmic Performance Metrics Tailored for Prognostics*. Paper presented at the IEEE Aerospace Conference, Big Sky, MT.
- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2009b). On Applying the Prognostics Performance Metrics. Paper presented at the Annual Conference of the Prognostics and Health Management Society (PHM09) San Diego, CA.

- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2010). Metrics for Offline Evaluation of Prognostic Performance. *International Journal of Prognostics and Health Management*, 1(1), 21.
- Saxena, A., & Roemer, M. (2013). *IVHM Assessment Metrics*: SAE International.
- Saxena, A., Roychoudhury, I., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2012). *Requirement Flowdown for Prognostics Health Management*. Paper presented at the AIAA Infotech@Aerospace, Garden Grove, CA.
- Sharp, M. E. (2013). Simple Metrics for Evaluating and Conveying Prognostic Model Performance To Users With Varied Backgrounds. Paper presented at the Annual Conference of the Prognostics and Health Management Society (PHM13), New Orleans, LA.
- Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu,
 B. (2006). *Intelligent Fault Diagnosis and Prognosis for Engineering Systems* (1st ed.). Hoboken, New Jersey: John Wiley & Sons, Inc.
- Wang, T., & Lee, J. (2009). On Performance Evaluation of Prognostics Algorithms. Paper presented at the Machinery Failure Prevention Technology, Dayton, OH.

BIOGRAPHIES

Abhinav Saxena is a Research Scientist with SGT Inc. at the Prognostics Center of Excellence of NASA Ames Research Center, Moffett Field CA. His research focus lies in developing and evaluating prognostic algorithms for engineering systems using soft computing techniques. He has co-authored more than seventy technical papers including several book chapters on topics related to PHM. He is also a member of the SAE's HM-1 committee on Integrated Vehicle Health Management Systems and IEEE working group for standards on prognostics. Dr. Saxena is the editor-in-chief of International Journal of PHM and has led technical program committees in several PHM conferences. He is also a SGT technical fellow for prognostics. He has a PhD in Electrical and Computer Engineering from Georgia Institute of Technology, Atlanta. He earned his B.Tech in 2001 from Indian Institute of Technology (IIT) Delhi, and MS Degree in 2003 from Georgia Tech. He has been a GM manufacturing scholar and is also a member of several professional societies for PHM including PHM Society, SAE, IEEE, AIAA, and ASME

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Table 2. Recently published metrics in prognostics literature.

Metric	Description	Formula				
Online Performance	Online Performance Evaluation					
RUL Online Precision Index (RUL-OPI) (Orchard, Tang, Goebel, & Vachtsevanos, 2009)	RUL-OPI quantifies and tracks the precision of predicted RUL distributions by quantifying the length of 95% confidence bounds (CI(i)) normalized by the predicted RUL ($r(i)$) at any given time instant. An algorithm with a high index (close to 1) is preferred, which indicates high precision or narrow confidence bounds.	$I(i) = e^{-\left(\frac{\sup\{CI(i)\}-\inf\{CI(i)\}}{r(i)}\right)}$				
Dynamic Standard Deviation (DStd) (Olivares, Muñoz, & Orchard, 2013)	DStd quantifies the stability of predictions within a time window (Δ). Variance between individual predictions made within the time window is computed. The metric is normalized to a range [0,1] using the logistic function φ for easy comparisons.	$DStd = \varphi \left(Var \left(E \left\{ EOL \mid y_{1:j} \right\} \right)_{j \in \Delta} \right)$				
Critical- α Performance Measure (Olivares et al., 2013)	Looking from the perspective of actionable decision making, this measure computes the critical percentile (α) of an RUL distribution that would define a Just-In-Time-Point (JITP) for that application. JITP must always occur before actual failure, and hence the value of this metric lies in interval (0,0.5] and should be maximized to avoid unnecessary conservatism in decision making.	$\begin{split} & \alpha_{\text{crit}} = \underset{\alpha}{\arg\max} \Big\{ \text{JITP}_{\alpha\%}(k_{\text{pred}}) \leq \text{EOL} \Big\}; \\ & \forall k_{\text{pred}} \in [1, \text{EOL}] \end{split}$				
Accuracy and Precision over fixed horizon (Liu & Sun, 2012)	The accuracy metric (Ac) computes the probability mass of the predicted RUL within the acceptable α bounds and compares them to actual states realized at the end of the short horizon window. Similarly the precision (Pr) metric compares the spread (based on confidence intervals (CI)) of the predicted (P) probability density function to the true pdf (T) at the end of one horizon window. It is however not clear how the true pdf is obtained for comparison, where one would expect only a point observation from an actual event.	$\begin{aligned} & \operatorname{Ac} = \int_{\alpha^{-}}^{\alpha^{+}} \varphi_{p}(c) \operatorname{dc} \operatorname{or} \sum_{\alpha^{-}}^{\alpha^{+}} \varphi(c) \\ & \operatorname{Pr} = \begin{cases} 1 - \frac{\operatorname{CI}_{T} - \operatorname{CI}_{P}}{\operatorname{CI}_{T}} & \text{if } \operatorname{CI}_{T} \ge \operatorname{CI}_{P} \\ 1 - \frac{\operatorname{CI}_{P} - \operatorname{CI}_{T}}{\operatorname{CI}_{\max} - \operatorname{CI}_{T}} & \text{if } \operatorname{CI}_{T} \le \operatorname{CI}_{P} \le \operatorname{CI}_{\max} \\ 0 & \text{if } \operatorname{CI}_{P} \ge \operatorname{CI}_{\max} \end{cases} \end{aligned}$				
Metrics Dealing with Uncertainty in Predictions						
	β -criterion specifies desired level of overlap between	a ⁺ : Acceptable limit				

	<i>p</i> -citiention specifies desired level of overlap between
	predicted RUL PDF and the acceptable error bounds (α ⁻ ,
	α^+) around observed EOL.
0	Further extensions to β -criterion were proposed to bound
b-criterion (Saxena et al	probabilities of early (β) and late (β) predictions that are
al., 2010; Saxella et al.,	guided by higher level system requirements.
2012)	These criteria apply to situations described in Section 3.2.



	PIT allows to assess how well a predicted distribution	$PIT: z_i = F(x_i)$ s.t.
	match the variability in the actual process. Ground truth	$F(x) = \int_{-\infty}^{x} \pi(\xi) d\xi = P(X < \xi)$
	RUL values from several run-to-failure datasets are	$Z = F(X) \sim U(0, 1)$
	transformed into corresponding PIT values using the	Z = P(X) = 0(0,1)
	cumulative distribution functions for the predicted RULs.	0.9-
bility Integral	Closer the transformed values lie to a uniform distribution	0.8-
form (PIT) and	U(0,1) better the predicted distribution represents the	0.7
ased metrics	observed process.	200- 2005-
Bruno P. &	To check this resemblance a graphical prognostic	0.4 Algo 1 Algo 2
yama, 2013)	performance plot (PPP) was suggested with a quantitative	0.3 - reference
-	measure prognostic quality index (q). Further, a	0.2

dex(q). significance level of the result can be determined based on hypothesis testing. Other such measures are also possible.



Probability Integral
Transform (PIT) and
PIT based metrics
(Leao Bruno P. &
Yoneyama, 2013)

Prediction Method	Prediction Model	Applicability	Accuracy	Timeliness	Confidence
Type I Reliability analysis based predictions	Population-based statistics data from (mostly controlled) experiments or usage history data	Predict mean life of a component. Correctness of predictions is meaningful for a fleet in general, and not for an individual unit	Mean-life metrics such as MTBF, MTBR, etc. can be predicted and then compared to observations from actual field data. These, errors in predictions can be used as a metric of accuracy. Otherwise, if maintenance actions based on these metrics are effective, then any observed change in mean-life estimates can be interpreted as a measure of effectiveness (accuracy, timeliness) of such predictions.		Probability of success metrics such as RxCy specifying x% reliability with y% confidence. E.g. R96C90 is a popular metric in automotive industry
Type II Damage accumulation model based predictions	Unit specific load history data + population based Damage accumulation model	Predict remaining life of an individual unit based on population model	Metrics like alpha- lambda accuracy and	Prediction horizon, and lambda, the time	β -criterion (Saxena, Celaya, Saha, Saha, & Goebel, 2009a) assesses confidence in prediction correctness,
Type III Condition based predictions - Prognostics	Unit specific degradation model (data-driven or physics based), load history, and condition monitoring data.	Predictions customized for individual unit by learning specific individual behavior	relative accuracy quantify correctness of prognostic algorithms (Saxena et al., 2010)	window modifier, based metrics assess timeliness aspects of prognostics	Robustness (Guan et al., 2010) and sensitivity metrics (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006) assess confidence via offline analysis
Type IV Data Analytics based predictions – Predictive analytics	Rich set of data from multiple units in a variety of operating conditions + analytical data model for pattern matching	Predictions for individual unit based on rich operational history data	Classification error rate metrics (such as false positives, false negatives), aggregate error metrics (such as MAPE, MSE, MAD, etc) to evaluate predictions on multiple units.	Timeliness may be expressed by length of history sequence considered for accurate predictions.	Similarity scores between two high dimensional history vectors establish confidence. Similarity metrics such as precision and recall are often employed

Table 3. Classification of prediction methods and description of metrics typically used for performance evaluation.

Advanced Data Mining Approach for Wind Turbines Fault Prediction

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ABSTRACT

Wind turbine operation and maintenance costs depend on the reliability of its components. Thus, a critical task is to detect and isolate faults, as fast as possible, and restore optimal operating conditions in the shortest time. In this paper, a data mining approach is proposed for fault prediction by detecting the faults inception in the wind turbines, in particular pitch actuators. The role of the latter is to adjust the blade pitch by rotating it according to the current wind speed in order to optimize the wind turbine power production. The fault prediction of pitch actuators is a challenging task because of the high variability of the wind speed, the confusion between faults and noise as well as outliers, the occurrence of pitch actuator faults in power optimization region in which the fault consequences are hidden and the actions of the control feedback which compensate the fault effects. To answer these challenges, the proposed approach monitors a drift from normal operating conditions towards failure condition. To achieve drift detection, two drift indicators are used. The first indicator detects the drift and the second indicator confirms it. Both indicators are based on the observation of changes in the characteristics of normal operating mode over time. A wind turbine simulator is used to validate the performance of the proposed approach.

1. INTRODUCTION

1.1. Basic definitions and motivation

The search for alternative clean energy is undoubtedly becoming more and more important in modern societies. The growing interest in wind energy production has led to the design of sophisticated wind turbines. Like every other complex and heterogeneous system, wind turbines are prone to faults that can affect their performance and increase maintenance costs. In addition, it is very difficult and even dangerous to access the turbines. Thus, it is crucial to design an automated diagnostics system in order to achieve the fault detection and isolation.

In general, fault diagnosis of wind turbines is a challenging task because of the high variability of the wind speed and the confusion between faults and noise as well as outliers. However, the fault diagnosis of pitch actuators is particularly a challenging task because of i) the occurrence of pitch actuator faults in power optimization region in which the fault consequences are hidden and ii) the actions of the control feedback which compensate the fault effects.

Operating conditions of a system may change from normal to faulty either abruptly or gradually. In the case of gradual change, the system begins to malfunction (degraded behavior) until the failure takes over completely. The prediction of the occurrence of a failure prior to its occurrence can help providing a time to achieve appropriate corrective actions leading to decrease the maintenance costs and to increase the availability time. This can be achieved by early diagnosis module. Therefore, early diagnosis of pitch actuators is of particular interest for wind turbines industry due to their operational & maintenance costs as well as their essential role in optimizing the energy production.

1.2. State of the art

Diagnosis approaches can be divided into two main categories: analytical model based and data mining approaches. Analytical model based approaches exploit the physical knowledge about the system dynamics and structure to construct a mathematical or analytical model. The conceptual realization of these models can vary according to the used approach as the parity space (Ozdemir, Seiler & Balas, 2011) (Blesa, Puig, Romera & Saludes, 2011), state estimation (Zhang, Zhang, Zhao Ferrari, Polycarpou & Parisini, 2011), unknown input observer (Odgaard & Stoustrup, 2011), Kalman filters, unknown input Kalman filters (Chen, Ding, Sari, Naik,

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Khan 2011), parameter & Yin, identification (Simani,Castaldi & Bonfe, 2011), state-parameter estimation, as extended Kalman filter approaches (LIU, 2011) etc. The application of model-based approaches for the fault diagnosis of wind turbines is difficult due to the wind turbine complexity and to the strong non-stationary of its environment. An alternative to the analytical modelbased approaches is data mining approaches. In the latter, the model is built using historical data about the system dynamical behaviors. The model is built by learning from data in order to link the input or observation space to the output or decision space. Examples of these approaches applied to fault diagnosis of wind turbines we can cite, support vector machines (SVM) (Laouti,Sheibat-Othman & Othman, 2011), neural networks (Schlechtingen & Santos, 2011), principal component analysis (Kim, Parthasarathy, Uluyol, Foslien, Shuangwen & Fleming, 2011), autoadaptive dynamical clustering (AuDyC) (Chammas, Duviella & Lecoeuche, 2013), self-feature organization map (Kim, Parthasarathy, Uluyol, Foslien, Shuangwen & Fleming, 2011), k nearest neighbors (Toubakh, Sayed-Mouchaweh & Duviella ,2013).

Few approaches have been proposed to achieve predictive diagnosis of wind turbines, in particular pitch actuators. This is due to the fact that modeling component degradation in strong nonlinear and complex non-stationary environments is very hard task. Examples of these methods, we can cite genetic programming algorithm (Kusiak & Verma, 2011), neural network, neural network ensemble, the boosting tree algorithm, and SVM (Kusiak & Li, 2010). These methods achieve the fault prediction using the Supervisory Control and Data Acquisition (SCADA) data. The latter have the disadvantage to be of limited size and thus they do not provide enough of information about components operating conditions. Thus, the prediction accuracy of specific faults is not sufficiently accurate.

1.3. Our approach

In this paper, a data mining based approach is proposed in order to achieve the prediction of faults that can impact wind turbine pitch actuators. Initial offline modeling allows constructing initial classes based on the historical data set. These classes are represented by restricted zones in the feature space. The latter is formed by sensitive features to pitch actuators' operating conditions in order to distinguish any drift from normal to fault operating conditions. The modeling tool is a dynamical clustering algorithm called AuDyC (Auto-Adaptive Dynamical Clustering) used to initialize the classes that will be dynamically updated. In this work, the faulty class, representing the failure operating conditions of pitch actuator, is considered to be a priori unknown. The only known class in advance is the one representing the pitch actuator normal operating conditions. Gradual degradations in pitch actuator operating conditions

are considered as a drift in the characteristics of normal class, representing the normal operating conditions, over time. This drift is characterized by a change in patterns distribution in the normal class in the feature space. The proposed approach monitors a change in the characteristics of this class in order to detect and confirm a drift, degradation, of pitch actuator normal operating conditions. Detecting and following this drift can help to predict the occurrence of pitch actuator failure. The drift is monitored using two drift indicators: one to detect a drift and the second to confirm it. When the drift is detected by the first indicator, a warning is emitted to human operators. Then, the second drift indicator confirms this drift in order to inform human operators of the necessity to react by taking the adequate correction actions.

The proposed data mining approach is composed of five main steps: processing and data analysis, classifier design, drift monitoring, updating and interpretation steps.

The paper is organized as follows. In section 2, the wind turbine benchmark and the generated fault scenarios are described. In section 3, the proposed approach to achieve fault prediction of pitch actuators is detailed. In section 4, the results based on the use of the wind turbine benchmark are presented. Finally, the conclusion and perspectives are discussed in section 5.

2. WIND TURBINE BENCHMARK DESCRIPTION

A benchmark model for Fault Detection and Isolation (FDI) and fault tolerant control (FTC) of wind turbines was proposed in (Odgaard & Stoustrup, 2009). The benchmark is based on the model of a generic three blade horizontal variable speed wind turbine with a full converter coupling and a rated power of 4.8 MW. The wind turbine model under study is composed of four parts: the blades, the drive train, the generator with the converter, and the controller. More details of the benchmark model can be found in (Odgaard & Stoustrup, 2009).

The controller operates in four zones (see Figure 1). Zone 1 is the start-up of the turbines, zone 2 is power optimization, zone 3 is constant power production and zone 4 is no power production due to a too high wind speed. The focus of this benchmark model is on the operation of wind turbine in zones 2 & 3.

Two control strategies are applied to optimize the energy production and keep it constant at its optimal value: the convertor torque control in zone 2 and the blades angle control in zone 3. In zone 2 (see Fig. 1), the wind turbine is controlled so that it produces as much energy as possible. To do so, the blades angle is maintained equal to 0° and the tip speed ratio is kept constant at its optimal value. The latter is regulated by the rotating speed control by tuning the convertor torque. Once the optimal power production is achieved, the blades angle control maintains the convertor torque constant and adjusts the rotating speed by controlling the blades angle. The latter modifies the transfer of the aerodynamic power of the wind on the blades.



Figure 1. Reference power curve for the wind turbine depending on the wind speed.

Figure 2 shows the overall wind turbine model structure where v_w denotes the wind speed, τ_r the rotor torque, ω_r the rotor speed, τ_g the generator torque, ω_g the generator speed, β_r the pitch angle control reference, β_m the measured pitch angles, $\omega_{r,m}$ the measured rotor speed, $\tau_{g,m}$ the measured generator torque, $\omega_{g,m}$ the measured generator speed, P_g the measured generated electrical power, $\tau_{g,r}$ the generator torque reference, and P_r the power reference.

The benchmark model permits to simulate the wind turbine behavior in two power zones: 1) zone 2 (power optimization) where τ_g is controlled and β_r is equal to zero and; 2) zone 3 (optimal energy production) where τ_g is kept constant and β_r is controlled. In this paper, we focus on pitch actuator faults as it is discussed in subsection 2.1.



Figure 2. Block diagram of the wind turbine model (Odgaard & Stoustrup, 2009).

2.1. Pitch System Model

The hydraulic pitch system is modeled as a closed loop of dynamic system. The state representation of the nominal pitch system dynamics is:

$$\begin{aligned} \dot{x}_{b} &= Ax_{b} + Bu \\ \dot{y}_{b} &= Cx_{b} \\ \begin{bmatrix} \dot{\beta}_{i} \\ \beta_{i} \end{bmatrix} &= A \begin{bmatrix} \dot{\beta}_{i} \\ \beta_{i} \end{bmatrix} + B \begin{bmatrix} \beta_{r} + \beta_{f} \end{bmatrix} \\ A &= \begin{pmatrix} 0 & 1 \\ 2 & 2f \end{pmatrix} \end{aligned}$$
(1)

$$B = \begin{pmatrix} 0 \\ \omega^2 \end{pmatrix}$$
(2)

$$C = \begin{pmatrix} 0 & 1 \end{pmatrix}$$
(3)

The state vector x_b is composed of pitch angular speed β_i , and position β_i for each blade i: $(i = 1, 2, 3) \cdot y_b$ is the measured pitch position, β_r is the pitch angle position reference provided by the controller, and β_f is the feedback pitch system (see Figure 3). ω_n, ζ are the parameters of the pitch system where ω_n represent the natural frequencies and ζ is the damping ratio.

The role of the pitch actuator is to adjust the pitch of a blade by rotating it; while the pitch angle of a blade is measured on the cylinder of the pitch actuator.



Figure 3. Block diagram of pitch system.

2.2. Fault scenarios

The pitch actuator fault considered in this paper is caused by air content increase in the actuator's oil. This fault is modeled as a gradual change in the parameters ω_n, ζ of pitch actuator n°3 (Odgaard & Stoustrup, 2009). Nine scenarios for this fault are generated in order to simulate slow, moderate and high degradation speeds represented by slow, moderate and high drift speeds. Each drift speed scenario is generated at three different time instances. Thus, parameters ω_n, ζ are changed linearly from ω_{n1}, ζ_1 to ω_{n2}, ζ_2 in a period of 30s, 60s and 90s, corresponding respectively to high, moderate and slow drift speeds. Then, the fault remains active for 100s. Finally the parameters decrease again to return to their initial values (see Figure 4).



Figure 4. Drift scenarios corresponding to high drift speed in 3 different time instances.

The goal of using three different drift speeds starting in three different instant times is to test the performance, drift detection and confirmation, in the case of slow, moderate and high degradation speeds occurring in different wind speed (zones 2 and 3). Actuator fault scenarios are summarized in Table1.

Table 1. Pitch actuator fault scenarios.

Fault N°	Drift	Fault	Period
	speed		
F _{1h}	30s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3200 _s -3330 _s
F _{1m}	60s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3200 _s -3360 _s
F _{1s}	90s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3200 _s -3390 _s

Fault N°	Drift	Fault	Period
	speed		
F _{2h}	30s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3300 _s -3430 _s
F _{2m}	60s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3300 _s -3460 _s
F _{2s}	90s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3300 _s -3490 _s

Fault N°	Drift	Fault	Period
	speed		
F_{3h}	30s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3400 _s -5330 _s
F _{3m}	60s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3400 _s -5560 _s
F _{3s}	90s	$\omega_{n1}, \zeta_1 \rightarrow \omega_{n2}, \zeta_2$	3400 _s -3590 _s

3. PROPOS ED APPROACH

In this section, a dynamical data mining approach is developed in order to achieve condition monitoring and fault prediction of pitch actuator. It performs this prediction by detecting a drift of the system operating conditions from normal to faulty modes.

The proposed approach is based on 5 steps developed in the following subsections (see Fig. 5).



Figure 5. Proposed approach steps.

3.1. Processing and data analysis step

This step aims at finding the features sensitive to the system operating conditions in order to construct the feature space. The position of the pitch actuators is measured by two redundant sensors for each of the three pitch positions ($\beta_{k,mi} k = 1, 2, 3, i = 1, 2$), with the same reference angle β_r provided to each of them. In order to enhance the robustness against noise, the measures are filtered by a first order filter using time constant $\tau = 0.06s$.

The research of sensitive features is based on the signals provided by the pitch sensors as well as the prior knowledge about the system dynamics. These features are chosen in order to maximize the discrimination between operating modes in the feature space. In this work, two-dimensional feature space is constructed for the actuator faults (Toubakh et al., 2013). Both features are residuals $\Delta\beta_A$, A = 1, 2 computed by (4) and (5). Residuals $\Delta\beta_A$, A = 1, 2, are generated by the comparison between the pitch angle measurement $\beta_{k,mi}$, i = 1, 2, k = 1, 2, 3 and the reference value of the pitch angle β_r (see Figure 3). The strong variability of the wind speed leads to a strong variability of the residuals

in the normal functioning mode. To overcome this problem which can cause false alarms, the residuals are computed within a time window in order to take into account the control variability $V(\beta_r)$. The size of this time window is determined experimentally to achieve a tradeoff between the delay of drift detection and false drift detection.

$$\Delta\beta_1 = \frac{\left|\beta_r - \beta_{k,m1}\right|^2}{V(\beta_r)} \tag{4}$$

$$\Delta\beta_2 = \frac{\left|\beta_r - \beta_{k,m2}\right|^2}{V(\beta_1)} \tag{5}$$

$$V(\beta_r) = \text{variance } (\beta_r) \tag{6}$$

3.2. Classifier Design step

This step aims at designing a classifier able to assign a new pattern to one of the learnt classes in the feature space. A new pattern characterizes the actual operating conditions (normal or faulty in response to the occurrence of a certain fault) of the system.

Figure 6 shows the classes representing normal and failure operating conditions of pitch actuator in the feature space constituted by the two residuals defined by (4) and (5). Due to the wind turbine non-stationary environments, an overlapping region is created between the normal and failure classes (see Figure 6). In this region, the consequences of the fault are hidden because the actuators are not solicited or are solicited for small angles. In both cases, normal and failure classes overlap because of pitch sensors noises and low wind speed (see Figures 6 and 7).



Figure 6. Large view of overlapping region for the third pitch actuator normal and failure operating conditions.



Figure 7. Feature space of the third pitch actuator normal and failure operating conditions.

In order to distinguish as much as possible the operating (normal/faulty) and to improve the conditions misclassification rate of the classifier, the normal and failure classes are split into three classes 1, 2 and 3 and the pitch actuator dynamics are represented by two different operating modes. The first one corresponds to the case of big pitch angles and high wind speed; while the second operating mode represents the case of small pitch angles and low wind speed (see Figure 8). Class 1 is the ambiguity class. It gathers the patterns processing pitch actuator normal or faulty operating conditions. This class represents the operating mode 1 (small angle and low wind speed). Class 2 represents the normal operating conditions class in operating mode 2 (large angle and high wind speed). Class 3 represents pitch actuator failure class in operating mode 2.



Figure 8. (a) Actuator decision space. (b) Operating modes 1 and 2 modeled by a finite state automaton containing two states.

3.2.1. Pattern decisions analysis

When a new pattern is classified in the ambiguity class, assigning it to normal or failure operating conditions is a risky decision since normal and failure classes are overlapped in this region of the feature space. In order to reduce this risk of misclassification, the decision about the status (normal or faulty) of any pattern classified in this region is delayed by assigning the label 'A' (ambiguity decision). Then, this ambiguity can be removed by analyzing the past and future decisions of this pattern. This pattern decisions analysis is achieved by using a set of decision rules allowing assigning to ambiguity patterns label 'N' or label 'F' (normal or faulty) as follows. Let us suppose that $X_A = \{x_t, x_{t+1}, \dots, x_{t+n}\}$ is a set of patterns associated with the decision 'A'. Let x_{t-1} be the previous pattern arrived just before x_t , $D(x_{t-1})$ be the decision of this pattern, x_{t+n+1} be the pattern arrived just after x_{t+n} , $D(x_{t+n+1})$ be the decision for this pattern. Then, decision $D(x), \forall x \in X_A$ can be updated as follows:

$$D(x_{t-1}) = N \land D(x_{t+n+1}) = N \Rightarrow D(x) = N, \forall x \in X_A$$
(7)

$$D(x_{t-1}) = F \wedge D(x_{t+n+1}) = F \Longrightarrow D(x) = F, \forall x \in X_A$$
(8)

$$D(x_{t-1}) = N \wedge D(x_{t+n+1}) = F \Rightarrow D(x) = A, \forall x \in X_A$$
(9)

$$D(x_{t-1}) = F \wedge D(x_{t+n+1}) = N \Longrightarrow D(x) = A, \forall x \in X_A$$
(10)

where \wedge refers to 'And' logical operation.

3.2.2. Classification approach

Auto-adaptive Dynamical Clustering Algorithm (AuDyC) is used as a classification method in order to design the classifier. AuDyC was chosen because it is -) dynamical, -) unsupervised classification method and -) able to model streams of patterns since it reflects always the final distribution of patterns in the features space. It uses a technique that is inspired from the Gaussian mixture model (Lecoeuche & Lurette, 2003), (Traore, Duviella & Lecoeuche, 2009). Let E^d be a d-dimensional feature space. Each feature vector $x \in E^d$ is called a pattern. The patterns are used to model Gaussian prototypes P^j characterized by a center $\mu_{pj} \in R^{d \times l}$ and a covariance matrix $\Sigma_{pj} \in R^{d \times d}$. Each gaussian prototype characterizes a class. A minimum number of N_{win} patterns are necessary to define one prototype, where N_{win} is a user-defined threshold. A class models an operating mode and groups patterns that are similar one to each other. The similarity criterion that is used is the Gaussian membership degree. Faults will affect directly this distribution and this will be seen on the continuously updated parameters. AuDyC will be associated with decision rules in order to design the classifier able to analyze the trajectory.

For more details on the functionalities of AuDyC, then adaptation like merging classes, splitting classes etc. The rules of recursive adaptation and the similarity criteria in AuDyC, can be found in (Lecoeuche & Lurette, 2003), (Traore et al., 2009).

3.3. Updating step

The updating step aims at reacting to the changes in the feature space. AuDyC is dynamic since it continuously updates the parameters by using the recursive adaptation rules (11), (12). In such a way, its validity and performance over time is preserved.

$$\mu_{pj}(t) = \mu_{pj}(t-1) + f(\mu_{pj}(t-1), x^{\text{new}}, x^{\text{old}}, N_{\text{win}})$$
(11)

$$\sum_{pj} (t) = \sum_{pj} (t-1) + g (\sum_{pj} (t-1), \mu_{pj} (t-1), x^{\text{new}}, x^{\text{old}}, N_{\text{win}})$$
(12)

Where x^{new} and x^{old} are the newest arrived pattern and the oldest pattern in the time window N_{win} respectively.

Initial offline modeling allows the construction of initial classes that characterize knowledge from historical data. The historical data are usually sensor data that are saved. The modeling tool AuDyC used to initialize the feature spaces is based on extracted features from historical data, that will be online dynamically updated. Knowledge of failure modes given from (labeled) historical data can help building a classification scheme for fault diagnosis. However, in reality, these data are hard to obtain.

In this work, we suppose that only data corresponding to normal operating conditions (normal class) are known in advance. The training of the process by applying AuDyC is made based on features that are extracted from historical sensor data once finished; the class corresponding to normal operating mode is retained. We denote this class by $C_N = (\mu_N, \Sigma_N)$.

In online functioning, the parameters of C_N are dynamically updated by AuDyC for each new pattern arrives in operating mode 2. This yields changes in the class parameters which continuously reflect the distribution of the newest arriving patterns. We denote by $C_e = (\mu_e, \Sigma_e)$ the

evolving classes in the feature space. We have $C_{p}(t=0) = (\mu_{e}, \Sigma_{e}) = C_{N}$.

In operating mode 1, normal and faulty behaviors cannot be distinguished. Thus, in the proposed approach, the decisions about the status (normal/faulty) of patterns located in this region are delayed. Therefore in this case, the classifier will not be updated in order to avoid integrating in the drift time window useless patterns. In order to detect the drift as soon as possible, AuDyC updates the class parameters by using a window that contains only the patterns belonging to operating mode 2. AuDyC is dynamic by nature in the sense that it continuously updates the parameters of the classes as new patterns arrive.

3.4. Drift Monitoring step

The key problem of drift monitoring is to distinguish between variations due to stochastic perturbations and variations caused by unexpected changes in a system's state. If the sequence of observations is noisy, it may contain some inconsistent observations or measurements errors (outliers) that are random and may never appear again. Therefore, it is reasonable to monitor a system and to process observations within time windows in order to average and reduce the noise influence. Moreover, the information about possible structural changes within time windows can be interpreted and processed more easily. As a result, a more reliable classifier update can be achieved by monitoring within time windows. The latter must include enough of patterns representing the drift. To distinguish the useful patterns, the pitch actuator dynamics are represented by two different operating modes. In the operating mode 2, the degradation consequences of pitch actuator can be observed. Therefore, all patterns in this mode are useful to be analyzed and to be included in the drift time window. In the operating mode 1, the degradation consequences are masked. Patterns representing normal operating conditions cannot be distinguished from patterns representing pitch actuator degradations. Therefore in this case, no decision (normal/drift) will be taken in order to avoid integrating in the drift time window useless patterns.

The proposed methodology makes use of class parameters which are dynamically updated at each time but only with the patterns belonging to operating mode 2. Drift indicators are extracted from these parameters and detection of faults inception will be made based on their values. We define $I_{h1}(x)$, $I_{h2}(x)$ as:

$$I_{h1}(x) = d_{Mah}\left((\mu_N, \Sigma_N), \mu_e\right)$$
(13)

$$I_{h2}(x) = d_E(\mu_N, \mu_e)$$
(14)

Where d_E, d_{Mah} are, respectively, the Mahalanobis and Euclidean metrics. Euclidean metric computes the distance between center of the normal class μ_N and the center of evolving class μ_e ; on the other side Mahalanobis metric computes the distance between the normal class C_N and evolving class center μ_e .

$$d_{Mah}(C_N, \mu_e) = \sqrt{(\mu_N - \mu_e) \Sigma_N^{-1} (\mu_N - \mu_e)^T}$$
 (15)

$$d_{E}(\mu_{N},\mu_{e}) = \sqrt{(\mu_{N}-\mu_{e}) \times (\mu_{N}-\mu_{e})^{T}}$$
(16)

3.5. Interpretation step

This step aims at interpreting the detected changes within the classifier parameters and structure. This interpretation is then used as a prediction about the tendency of the future development of the wind turbine current situation. This prediction is useful to formulate a control or maintenance action.

In this work we have two indicators of change $I_{h1}(x)$, $I_{h2}(x)$. If one indicator exceeds a certain threshold *th*, the drift alarm will be launched. This means that the pitch actuators state has been moved (drift) away from the normal class. The second indicator aims at confirming the drift detection. The reason behind the use of two distance metrics (Euclidean and Mahalanobis ones) in the same time is to exploit the complementarily between them. Indeed, the Mahalanobis metric calculates the distance between the gravity center of the evolving class and the initial class. This will give more reactivity in case of change; while the Euclidean metric confirms this change by calculating the distance between the gravity center evolving class. The selection of *th* is motivated statically.

4. EXPERIMENTATION AND OBTAINED RESULTS

The failure of pitch actuator is caused by a continuous degradation of its performance over time. This degradation can be seen as a continuous drift of the normal operating conditions characteristics (normal class) of the pitch actuator. Detecting and following this drift can help the prediction of the occurrence of the pitch actuator failure. The two monitoring indicators defined by (13) and (14) are used to detect and to confirm this drift for the nine scenarios defined in section 2.

Figures 10 and 11 show the obtained results using the two drift detection indicators defined by (13) and (14). Table 2 shows the values of these indicators for the nine defined drift scenarios. These values represent the required time (starting from the drift beginning) to detect and confirm the drift occurrence. Thus, they can be used as an evaluation criterion to measure the time delay to detect a drift before its end.



Figure 10. Drift indicator based on Mahalanobis distance of the third pitch actuator.



Figure 11. Drift indicator based on Euclidean distance of the third pitch actuator.

Table 2. Results of drift detection and confirmation forthe nine drift scenarios.

Fault	Drift	I _{h1}	I _{h2}	Period
N°	speed			
F _{1h}	30s	7 _s	11.10 _s	$3200_{s} - 3330_{s}$
F _{1m}	60s	14.40 _s	28.70 _s	3200 _s -3360 _s
F _{1s}	90s	28.70 _s	31.40 _s	3200 _s -3390 _s

Fault	Drift	I _{h1}	I _{h2}	Period
N°	speed			
F _{2h}	30s	10.70 _s	11.50 _s	3300 _s -3430 _s
F _{2m}	60s	18.50 _s	21.40 _s	3300 _s -3460 _s
F _{2s}	90s	21.30 _s	31.60 _s	3300 _s -3490 _s

Fault	Drift	I _{h1}	I _{h2}	Period
N°	speed			
F _{3h}	30s	9.90 _s	10.70 _s	$3400_{s} - 5330_{s}$
F _{3m}	60s	13.00 _s	20.30 _s	3400 _s -5560 _s
F _{3s}	90s	22.70 _s	29.30 _s	3400 _s -3590 _s

5. CONCLUSION AND FUTURE WORK

In this paper, a methodology of condition monitoring and fault prediction was established. It is based on dynamical architecture of fault prediction. It was based on monitoring dynamically updated evolving class parameters. The methodology was tested on a benchmark of a wind turbine. It was shown that under the assumptions developed in this paper, the methodology has given promising results for different scenarios of simulation.

Future work will focus on the fault prediction and prognostics of other wind turbine critical components as the converter and drive train.

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REFERENCES

- Blesa, J., Puig, V., Romera, J. & Saludes, J. (2011). Adaptation of set theoretic methods to the fault detection of wind turbine benchmark. (8316–8321), August 28 -September 2, in Proceedings of IFAC World Congress. Milan, Italy. doi: 10.3182/20110828-6-IT-1002.01842
- Chammas, A., Duviella, E., & Lecoeuche S. (2013). Fault Diagnosis of Wind Turbine Drive Train Faults based on Dynamical Clustering, (5650 - 5655), December 10-13, in Proceedings of CDC Firenze, Italy . doi: 10.1109/CDC.2013.6760779
- Chen, W., Ding, S., Sari, A., Naik, A., Khan, A., & Yin, S. (2011), Observerbased fdi schemes for wind turbine benchmark. General Guidelines. (7073–7078), August 28 September 2,in Proceedings of IFAC World Congress 2011. Milan, Italy. doi: 10.3182/20110828-6-IT-1002.03469
- Laouti, N., Sheibat-Othman, N., & Othman, S. (2011). Support vector machines for fault detection in wind turbines. (7067–7072) ,August 28 - September 2, in Proceedings of IFAC World Congress. Milan, Italy. doi:10.3182/20110828-6-IT-1002.02560
- Lecoeuche, S. & Lurette, C. (2003) Auto-adaptive and dynamical clustering neural network. (350–358) June 26–29. in ICANN'03 Proceedings, Istanbul, Turkey. doi: 10.1007/3-540-44989-2_42
- LIU .W, (1999). An extended Kalman filter and neural network cascade fault diagnosis strategy for the glutamic acid fermentation process. Artificial intelligence in engineering A. page 131-140, vol. 13, n° 2, doi.org/10.1016/S0954-1810(98)00007-7
- Odgaard, P., & Stoustrup, J. (2009), Fault tolerant control of wind turbines a benchmark model.(155–160), June 06-07, in Proceedings of the 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes. Sants Hotel, Spain. IFAC, doi: 10.3182/20090630-4-ES-2003.00026

- Odgaard, P., & J. Stoustrup. (2010). Unknown input observer based detection of sensor faults in a wind turbine. (310-315), September 8-10, in Proceedings of Control Applications (CCA), Yokohama, Japan. doi: 10.1109/CCA.2010.5611266
- Ozdemir, A., Seiler, P., & Balas, G. (2011). Wind turbine fault detection using counter-based residual thresholding. (8289–8294), August 28 - September 2, in Proceedings of IFAC World Congress. Milan, Italy. doi:10.3182/20110828-6-IT-1002.01758
- Kim, K., Parthasarathy, G., Uluyol, O., Foslien , W., Shuangwen, S., Fleming P. (2011). Use of SCADA Data for Failure Detection in Wind Turbines. August 7-10, , in Proceedings of the Energy Sustainability Conference and Fuel Cell Conference, Washington, USA. doi: DE-AC36-08GO28308.
- Kusiak, A., Li, W. (2011). The prediction and diagnosis of wind turbine faults, in Proceedings of Renewable Energy, volume 36, Issue 1Pages 16-23. doi:10.1016/j.renene.2010.05.014
- Kusiak, A., Verma, A. (2011). A Data-Driven Approach for Monitoring Blade Pitch Faults in Wind Turbines, Sustainable Energy, page 87-96. doi: 10.1109/TSTE.2010.2066585
- Simani, S., Castaldi, P., & Bonfe, M. (2011). Hybrid modelbased fault detection of wind turbine sensors,(7061–7066), August 28 - September 2, in Proceedings of IFAC World Congress, Milan, Italy, doi: 10.3182/20110828-6-IT-1002.01311
- Schlechtingen, M., & Santos, I. F. (2011) Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection., Mechanical Systems and Signal Processing. Page 1849–1875. doi: org/10.1016/j.ymssp.2010.12.007.
- Toubakh; H, Sayed-Mouchaweh, M. ; Duviella, E. (2013) Advanced Pattern Recognition Approach for Fault Diagnosis of Wind Turbines. (368 - 373) Decembre 4-7. in Proceedings of 12th ICMLA, Miami, USA. doi: 10.1109/ICMLA.2013.150
- Traore, M., Duviella, E., & Lecoeuche, S. (2009) Comparison of two prognosis methods based on neuro fuzzy inference system and clustering neural network. (1468-1473) June 06-07. in 7th IFAC symposium on Fault Detection, Supervision and Safety of Technical Processes, Sants Hotel, Spain. doi: 10.3182/20090630-4-ES-2003.00239
- Zhang, X., Zhang, Q., Zhao, S., Ferrari, R. M., Polycarpou, M. M. & T. Parisini (2011). Fault detection and isolation of the wind turbine benchmark: An estimation-based approach, (8295–8300), August 28 -September 2, in Proceedings of IFAC World Congress 2011. Milan, Italy. doi:10.3182/20110828-6-IT-1002.02808

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Fault Diagnosis Methods for Wind Turbines Health Monitoring: a Review

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ABSTRACT

Recently, the rapid expansion of wind energy activity has led to an increasing number of publications that deal with wind turbine health monitoring. In real practice, implementing a prognostics and health management (PHM) strategy for wind turbines is challenging. Indeed, wind turbines are complex electro-mechanical systems that often work under rapidly changing environment and operating load conditions. Although several review papers that address wind turbines fault diagnosis were published, they are mostly focused on a specific component or on a specific category of methods. Therefore, a larger snapshot on recent advances in wind turbine fault diagnosis is presented in this paper. Fault diagnosis approaches could be grouped in three major categories according to the available a priori knowledge about behavior: the system quantitative/qualitative model, signal analysis and artificial intelligence based approaches. Each of the proposed methods in the literature has its advantages and drawbacks. Therefore, a comparison between these methods according to some meaningful evaluation criteria is conducted.

1. INTRODUCTION

Wind power industry continues to show a significant worldwide growth during the last decade. However, due to the competitive environment associated with the power generation industry, costs for operation and maintenance (O&M) of wind turbines need to be reduced (Arabian-Hoseynabadi, Oraee, & Tavner, 2010). Prognostics and Health Management (PHM) is one of the best strategies to achieve such purpose. Indeed, inspection tasks and time based maintenance activities are often expensive and require undesired downtime to be performed (Lu, Li, Wu, & Yang, 2009). Moreover, implementing a PHM policy allows to support system long-term performance through accurate monitoring, incipient fault diagnosis and prediction of impending faults (Kalgren, Byington, & Roemer, 2006). A fault diagnosis function estimates the current system health state from health features or sensors measurements. Whereas, a prognosis procedure seeks to predict when a potential upcoming failure will occur given the current system health state and the future usage conditions (Roemer, Nwadiogbu & Bloor, 2001).

However, a number of challenges remain to be met while performing wind turbines health assessment tasks owing to:

- The complex structure of the wind turbine (Fischer, Besnard & Bertling, 2012)
- The non-linearity and non-stationarity of the aerodynamics of such system (Lu et al., 2009)
- Fault tolerant nature of its control system (Simani, Castaldi & Tilli, 2011).

In order to address these constraints, a better understanding of the multiple failure modes associated with various components and their interactions is needed. In addition, symptoms related to the operating loads, environmental conditions and maintenance scenarios should be distinguished from actual wind turbine performance loss. Then, fault diagnosis and prognosis functions could be reliable.

Although a number of review papers addressing these topics have been published (Hameed, Hong, Cho, Ahn, & Song, 2009), (Sharma & Mahto, 2013), (Azarian, Kumar, Patil, Shrivastava & Pecht, 2011), (García Márquez, Tobias, Pinar

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Pérez & Papaelias, 2012), (Nie & Wang, 2013), (Lu & Sharma, 2009) (Sheng, 2011), they are mostly focused either on a particular component (gearbox components, insulated gate bipolar transistors (IGBTs)...) or on condition monitoring techniques and signal analysis tools. Therefore, in this review paper, a larger snapshot of recent diagnosis research works is explored in order to compare the proposed methods according to some meaningful evaluation criteria. Prior to that, a brief description of the wind turbine system and the most common condition monitoring tools is given.

2. WIND TURBINES HEALTH MONITORING

A wind turbine is a rotating mechanical device that converts wind kinetic energy to practical mechanical energy, resulting in electricity production. The rotary part can be either vertical or horizontal. The most recently used wind turbines are horizontal-axis based with two or three blades. These turbines also have a nacelle, which is held up by the tower and contains the gearbox and the generator. The gearbox increases the speed of the low-speed shaft to a suitable value required by the generator. A yaw system, which turns the nacelle and the rotor to face the wind. enables the turbine to capture the maximum amount of energy. According to the type of the generation system, the gearbox and the converter, different wind turbines categories can be distinguished (Kahrobaee & Asgarpoor, 2011). Among them, the variable-speed wind turbines offer advantages such as four quadrant power capabilities, maximum aerodynamic efficiency and reduced mechanical stress (Flórez, 2012). The double fed induction generator (DFIG) is today one of the most popular schemes for variable-speed wind turbines which has been introduced to replace the fixed-speed, squirrel-cage induction generators (Figure 1). In general terms, from the viewpoint of health monitoring, fixed speed turbines have a greater occurrence of mechanical failures (often in the gearbox) while electric failures are predominant in variable-speed turbines. More details about wind turbines configurations and their failures modes could be found in several papers (Fischer et al., 2012) (Arabian-Hoseynabadi et al., 2010), (Kahrobaee & Asgarpoor, 2011).



Figure 1. Typical configuration of a DFIG-based wind turbine (Flórez, 2012).

2.1. Condition Monitoring Systems for wind turbines

Among the review papers on wind turbines health monitoring and fault diagnosis, several of them were focused on Condition Monitoring Systems (CMS) tools used for that purpose. A CMS includes a set of sensors, signal acquisition and processing software, cabling and installations that gives continuous information about the monitored component condition. The CMS is used on wind turbines (especially off-shore ones) in order to monitor the most critical components such as gearboxes, generators, main bearings and blades. García Márquez et al. (2012) found that vibration analysis is the most known technology employed in wind turbines, especially for rotating equipment such as gearboxes components and bearings that supports the low speed shaft. Acoustic emission analysis is another condition monitoring tool used for rotating wind turbines components as well as for the blades (Hameed et al., 2009). In addition, oil analysis is typically applied to the gearbox and may have two purposes: (1) guaranteeing the oil quality (by measuring the oil temperature, its contamination and moisture) or (2) monitoring various rotating parts condition/wear (by looking for oil contamination or variation of particulates properties) (Sharma & Mahto, 2013). For more thorough summaries on condition monitoring techniques related to different wind turbines subassemblies, see (Hameed et al., 2009) and (Lu & Sharma, 2009).

Based on the above references, it is worth mentioning that:

- For the drive train components, the variable-speed operation and the stochastic characteristics of the aerodynamic loads prevent the usage of traditional frequency domain analysis techniques. Therefore, time-frequency analysis (e.g. wavelet transforms) is more suitable (Lu et al., 2009),

- The acoustic emission based tools give earlier warning of wind turbines gearbox failure at low-speeds compared to the classical vibration-based ones. However, acoustic emission techniques require higher sampling rates and they may not be a cost-effective solution to the gearbox fault detection (Azarian et al., 2011),

- Despite many research achievements in developing condition monitoring techniques, their implementation in practice still faces some challenges. Indeed, they still suffer from false alarms and they do not demonstrate satisfactory performance in the detection of incipient faults especially those related to electrical/electronic components (Yang, Tavner, Sheng & Court, 2012).

A CMS has the advantage to be accurate in monitoring specific kinds of failures. However, it requires more sensors and equipment to be installed in wind turbines as well as higher data storage costs resulted from a higher sampling rate of the acquired signals. To date, and because of these high implementation costs, such systems are more used for offshore wind turbines where maintenance visits are more complicated (Yang, Tavner, Crabtree & Wilkinson, 2008).

2.2. Towards SCADA data based health monitoring

In comparison with a CMS which is intended only to health monitoring purpose, the Supervisory Control and Data Acquisition (SCADA) system is able to resolve certain supervisory control tasks by automatically starting, stopping, and resetting the turbines in case of small fluctuations (Verma, 2012). Furthermore, SCADA records tend to be a major data source for monitoring wind turbines condition in the last years (Sharma & Mahto, 2013). Indeed, SCADA data might be fault informative. These data are of two types: status codes and operational data. The status data are recorded whenever the system undergoes status changes, whereas the operational data are recorded at predefined time intervals (Kusiak & Verma, 2011). Operational SCADA data include operational variables such as the produced power, the wind speed, some components temperatures and even vibration and oil debris monitoring data in some cases (Nie & Wang, 2013). Thus, SCADA based health monitoring is considered to be a cheaper solution than CMS since no additional sensors are required. However, wind turbines SCADA systems usually limit the amount of data to a number of records (10 min average data) and they are not initially designed for condition monitoring purposes. Then, conventional condition monitoring approaches which are developed for highly sampled CMS data are mostly not valuable and an appropriate SCADA data analysis tool is needed (Yang, Court & Jiang, 2013).

3. WIND TURBINES FAULT DIAGNOSIS APPROACHES

Regardless of used condition monitoring tools, several fault detection and diagnosis methods have been developed. In general and according to the nature of the available process knowledge, these methods can be categorized into three main classes: model-based, signal analysis and artificial intelligence (AI) methods.

• Model based methods

For this first broad category, a priori knowledge about the system operation modes is complete enough to be formalized into a quantitative or qualitative model. The quantitative models are in the form of fundamental laws described by mathematical relationships on the system input-output measurements. The quantitative models based approaches are of two categories: parameter estimation, and output observer based approaches.

The parameter estimation based methods use a system identification technique on input/output measurements in order to monitor the evolution of the system characteristic parameters against a nominal parameter set. Output observer (or residual generation) methods use an observer, often a Kalman filter, in order to assess the difference between the actual and the estimated output (reconstructed from the system model and controlled inputs). However, qualitative models use qualitative relationships or knowledge bases to draw conclusions regarding the state of a system and its components (Katipamula & Brambley, 2005). Hence, a qualitative model could be either a qualitative physics-based, discrete event or rule-based model.

• Signal analysis methods

Signal analysis methods are based on time and frequency domain analysis without any explicit mathematical model. Only knowledge about suitable fault features is required. Fault features can be derived from raw signals (vibration, acoustic emission, electrical signatures...) in order to evaluate the system operating state. Fast Fourier transformation, cepstrum (spectral representation of signals) and envelope curve analysis are some common approaches. More details about these techniques are given in (Jardine, Lin & Banjevic, 2006).

Artificial intelligence methods

When a process is too complex or poorly known to be monitored through quantitative or qualitative models, and if signal analysis techniques do not allow an unambiguous diagnosis, artificial intelligence (AI) approaches can be used to overcome these limitations. AI based methods learn the complex model exclusively from available historical data (Venkatasubramanian, Rengaswamy, Kavuri & Yin, 2003). Artificial neural networks and clustering/classification techniques belong to this category of methods.

Without concern of exhaustiveness, the present review gives some examples from recent wind turbine fault diagnosis studies in order to illustrate each category of methods.

3.1. Literature review

Different wind turbines components are considered within the reviewed works. Moreover, both CMS and SCADA based monitoring tools could be found. The only differentiator is the category of the fault diagnosis methods used.

Within the quantitative model based fault diagnosis category, Chen, Ding, Sari, Naik, Khan and Yin (2011) put forward an observer-based fault detection and isolation scheme for the wind turbine pitch system and the drive train. They utilized a Kalman filter for residual generation. Then, a generalized likelihood ratio test and a cumulative variance index were applied for residual evaluation. Test data were extracted from a wind turbine simulator proposed within (Odgaard, Stoustrup & Kinnaert, 2009). Another example of an observer based approach implemented using SCADA data is reported in (Guo, 2011). In this paper, the normal behaviour of the generator bearing temperature is modelled based on a nonlinear state estimate technique (NSET). When residuals between the NSET estimates and the

measured values exceed predefined thresholds, an incipient fault is flagged. Effectiveness of this approach was evaluated by the analysis of a manual drift added to the historical SCADA data. Simani et al. (2011) performed a parameter identification/estimation based method for converters fault diagnosis. Since the studied component is non-linear and the wind speed measurement is highly noisy, a fuzzy multiple model was considered. Such model consists of a collection of several local affine models, each of them describes a different operating mode. Thus, they used a fuzzy clustering technique in order to determine the regions in which the measured data could be approximated by local models. The effectiveness of such method was shown on a simulated process. On the other hand, Kostandyan and Sørensen (2012) explored a physics of failure model in order to assess the accumulated linear damage for a given load profile. It is applied to evaluate the damage value and predict the wind turbines power electronics reliability.

Regarding the qualitative model based approaches, Echavarria, Tomiyama, Huberts and Van Bussel (2008) developed a model-based reasoner for the overall system. The authors used qualitative physics in order to describe the behavior of the wind turbine in terms of qualitative characteristics changes over time. Such approach allows the possibility to model systems of higher complexity such as wind turbines. Work done by Rodriguez, Garcia, Morant, Correcher and Quiles (2008) has shown that Petri Nets are also suited for system-level modeling and namely for wind turbines fault diagnosis.

Within the scope of this review, signal analysis based fault diagnosis works are the most prevalent in the literature. Classical signal processing techniques were widely applied for studying wind turbines components, mainly the gearbox and the generator components. Indeed, Yang et al., (2008) applied a wavelet-based adaptive filter in order to extract the energy of the generator power signal at prescribed, faultrelated frequencies. In addition, the signal non-stationarity was treated by adjusting the filter bandwidth according to the fluctuation of the wind speed. Both mechanical and electrical abnormalities were assessed experimentally on a wind turbine test rig. A similar work on generator fault diagnosis is done by Amirat, Choqueuse and Benbouzid (2010). They highlighted the use of the Hilbert transformation on the stator current data. Vibration signals were also widely used with classical signal processing tools in both time and frequency domain (Zhang, Verma & Kusiak, 2012) (Liu, Zhang, Han & Wang, 2012).

The construction of some SCADA data curves and studying their deviation from a reference one is being more adopted for a global wind turbine health monitoring. This kind of approaches is specific to wind energy domain and can be integrated among AI methods. Kusiak and Verma (2013) studied three operational curves: power curve, rotor curve and blade pitch curve, which plot three measurements against the wind speed. A k-means clustering and Mahalanobis distance were used to extract smooth performance curves by removing outliers without any pretreatment on raw data. The obtained performance curves will be considered as baseline curves to detect fault drifts. In a similar manner, Yang et al. (2013) established several reference plots by extracting correlations between relevant SCADA variables. However, input variables were first preprocessed and normalized relatively to the wind speed or to the generator speed values in order to obtain smooth curves.

With regards to more known AI based approaches, Laouti, Sheibat-Othman and Othman (2011) conducted a fault diagnosis for pitch system sensors and actuators by means of a support vector machine classifier. Fault features were manually constructed and a wind turbine simulator data was used for this purpose. For gearbox fault diagnosis, Kim, Parthasarathy, Uluyol, Foslien, Sheng and Fleming (2011) proposed a fault detection method based on SCADA measurements. They applied principal components analysis and a clustering technique in order to diagnose gearbox faults. Tong and Guo (2013) proposed an improved datamining algorithm for the extraction of association rules on status codes (considered as fault alarms). The purpose was to extract implied causal relationships between status codes that lead to an effective fault alarm. In such a way, the number of alarms was reduced and then operators' work efficiency improved. Kusiak and Li (2011) proposed to use the occurrence time of certain status codes which are related to the diagnosed faults in order to label the SCADA data. The obtained labeled training data set was then used by several data-mining algorithms (Neural network, standard classification and regression tree (CART), the Boosting Tree Algorithm (BTA), SVM...) in order to predict the diverter malfunction. Work done by Godwin and Matthews (2013) dealt with the development of an expert system for the classification and detection of wind turbine pitch faults. Decision rules were extracted by a decision tree-type rule learning algorithm and then validated by an independent expert. A similar approach could be found within (Yongxin, Tao, Wenguang & Dongxiang, 2012) where a trained decision tree was used in order to construct fault diagnosis rules of a wind turbines gearbox.

3.2. Review results and discussion

Based on this survey, major advantages and drawbacks of each category of wind turbines fault diagnosis approaches are listed hereafter:

- Monitoring data issued from CMS or SCADA systems can be used in implementing model-based and artificial intelligence approaches. However, signal analysis methods are mostly used when accurate and specific fault oriented acquisition system is available, i.e. with CMS.

- Quantitative model approaches, in particular parameter estimation based ones, have the advantage of identifying the abnormal physical parameters rather than faulty signal signatures that are more dependent to the load condition (Lu et al., 2009). However, modelbased approaches require a sufficiently accurate a priori knowledge to construct a mathematical or analytic model for the monitored system. This is hard to achieve in case of complex non-linear systems as wind turbines.
- Although qualitative models based approaches require deep knowledge about the wind turbines behavior, they have the ability to monitor the overall system via the causal knowledge and the laws governing the behavior of its subsystems (Venkatasubramanian, Rengaswamy, Yin & Kavuri, 2003).
- Signal analysis based approaches are easier to implement if a sophisticated data acquisition systems and sensors exists. However, successful implementation of such approaches is dependent on the construction of suitable fault-related features and reliable thresholds since subjective and unproven ones may result in wrong alerts (Yang et al., 2013).
- Artificial intelligence approaches achieve multidimensional analysis based on the combination of several sensors that monitor the same component. However their performance is highly dependent on the selection of training data set which must represent all operating modes for the wind turbine. In addition, since the obtained models are not usually transparent, the obtained results can be hard to be interpreted and demonstrated.

As a synthesis of this review, some criteria are proposed to compare these three categories of diagnosis methods (Table1). Such comparison could support the choice of the suitable fault diagnosis approach with respect to the initial needs. Chosen criteria for this comparison are the following:

- (1) System's non-stationary nature: ability to separate the actual degradation and environmental or load effects
- (2) Needed knowledge: ability to construct model without need to a priori knowledge
- (3) System level: ability to deal with system hierarchical levels (local component or global system point of view)

Table1 show the rank accorded to each category of methods regarding each criterion. A category is accorded the first rank when it satisfies the best the criterion in question. Considering the first criterion, quantitative model-based approaches, are the most suitable for dealing with the systems non-stationary nature, especially by using parameter estimation techniques. Signal analysis approaches can also deal with such non-stationarity by adjusting filters bandwidth according to the fluctuation of the wind speed (Yang et al., 2008).

	System non- stationarity	Needed knowledge	System level
Model Based	+ + +	+	+++
Signal Analysis	+ +	+ +	+
AI	+	+++	+ +

Table 1. Comparison of fault diagnosis methods

Artificial intelligence approaches are less suited when this constraint should be satisfied. Moreover, in terms of the third criterion, qualitative models are more appropriate for system level monitoring. Artificial intelligence methods can be also used if appropriate health features are afforded.

These results remain broad since they are extracted from a wide range of fault diagnosis approaches from the literature. Thus, such comparison does not substitute an effective implementation and comparison of most major methods with specific fault and real condition monitoring data.

4. CONCLUSION

Fault diagnosis methods developed for different wind turbine components such as gearbox, main bearings and generators are widely proposed. However, other critical wind turbine components such as blades, pitch systems and converters still need more focus. This is because of the -) hard modeling and detection of blades icing, deflection and fatigue and -) actions of the control feedback which compensate the pitch actuators and converter fault effects. In addition, the use of SCADA data for wind turbine health monitoring has led to the development of specific diagnosis methods for wind energy domain. The methods based on the analysis of wind turbine performance clearly separate out pre-failure data from other normal operating data. However, it is challenging to associate a drift in wind turbine performance to a particular failure using only global features as the produced power. Faults characterization requires often measurements about more of specific features related to the components dynamical behaviors. Thus, algorithms based on SCADA signals analysis should be combined with components oriented CMS based signals analysis. This combination helps to better diagnose components related faults.

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REFERENCES

- Amirat, Y., Choqueuse, V., & Benbouzid, M. E. H. (2010). Wind turbines condition monitoring and fault diagnosis using generator current amplitude demodulation. *Proceedings of IEEE Energy Conference and Exhibition (EnergyCon)*, pp. 310-315.
- Arabian-Hoseynabadi, H., Oraee, H., & Tavner, P. J. (2010). Failure modes and effects analysis (FMEA) for wind turbines. *International Journal of Electrical Power & Energy Systems*, 32(7), 817-824.
- Azarian, M. H., Kumar, R. S., Patil, N., Shrivastava, A., & Pecht, M. (2011). Applications of health monitoring to wind turbines. *Proceedings of Condition Monitoring and Diagnostics Engineering Management Conference*, pp. 304-313.
- Chen, W., Ding, S. X., Sari, A., Naik, A., Khan, A., & Yin, S. (2011). Observer-based FDI schemes for wind turbine benchmark. *Proceedings of IFAC World Congress*, pp. 7073-7078.
- Echavarria, E., Tomiyama, T., Huberts, H., & Van Bussel, G. (2008). Fault diagnosis system for an offshore wind turbine using qualitative physics. *Proceedings of EWEC conference*.
- Fischer, K., Besnard, F., & Bertling, L. (2012). Reliabilitycentered maintenance for wind turbines based on statistical analysis and practical experience. *IEEE Transactions on Energy Conversion*, 27(1), 184-195.
- Flórez Rodriguez D. M., *Sliding Mode Control in Grid-Connected Wind Farms for Stability Enhancement*, PhD Thesis, Universidad Carlos III de Madrid, Spain, June 2012.
- García Márquez, F. P., Tobias, A. M., Pinar Pérez, J. M., & Papaelias, M. (2012). Condition monitoring of wind turbines: Techniques and methods. *Renewable Energy*, 46, 169-178.
- Godwin, J. L., & Matthews, P. (2013). Classification and Detection of Wind Turbine Pitch Faults Through SCADA Data Analysis. *International Journal of Prognostics and Health Management*.
- Guo, P. (2011). WEC condition monitoring based on SCADA data analysis. *In IEEE Chineese Control Conference (CCC)*, pp. 5099-5103.
- Hameed, Z., Hong, Y. S., Cho, Y. M., Ahn, S. H, & Song, C. K. (2009). Condition monitoring and fault detection of wind turbines and related algorithms: a review. *Renewable and Sustainable Energy Reviews*, 13(1), 1-39.
- Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, 20(7), 1483-1510.

- Kahrobaee, S., & Asgarpoor, S. (2011). Risk-based failure mode and effect analysis for wind turbines (RB-FMEA). *In IEEE North American Power Symposium* (*NAPS*), pp. 1-7.
- Kalgren, P. W., Byington, C. S., & Roemer, M. J. (2006). Defining PHM, a lexical evolution of maintenance and logistics. *In IEEE Autotestcon*, pp. 353-358.
- Katipamula, S., & Brambley, M. R. (2005). Review article: methods for fault detection, diagnostics, and prognostics for building systems—a review, Part I. *HVAC&R Research*, 11(1), 3-25.
- Kim, K., Parthasarathy, G., Uluyol, O., Foslien, W., Sheng, S., & Fleming, P. (2011). Use of SCADA data for failure detection in wind turbines. *In International Conference on Energy Sustainability*, pp. 2071-2079.
- Kostandyan, E. E., & Sørensen, J. D. (2012). Physics of failure as a basis for solder elements reliability assessment in wind turbines. *Reliability Engineering & System Safety*, 108, 100-107.
- Kusiak, A., & Li, W. (2011). The prediction and diagnosis of wind turbine faults. *Renewable Energy*, 36(1), 16-23.
- Kusiak, A., & Verma, A. (2011). A data-driven approach for monitoring blade pitch faults in wind turbines. *IEEE Transactions on Sustainable Energy*, 2(1), 87-96.
- Kusiak, A., & Verma, A. (2013). Monitoring wind farms with performance curves. *IEEE Transactions on Sustainable Energy*, 4(1), 192-199.
- Laouti, N., Sheibat-Othman, N., & Othman, S. (2011, August). Support vector machines for fault detection in wind turbines. *In Proceedings of IFAC World Congress*, pp. 7067-707.
- Liu, W. Y., Zhang, W. H., Han, J. G., & Wang, G. F. (2012). A new wind turbine fault diagnosis method based on the local mean decomposition. *Renewable Energy*, 48, 411-415.
- Lu, B., Li, Y., Wu, X., & Yang, Z. (2009). A review of recent advances in wind turbine condition monitoring and fault diagnosis. *In Power Electronics and Machines in Wind Applications Conference*, pp. 1-7.
- Lu, B., & Sharma, S. K. (2009). A literature review of IGBT fault diagnostic and protection methods for power inverters. *IEEE Transactions on Industry Applications*, 45(5), 1770-1777.
- Nie, M., & Wang, L. (2013). Review of Condition Monitoring and Fault Diagnosis Technologies for Wind Turbine Gearbox. *Procedia CIRP*, 11, 287-290.
- Odgaard, P.F., Stoustrup, J., & Kinnaert, M. (2009). Fault tolerant control of wind turbines- a benchmark model. *IFAC symposium on fault detection, supervision and safety of technical processes*, 155-160.
- Rodriguez, L., Garcia, E., Morant, F., Correcher, A., & Quiles, E. (2008). Application of latent nestling method using coloured petri nets for the fault diagnosis in the wind turbine subsets. *In IEEE International Conference* on Emerging Technologies and Factory Automation, pp. 767-773.

- Roemer, M. J., Nwadiogbu, E. O., & Bloor, G. (2001). Development of diagnostic and prognostic technologies for aerospace health management applications. *In IEEE Aerospace Conference*, pp. 3139-3147.
- Sharma, S., & Mahto, D. (2013). Condition monitoring of wind turbines: a review. *International Journal of Scientific and Engineering Research*, 4(8), 35-50.
- Sheng, S. (2011). Investigation of Various Condition Monitoring Techniquest Based on a Damaged Wind Turbine Gearbox. *International workshop on structural health monitoring*, Stanford, California.
- Simani, S., Castaldi, P., & Tilli, A. (2011). Data-driven approach for wind turbine actuator and sensor fault detection and isolation. *In Proceedings of IFAC World Congress*, pp. 8301-8306.
- Tong, C., & Guo, P. (2013). Data mining with improved Apriori algorithm on wind generator alarm data. *In Chinese Control and Decision Conference (CCDC)*, pp. 1936-1941.
- Venkatasubramanian, V., Rengaswamy, R., Kavuri, S. N., & Yin, K. (2003). A review of process fault detection and diagnosis: Part III: Process history based methods. *Computers & chemical engineering*, 27(3), 327-346.
- Venkatasubramanian, V., Rengaswamy, R., Yin, K., & Kavuri, S. N. (2003). A review of process fault detection and diagnosis, Part II: Qualitative models and search strategies. *Computers in Chemical Engineering* 27(3), 313-326.
- Verma, A. P. (2012). Performance monitoring of wind turbines: a data-mining approach. Doctoral dissertation. The University of Iowa, Iowa, USA.
- Yang, W., Court, R., & Jiang, J. (2013). Wind turbine condition monitoring by the approach of SCADA data analysis. *Renewable Energy*, 53, 365-376.
- Yang, W., Tavner, P. J., Crabtree, C. J., & Wilkinson, M. (2008). Research on a simple, cheap but globally effective condition monitoring technique for wind turbines. In International Conference on Electrical Machines, pp. 1-5.
- Yang, W., Tavner, P. J., Sheng, S., & Court, R. S. (2012). Information Entropy: an effective approach for wind turbine condition monitoring. *EWEA conference*.
- Yongxin, F., Tao, Y., Wenguang, Y., & Dongxiang J. (2012). Study of fault diagnosis method for wind turbine with decision classification algorithms and expert system. *TELKOMNIKA Indonesian Journal of Electrical Engineering*, 10(5), 905-910.
- Zhang, Z., Verma, A., & Kusiak, A. (2012). Fault analysis and condition monitoring of the wind turbine gearbox. *IEEE Transactions on Energy Conversion*, 27(2), 526-535.

BIOGRAPHIES

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Economic Aspects of Prognostics and Health Management Systems in the Wind Industry

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ABSTRACT

Since Wind Turbines are one of the most dynamically stressed structures, all parts should be subjected to Prognostics and Health Management System. This is especially true for the supporting structure since it is exposed to high fatigue loads. The current technical trend in the O&M business is to improve the life-time of these supporting structures. In particular, when considering the supporting structure of a wind turbine from a civil engineering perspective; a long term approach is most beneficial in financial, ecological and social aspects. To meet the challenge of managing the life-time of wind turbine supporting structures efficiently, it is necessary to develop technical concepts assessing the consumed life-time of a wind turbine. Future PHM systems of wind turbines must include this function.

The global O&M market in the wind energy industry grew in the period from 2005 to 2011 at a rate of around 18 per cent, annually. The main growth driver is the aging overall turbine park. Especially in the European onshore wind market there will be a profit migration of the O&M business at the expense of new construction until 2020. Until the year 2020, three quarters of the total profit in the wind energy industry will be occupied by O&M services (Oliver Wymann, 2011).

This paper discusses the special economic aspects of Prognostics and Health Management Systems focusing on a remaining lifetime prediction as a basic maintenance system in application within the wind industry. Besides studies of the future O&M market development, concepts to lower the levelized cost of energy through PHM from a macroeconomic perspective will also be discussed.

Keywords: Wind O&M market, Lifetime management, Levelized cost of energy, return on investment analysis.

1. INTRODUCTION

Europe is currently in the energy transition process from conventional and fossil power technologies to renewable energy technologies. Fossil fuels helped to build the modern world we know in Europe. But with the goal to preserve the ecological balance for future generations and not to continue robbing natural resources for blind growth, the task of the generations in this century is to transform our energy system into a renewable one. Additionally renewable resources also enable people in developing countries quick and useful access to energy for their daily lives. We live in a transformative moment in history in which we should not waste time anymore and use this unique gift of our planet.

In this context it is worthwhile to remember a famous quote of the theoretical physicist and mastermind Albert Einstein:

"Imagination is more important than knowledge. Knowledge is limited; Imagination encircles the world."

With this background the paper is concerned with the possibilities and potentials of PHM systems to economically optimize the operation of wind power plants.

2. GLOBAL WIND MARKET DEVELOPMENT

The global wind market is mainly characterized through a mature onshore market and a growing offshore market. The pioneers of the past in the onshore wind energy developments were the USA, Denmark, Germany and Spain (GWEC, 2012). Those countries represented the starting points for the global onshore wind energy development. Despite the growing Asian market, Europe is still the continent with the highest installed wind power capacity. Furthermore Latin America, India, Africa and Canada are also very dynamic markets. Until today roughly 80 countries contribute in developing the global onshore wind energy market. As shown in Figure 1 the current total global installed capacity accounts 282 GW. Average annual growth rates of about 28 % characterized the dynamic development (GWEC, 2012).

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At the end of 2012 the European market added 108 GW to its installed wind power capacity. A share of 78 GW was installed in the leading markets, namely Germany, Spain, France, Italy and the UK. Within the major players, Germany is still the leading wind energy market in Europe and conducts 32 GW installed wind power. The new major finalized offshore projects on the British coast made UK the European country with the highest capacity growth rate (EWEA, 2013).

In regards to the capacity growth rates, Asia beat the European growth rates for the first time in 2009. In 2010 Asia installed more new wind turbines than the USA and Europe combined. The main driver in Asia is the Chinese market. Figure 2 shows the distribution of the current global cumulative installed wind turbine capacity for the leading countries.



■ Africa & Middle Fast ■ Pacific

Figure 3: Cumulative capacity forecast per region (GWEC, 2012).

Besides the already mentioned rapid Asian market growth Figure 3 also shows the developing markets in Latin America, Africa and the Middle East region as well as the Pacific area. Especially in Morocco for example, there are excellent locations for converting wind energy. However the limiting factors in these regions are the unstable political and social frameworks.

The previously mentioned leading role of Germany in the European market is graphically expressed in Figure 4. The second largest wind market in Europe is located in Spain which undergone flourishing development in the early 2000s. Currently the restrictive and backward renewable energy policy in Spain leads the local wind energy market development almost to a deadlock.



Figure 2: Global wind turbine capacity distribution (GWEC, 2012).



Figure 4: European wind turbine capacity distribution (EWEA, 2013).

The European wind energy market can be subdivided into an onshore market segment and an offshore market segment. Figure 5 shows the market development in those areas considering the annual installations in the last decade. Despite the fact that there are plenty of research as well as market activities in the new offshore business, the lion's share considering real operative business is still clearly covered by onshore turbines. The presented European market setup is also valid for the German market as Table 1 points out. A special feature of the mature German market is the growing importance of repowering activities as more and more turbines reach their designed life-times. The alternative to repowering is plant life extension with the support of PHM systems in application. Special macroeconomic aspects of this opportunity will be discussed later in the article.

Due to the fact that major players of the European wind energy market are currently revising their policies and subsidies – causing uncertainty on the investors' side – European market growth will decelerate.

However, new positive market developments are recognized in Latin America. In the last five years Brazil has gone from a fledgling wind market to a generic business development base. Brazil alone installed more than twice the amount of grid-connected turbines than all other Latin American countries combined.

Another future flourishing market will be South Africa. The South African government is currently tendering big wind turbine projects in the mountain regions northwest and northeast of Cape Town.



(EWEA, 2013).

Table 1: German onshore wind market
(Deutsche WindGuard GmbH, 2013a).

(Deutsene Whidouard Onion, 2015a).						
Devel	opment in the German Onshore Wind Market	Number	Capacity [MW]			
2012	Cumulative installed wind turbines - 31.12.2012	22907	30989			
승규 의	Gross new installed wind turbines in 2013	1154	2998			
velo 1013	- Repowering	269	766			
Dev T	Dismantling in 2013	416	258			
2013	Cumulative installed wind turbines - 31.12.2013	23645	33730			

3. DEVELOPMENTS IN THE WIND O&M MARKET

In Europe the general market environment is characterized by a mature onshore market and a growing offshore market. In future the European market will experience a profit migration from new installations to O&M services. The European wind service market currently has a size of 2.3 bn. \notin . Furthermore the European wind energy servicing market occupied in recent years roughly half of the global wind energy servicing market size. The European market will grow up to 2.7 bn. \notin until 2020, as shown in Figure 6. From 2005 until 2011 the European O&M market grew about 18 % annually on average. Germany's maintenance market will be the largest and reach 1 bn. \notin in 2020.

The main market players in the European O&M business in the wind industry are the service departments of the Original Equipment Manufacturers (OEM), Independent Service Providers (ISP) and the Wind Farm Owners (WFO). ISPs currently mainly concentrate their business activities on special turbine types and regional areas. Due to the decreasing margins in production of wind turbines, the OEMs build increasingly their businesses on complete packages of wind power plants including all services over a life-time of 20 years. In doing so, they secure their market positions facing new business models such as ISPs (BWE, 2012).



Figure 6: European service market development (Deloitte / TaylorWessing, 2012).

Looking into the latest statistics of the German wind energy association – Bundesverband WindErnergie e.V. – it can be seen that the OEM service concepts still dominate the market with a 90 % share of OEM service contracts in the German wind energy market (BWE, 2012). However, different studies predict that the current 10 % market share of the ISPs will rise up to 30 % in 2020 (Oliver Wymann, 2011). Additionally the ISPs are also searching for new market possibilities in Poland, France and Italy.

From a macro-economic perspective this represents positive development. The growing number of competitors in the O&M market will lead to increased price pressure and lower the current high maintenance costs.

Until now the onshore market clearly dominated the O&M business. In the year 2012 about 91 % turnover was reached in the onshore market and 9 % turnover in the offshore market. The increasing average age and the large number of turbines in the onshore market provide a good basis for future business developments. In the coming years more and more turbines will exceed their designed lifetime of 20 years. In the year 2012 about 860 turbines were older than 20 years. Predictions say that in the year 2020 we will have 8,200 turbines over 20 years in operation (Fraunhofer IWES, 2013). Despite having relatively less turbines, the offshore sector still offers market potential for players in the O&M market. The core problem which needs to be solved soon in the offshore maintenance business is the high maintenance $\cos t - 2$ to 4 times higher than in the onshore sector (IRENA, 2012).

4. COST STRUCTURE OF A WIND TURBINE PROJECT

Prior to analyzing economic concepts of PHM systems in the wind industry it is necessary to get a clear understanding of the cost structure in that business branch. On the highest level the cost structure can be subdivided into investment costs and operation costs. Furthermore, the investment costs are categorized into primary investment costs and secondary investment costs.

The main investment costs come directly from the wind turbines' physical components. Main cost drivers are the following subsystems: gear box, rotor blades, generators and particularly the towers. The specific investment costs of wind turbines rise with increasing hub heights but decrease with increasing power of the turbine. This correlation is mainly lead by the influencing high costs of the supporting structure of turbines. The specific tower costs rise with increasing turbine power. On average the primary investment cost shares of the tower structure range from 24 % to 32 % for a wind turbine in the onshore market. In comparison rotor blades on average cost from 21 % to 24 % of primary investment, and the gearboxes cost from 10 % to 18 % of primary investment. Those three subsystems represent the most important cost shares of the wind turbine

and therefore are important working points for the installation of a PHM system.

The secondary investment costs contain on a basic level the foundation of the wind turbine, the grid connection as well as the prior planning activities and during the turbine construction phase. The main cost share of on average 18 % is occupied by the foundation costs. Together with the above-mentioned importance of the supporting structure from an economic perspective, the supporting structure components tower and foundation are of particular interest for PHM future systems in application in the wind industry.

Figure 7 illustrates the investment cost structure of an example 3 MW onshore wind turbine in Southern Germany.

The second main cost category of wind turbines is the operating costs. By definition the operating costs contain all expenses necessary to ensure a safe and reliable operation of the turbine over the whole life span. Core expenses are maintenance and repair, leasing costs, commercial and technical operation management, insurance costs, savings and miscellaneous costs.

Due to the importance of maintenance and repair costs in the distribution of the operating costs the majority of the wind turbine owners prefer full service contracts. The duration of those full service contracts for wind turbines range from 10 years to 15 years. Full service contracts include the benefits of all maintenance and repair costs by default defined in the wind industry as well as all unplanned maintenance and repair activities beyond the warranty of the Original Equipment Manufacturer (OEM). Additionally providers of such full service contracts guarantee a certain level of availability of the wind turbine over the lifetime. The guaranteed availability levels range from 95 % to 99 %. The main providers for full service contracts are on the one hand the OEMs and on the other hand the so called Independent Service Providers (ISPs). In particular, the wind turbine owners profit in this framework from a calculable cash flow plan of their wind turbine project with minimized risks.



Figure 7: Distribution of investment costs – Onshore.

A recent poll of the German wind energy association – Bundesverband WindEnergie e.V. - came to the result that

34 % of the overall wind turbines in the German market are serviced in standard service contracts and 64 % of the turbines in full service contracts (BWE, 2012).

To proceed with the analysis of the distribution of the operating costs it is appropriate to subdivide operations costs in to the first half of the planned lifespan of a wind turbine project and the second half of the lifespan.

Figure 8 shows the proportional distribution of operating expenses of an average onshore wind turbine project. Most importantly, the high amount of maintenance and repair as well as the increasing development in the second half of the life span is remarkable. In the second half of the lifetime wind turbines cause 30 % to 43 % more O&M costs compared to the first half.

The whole renewable energy branch in Europe is currently under cost pressure in the energy transition process. On the route to a renewable energy system the basic challenge is to further reduce the energy production costs of the different technologies. PHM systems can certainly help to solve these complex problems on a technical basis.

To illustrate this point; Germany spends in 2013 23 bn. \in for feed-in tariffs and other subsidies for renewable energy sources. Those costs have to be optimized and the technologies will have to be further developed to marketability. However, the wind energy technology already covers an important and economical part of the renewable capacities in the power system and represents therefore a valuable development base. The key concept from a macro economic standpoint is to reduce the Levelized Cost of Energy (LCOE) of a specific generation technology – in this case, wind energy.



Figure 8: O&M cost dependence from turbine age (Deutsche WindGuard GmbH, 2013b).

5. PHM TO LOWER THE LEVELIZED COST OF ENERGY

In order to evaluate the total costs of production of electricity the concept of Levelized Cost of Energy (LCOE) can be applied.

In the case of wind energy this concept describes the costs incurring for the conversion of wind energy into electricity. The streams of costs for wind energy are converted to a net present value using the time value of money. In general the LCOE represent the price at which electricity must be generated from, at a specific source to break even over the lifetime of the project. All costs over the lifetime of a given project are summarised and included, discounted to the present time $t = t_0$ and levelized based on the annual energy production of the particular project.

In case of wind turbines the generated electricity represents future income and is discounted cash flow in the model. In Ct the annual overall costs are summarized. The parameter includes: General fixed and variable costs of the wind turbine project, all costs incurring from maintenance activities, insurance costs as well as recycling costs of the wind turbine. In case of wind energy projects there are no fuel costs to consider, which would normally represent an important parameter in economic evaluations of conventional power plants. The used discount rate for the study is exemplary derived from the theory of Weighted Average Cost of Capital (WACC). Under consideration of the current financial market the WACC discount rate depends from the amount of equity capital in the certain project, the calculative return of equity capital and the amount of bonded capital (Berk, J., 2011).

One applicable formula to calculate the LCOE with this international known approach is the following:

$$\frac{I_0 + \sum_{t=1}^n \frac{C_t}{(1+i)^t}}{\sum_{t=1}^n \frac{Y_{el}}{(1+i)^t}}$$
(1)

The goal of this approach is to enable the comparison of the energy production costs from different conventional and renewable sources from a macro-economic perspective. The method of levelized cost of energy is not suited to give evidence to the cost effectiveness of a certain wind turbine project. For those purposes one needs a defined cash flow calculation over the lifetime of the certain project. Furthermore, the resulting prices of the LCOE approach also can not be compared to current energy prices in the energy stock market – e.g. at the European Energy Exchange (EEX) in Leipzig, Germany. The stock prices are dependent on weather and grid conditions and mainly influenced by the global market conditions in short term. Those effects cannot be represented with LCOE prices.

Figure 9 compares the different energy converting technologies which are currently available in the energy system.

Considering specific investment costs between 1000 and $1800 \notin / kW$ in the onshore area the levelized cost of energy of onshore wind turbines range between 45 and 107 \notin / kW

MWh. At good wind locations onshore wind turbines are already able to produce power cheaper than conventional new coal and gas power plants. If this positive development continues, in future onshore wind turbines might be possibly cheaper than average brown coal capacities in the energy system. Offshore wind turbine technology costs currently between 119 and 194 € / MWh providing specific investment costs ranging from 3400 € / kW to 4500 € / kW Fraunhofer ISE, (2013). Here, LCOE of offshore technologies are approximately double the LCOE of onshore wind technologies. The expensive installation process especially, and the high O&M costs contribute to that setting. But in general the LCOE of renewable energy sources decrease in preparation of the future renewable energy system, while the LCOE of conventional power plants will continue to rise.

Figure 10 describes on top level how the LCOE of a wind turbine project come together on an annual basis. The left side represents the cost side subdivided in the annual capital cost as well as the annual operation and maintenance cost. The right side represents the denominator side.



Figure 9: Comparison of renewable energy LCOE (Fraunhofer ISE, 2013).



The annual energy yield is dependent on the specific turbine characteristics as well as the location characteristics. Derived from technical and mathematical relationships in order to optimize and reduce the levelized cost of energy of wind turbine technologies, three main strategies connected with PHM systems can be clarified:

- 1) Lower O&M costs.
- 2) Increase power output.
- 3) Increase the lifetime of wind turbines.

Consequently PHM systems for the wind industry in future will have to focus holistically in those three dimensions according to Figure 11.

To analyze the economic impact of optimizing those three parameters it is worthwhile to conduct a generic sensitivity analysis.

As general setup of the sensitivity analysis the study focuses on a typical onshore wind turbine class ranging from 2 to 3 MW. The overall operating costs in the years one to ten are fixed to $25.1 \notin /$ MWh on average according to Deutsche WindGuard GmbH, (2013b) in the study presented here. In the years eleven to twenty the operating costs are fixed to on average 26.3 $\notin /$ MWh for the analyzing calculation conducted here. Furthermore the discount rate is defined by 3.8 % after the WACC-approach over the whole sensitivity analysis.



Figure 11: Focusing dimensions of PHM for wind turbines.



Figure 12: Effect on LCOE by enhancing reference yield.

Firstly the study is modifying the annual energy yield which corresponds to the PHM function of helping to increase the annual power output – e.g. through higher availability in the power grid. A typical value of 2,882 MWh/kW/a as 100 % reference value for the ideal onshore wind turbine was set.

As shown in Figure 12, the annual energy yield has a high impact on the LCOE. With every 10 % increase of annual energy yield the technology costs of onshore wind turbines fall about $4.65 \notin /$ MWh on average.

In the next step the variation of the production costs was conducted, corresponding to the PHM function of lowering the O&M expenses.

This time a fixed typical onshore turbine characteristic was set as object of investigation, which is defined in Table 2. With an 80% reference yield of 2,537 MWh/kW/a the 2.45 MW onshore turbine with specific investment costs of 1785 \notin / kW is typical for Southern German wind farm locations Deutsche WindGuard GmbH, (2013b).

In a total of ten steps the annual operation costs were decreased in steps of 5% relating to the initial configuration. Corresponding to the formulas, every 5% economization in the annual operating costs – mainly maintenance costs – reduces the technology costs by about $1.28 \notin$ / MWh. As shown in Figure 13 this variation has a linear decreasing effect on the LCOE. It has to be said that an operating cost reduction of about 50% might be difficult to reach with PHM support – furthermore the operating costs will have fixed cost components which will have to remain – however the trend and influence of this parameter can be derived in that part.

Table 2:	Turbine	param.	for	LCOE	effects	var.	C
1 4010 2.	raronne	param	101	LCCL	erreets	·	\sim

Turbine characteristic						
Power 2,45 MW						
Specific investment costs	1785	€/kW				
Reference yield	2,537	MWh/kW/a				



Figure 13: Effect on LCOE by reducing the operating costs.

Last but not least the lifetime of the wind turbine project was varied addressing the PHM function of optimal lifetime management. The lifetime enhancement was modelled in ten steps increasing 5 years with every step - starting with the default lifetime of 20 years. Due to the fact that the operating costs of older wind plants will rise, the calculation used a linear increase of operation costs of $1.2 \notin$ / MWh per decade extra lifetime as shown in Table 3.

As shown in Figure 14 on average every five years lifetime enhancement reduces the LCOE of onshore wind energy by about 1.53 € / MWh. It well could be that in reality the operating costs do not increase in a linear manner with every decade. Assuming proper use of the installed PHM system might lead to a lower increase of operating costs of older wind turbines. The vision of lifetimes of 50 years and beyond has so far not been technically proved in the wind energy market, but considering typical civil engineering buildings with a similar number of load cycles - e.g. bridges - from a macro economic standpoint it is worthwhile to work on that vision enabled to PHM systems. This vision is especially challenging for PHM engineers because from a technical point of view wind turbines can be defined as aero generation systems including many mechanical and electro technical elements with different fault modes to be detected and managed via PHM systems. Certainly the human safety level must not be influenced in a negative way considering enhanced lifetimes of wind turbines.

\mathbf{T}	Table 3:	Increase	of c	perating	costs	over	lifetime
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Lifetime	C _t - Operating costs €/MWh
Year 1 10	25,1
Year 11 20	26,3
Year 21 30	27,5
Year 31 40	28,7
Year 41 50	29,9
Year 51 60	31,1
Year 61 70	32,3



Figure 14: Effect on LCOE by enhancing the lifetime.

Finally Figure 15 displays all three investigated PHM functions at wind turbines and their optimizing effect on the wind energy production costs in the energy system. Theoretically the effects of the functions in the LCOE parameter study here were separated, but in reality the effects will have to be combined – e.g. enhancing the turbine's lifetime in reducing operation loads can certainly also lead to reduced maintenance and repair costs because e.g. the main shaft bearings see lower load amplitudes – which would lead to further LCOE cost optimizations enabled to those generated synergies of PHM functions.



Figure 15: Summary of LCOE optimizing effects of PHM functions at wind turbines.

6. CONCLUSION

The last paragraph is dedicated to a short summary of the main findings of the contributed work here as well as a quick forecast for future research activities.

As pointed out in chapter 2 the global wind industry is already an important business branch in Europe, especially in Germany, France and UK. Under the provision of supporting policies its positive development will continue in the coming decades.

Furthermore, mainly due to the aging overall wind park and limited locations in Europe in the future there will be a business migration in the wind industry from new installations to O&M services. The O&M market for wind turbines is not yet settled and offers various opportunities for market entries of new players. The Independent Service Providers especially, currently use this situation and cause dynamic market development. As for onshore wind turbines, they currently occupy the lion's share in the O&M area.

As we saw in the cost structure of a wind turbine project in chapter 4, the supporting structure, beside the rotor blades and the powertrain is a core element. The operating costs of a turbine are dominated by the O&M expenses, increase with the turbine's lifetime and represent a center leverage point to optimize wind turbine systems with PHM.

Chapter 5 presented the concept of Levelized Cost of Energy as a method to evaluate cost effectiveness from a macro economic standpoint and to compare wind energy with other energy conversion technologies. It was derived that PHM systems should be developed in three dimensions for the use of economizations of wind turbines, they are: Lower the O&M expenses, increase power output and increase the lifetime of wind turbines.

A conducted parameter study analyzed the three PHM functions and their effects on the macro-economic production cost of wind energy separately. Increasing the energy yield as well as enhancing the lifetime of wind turbine projects had crucial effects on the cost effectiveness. However in reality those effects should be combined in a suitable way in a PHM system for wind turbines to leverage reasonable and connected synergies.

Future research activities should continue considering wind energy as a main pillar in our energy system and therefore develop technologies enabling cost effective energy production from renewable energy sources. PHM systems are a core tool to reach that goal in case of wind turbines. Knowledge already acquired from PHM systems in the automotive, aviation and space area will have to be merged for the application for wind turbines.

NOMENCLATURE

- *I*₀ total investment costs
- C_t operating costs at time t
- *Y_{el}* annual energy yield
- i discount rate
- *n* year in operating life

REFERENCES

- Berk, J. (2011). *Corporate finance*. Pearson. Boston Mass. / London.
- BWE, (2012). *Two-thirds of all operators use full-service contracts*. Wind Energy Market 2012. Bundesverband WindEnergie e.V., Berlin, Germany.
- Deloitte / TaylorWessing, (2012). European Wind Service Study. Know how the land lies. Deloitte / TaylorWessing. Berlin/Hamburg, Germany.
- Deutsche WindGuard GmbH, (2013a). *Status des Windenergieausbaus an Land in Deutschland*. Deutsche WindGuard GmbH. Varel, Germany.
- Deutsche WindGuard GmbH, (2013b). Kostensituation der Windenergie an Land in Deutschland. Deutsche WindGuard GmbH. Varel, Germany.
- Durham University, (2011). Reliability focused research on optimizing Wind Energy systems design, operation and maintenance: tools, proof of concepts, guidelines & methodologies for a new generation. Durham University. Durham, UK.
- EWEA, (2013). *Wind in Power. 2012 European Statistics.* European Wind Energy Association. Brussels, Belgium.
- Fraunhofer ISE, (2013). *Stromgestehungskosten Erneuerbare Energien*. Fraunhofer Institut für Solare Energiesysteme. Freiburg, Germany.
- Fraunhofer IWES, (2013). *Windenergie Report Deutschland* 2012. Fraunhofer Institut für Windenergie und Energiesystemtechnik. Kassel, Germany.
- GWEC, (2012). *Global Wind Energy Outlook 2012*. Global Wind Energy Council. Brussels, Belgium.
- IRENA, (2012). Renewable Energy Technologies: Cost Analysis Series. Wind Power. International Renewable Energy Agency. Abu Dhabi, United Arab Emirates.
- Oliver Wymann, (2011). *Wind 2020+: Boom-market O&M. The underestimated profit machine*. Olyver Wymann. München, Germany.

Sandborn, P. (2009). PHM Return on Investment (ROI). Use of PHM in Maintenance Planing. University of Maryland. MD, USA.

BIOGRAPHIES



Christian T. Geiss (M.Sc.) born in Karlsruhe, on the 23th February 1988 studied from 2007 until 2010 Industrial Engineering at the Baden-Württemberg Cooperative State University and graduated with a Bachelor of Engineering Degree. After working experiences at the third biggest utility company in Germany – EnBW Energie Baden-Württemberg AG –

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Fault Diagnostics of Planet Gears in Wind Turbine Using Autocorrelation-based Time Synchronous Averaging (ATSA)

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ABSTRACT

A planetary gearbox is widely used in various rotating systems because it can be used as a speed reducer or increaser without change in direction of shaft while transferring great driving power. Despite many attempts it is still challenging to diagnose potential faults of the planetary gearbox because of multiple contacts and axis rotation of planet gears resulting in complex vibration characteristics. This paper thus presents an original method to isolate vibration signals induced by the planet gears from the complex vibration signals for fault diagnostics of the planetary gearbox. First, an in-depth study on the vibration characteristics of planet gears is presented using the autocorrelation function of the vibration signal. The autocorrelation-based time synchronous averaging (ATSA) method is then developed for the isolation of the vibration signals produced by the planet gears. The vibration signals were utilized for extracting health related data which facilitate the efficient fault diagnostics of the planet gears. Case study with a wind turbine testbed showed that the proposed method can diagnose the root crack of the planet gears.

1. INTRODUCTION

A planetary gearbox is widely used in wind turbines (WTs) because it transfers great driving power without change in direction of shaft. However, it is at high risk because downtime of the most planetary gearboxes are severely long. For example, NoordzeeWind (2008) reported that planetary gearbox has the most critical downtime loss in wind turbines. This necessitates diagnostics of gearbox to prevent catastrophic failure with significant economic loss. Despite many attempts, however, it is still challenging to diagnose

potential faults of the planetary gearbox because of multiple contacts and axis rotation of planet gears resulting in complex vibration characteristics.

For robust diagnostics of the gearbox, vibration produced by the planet gears in the gearbox should be isolated from the complex vibration signal. Widely used vibration isolation tool is time synchronous averaging (TSA). Principle of TSA is to divide the vibration signal into multiple segments whose length correspond to one rotation of the gear and conduct ensemble averaging for them. This requires very simple processing, however, TSA for planet gear requires more advanced approach because 1) the sensory signal is mixed up by multiple contacts in the planetary gearbox, and 2) rotating inner components change relative distance of the planet gears from a sensor because the vibration sensor is fixed on the top of the gearbox housing.

To overcome the presented challenges, McFadden and Howard (1990) proposed to extract the signal only when the planet gear of interest passes the vibration sensor with the help of narrow-ranged Square window function. Likewise, most advanced TSA involves extraction of vibration when the planet gears of interest is adjacent to the vibration sensor. Various kinds of window functions were developed for advanced TSA. McFadden (1994) compared various kinds of window functions, and advanced the previous TSA (McFadden et al., 1990) by adopting narrow-ranged Hann window function. Samuel, Conroy and Pines (2004) adopted using narrow-ranged Tukey window which has flat top in shape pointing out that extracted signal with Hann window (McFadden, 1994) cannot represent the vibration signal of interest well because the Hann window does not have flat top which lead to distortion of the target signal. Although TSA with optimized size and shape of the window function can properly isolate the signal of interest for effective diagnostics, it cannot be used for planetary gearbox in WTs because stationary signal, which is necessary for TSA, is rarely

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acquired in WTs. For example, a recent study which successfully performed diagnostics of planetary gearbox using a TSA with narrow-ranged Hann window used about 700 carrier cycles of data which corresponds to 40 minutes of typical WTs' operation (Lewicki, Ehinger & Fetty, 2011). Because 40 minutes of stationary operation cannot occur in WTs, TSA with more wide-ranged window function is needed. Although wide-range window function was designed to prevent any loss of data by Forrester (2001), Samuel, Conroy and Pines (2004) pointed out that such excessive wide-ranged window can distort the natural vibration characteristics of the planet gears.

This paper proposes more advanced TSA for isolation of vibration produced by planet gears. Different from the previous studies, range of newly designed window function is in between range of narrow-range window function and that of wide-range window function. This paper suggests a guideline for determining range of window function of TSA with autocorrelation function. Developed TSA, thus, is referred to as autocorrelation-based TSA (ATSA). For demonstration of proposed ATSA, a testbed for planetary gearbox was designed. This testbed typically simulates a large scale of wind turbine with combination of two planetary gearboxes which have 20:1 and 4.08:1 of gear ratio respectively. A faulted planet gear was assembled to a gearbox with 4.08:1 of ratio to depict abnormal condition of the gearbox. Two kinds of health data were obtained from the results of ATSA, and they successfully classified condition of the normal and abnormal gearboxes.

This paper consists of three parts. First, vibration isolation methods for a spur gear and planet gear are briefly reviewed. Second, autocorrelation-based time synchronous averaging (ATSA) is proposed. Finally, proposed ATSA is validated in demonstration section.

2. REVIEW OF VIBRATION ISOLATION METHOD

Vibration isolation methods help to investigate nature characteristics of vibration produced by the gear of interest which is originally buried by the other kinds of vibration sources. Most widely used technique is time synchronous averaging (TSA). In this section, basic TSA which can be used for spur gears is introduced. And then, advanced TSA for planet gears will be presented based on the previous studies.

2.1. Time Synchronous Averaging for Spur Gears

Every measured signal has multiple coherent and noncoherent components from various sources. D. Hochmann and Sadok (2004) attempted to describe the synthesized sensory signal from the sensor with three main components: synchronous coherent signals (S(t)), non-synchronous coherent signals (N(t)), and non-coherent random signals (R(t)).



Figure 1. Procedures of time synchronous averaging

$$v(t) = S(t) + N(t) + R(t)$$
(1)

Time synchronous averaging (TSA) was developed to suppress the non-synchronous coherent signal and the noncoherent random signal, and to estimate approximated synchronous coherent signal $(\overline{S(t)})$. Basic TSA is composed of three main steps as shown in Figure 1. The first step is to resample the vibration signal to have same number of samples per rotation of the gear, where f_{rs} in Figure 1 denotes the number of samples per rotation of the target gear (Blough, 2006). Linear interpolation method enables the resampling of signal by assigning constant number of samples per rotation of the target gear with the help of encoder (Decker & Zakrajsek, 1999). In second step, the vibration signal is divided into multiple segmented sets. Data length of every sets corresponds to one rotation of the gear. Third step is to perform ensemble averaging of the segmented sets. Because non-synchronous coherent signals (N(t)), and non-coherent random signals (R(t)) would have Gaussian noise characteristics, they converges to zero as the number of averaging increases. Whereas, synchronous coherent signals (S(t)) remains its origin because each segmented sets correspond to one rotation of the gear which generate almost identical signal in respect to phase and magnitude. TSA resulting in the estimation of the synchronous coherent signal $(\overline{S(\theta)})$ can be defined as (Barszca & Randall, 2009):

$$\overline{S(\theta)} = \frac{1}{N} \sum_{i=0}^{N-1} v(\theta + i \cdot f_{rs})$$
(1)

2.2. Time Synchronous Averaging for Planet Gears

Planetary gearbox is composed of sun gear, ring gear, carrier and planet gears as shown in Figure 2. In WTs, ring gear is fixed on the gearbox housing to make planet gears rotate around the sun gear with the help of rotating carrier. In this case, carrier is connected to the low speed shaft with high level of torque, and sun gear is connected to the high speed shaft with low level of torque. Because vibration sensors are fixed on the surface of the gearbox housing, relative distance of the planet gears to the sensor varies. Therefore, planet gear which dominantly produce signals to the sensor shifts. When the whole acquired signal is considered at a time, thus,



(a) (b) Figure 2. (a): Planetary gearbox, (b): Inner side of the gearbox

it is impossible to focus on diagnostics of a specific planet gear which lead to inaccuracy in diagnostics result. Therefore, TSA for planet gears involves the use of the window function for the purpose of extraction of vibration signal of interest. Various types of window function can serve as an extraction tool for TSA of the planet gears. Among them, Hann window (McFadden, 1994, Lewicki, Ehinger & Fetty, 2011, Hood & Darryll, 2011), Tukey window (Samuel et al., 2004, Smidt, 2009) and Cosine window (Forrester, 2001, Yu, 2011) were most widely used. Figure 3 illustrates the mentioned window functions. As can be seen through the figure, Hann and Tukey window covers just a few teeth of the gear whereas Cosine window covers entire range. After defining the window function, TSA can be conducted. Procedures of advanced TSA for the planet gears are illustrated in Figure 4. First, window function extracts the vibration made by the planet gear of interest. The principle of the first step is that window function gives weight to the signal only when the planet gear of interest passes the vibration sensor. Second, mapping of the extracted vibration signal is required because of the teeth sequence which is the natural characteristics of the planetary gearboxes. Teeth sequence of the planet gear, $P_{n,p}(n_c)$, is defined as a function of carrier rotation, which can be defined as (Samuel et al., 2004):

$$P_{n_{c}}(n_{c}) = \text{mod}(n_{c}N_{r}, N_{p}) + 1$$
(2)



Figure 3. Various types of window function



Figure 4. Procedures of TSA for planet gear

Where n_c is the number of carrier rotation starting from location of the sensor, N_r and N_p is the number of teeth on the ring gear and planet gear respectively. Function of mod(a, b) calculates the remainder of a/b. Thus equation (2) derives teeth number of the planet gear which made the extracted vibration signal. With this information, the extracted vibration signal is transformed to the teeth domain as shown in Figure 4; Mapping to the teeth domain. In the final step, every transformed signals are aligned and averaged to make TSA signal.

3. AUTOCORRELATION-BASED TIME SYNCHRONOUS AVERAGING

In this section, autocorrelation function of sensory signal from the vibration sensor is introduced. It helps to understand vibration characteristics, and gives a guideline for defining efficient range of window function. For explanation of the proposed methods, a planetary gearbox with sun gear (31 teeth), ring gear (95 teeth), carrier and three planet gears (31teeth) was used as an example case.

3.1. In-depth Study on Vibration Characteristics Using Autocorrelation Function

Autocorrelation function can be used to characterize vibration characteristics of the planetary gearbox. Before presenting detailed representation of the autocorrelation function, understanding intuitive operating characteristics of the planetary gearboxes would be helpful. Figure 5 illustrates what happens in the gearbox as the gearbox operates. Suppose that the gear of interest (G_1) was located under the vibration sensor at the initial state where a diamond mark indicates meshing point (Figure 5 (a)). As carrier rotates counterclockwise, position of the planet gears also revolute counterclockwise as well. Since then, the planet gear of interest will recede from the sensor whereas another planet gear will approach the sensor. At one rotation of the planet gear $(n_{pr} = 1)$, vibration of G₃ will dominate the sensor signal instead of the gear of interest because it will be almost under the sensor (Figure 5 (b)). Figure 5 (c) reveals that the planet gear of interest will be adjacent to the sensor by distance of two teeth to dominate the sensory signal again at



Figure 5. Autocorrelation function of vibration signal

three rotation of the planet gear ($n_{pr} = 3$). At 95 rotation of the planet gear ($n_{pr} = 95$), every planet gears and meshing teeth will reset to the initial state as shown in Figure 5 (d). The minimum number of rotations for reset to the initial state is called as hunting tooth ratio (HTR) (Samuel, Conroy & Pines, 2004). Intuitively, it can be expected that vibration signal gathered from Figure 5 (a), Figure 5 (c) and Figure 5 (d) would have similarity in phase and magnitude because the meshing conditions are similar. Whereas, signal from Figure 5 (b) would have different vibration pattern without similarity and it can result in improper TSA. This kind of signals are the most challenging issue in using wide-range window function.

The task is to extend range of the window function for TSA while preventing similarity loss. Autocorrelation function can quantitatively characterize this phenomenon to define useful range for the window function. The definition of the sample autocorrelation function (R_{vv}) is mean of the signal (v(t)) multiplied by itself with time lag τ $(v(t + \tau))$, defined as (Bendat & Piersol, 2010):

$$R_{vv}(\tau) = E[v(t)v(t+\tau)]$$
(3)

This function gets high value when phase of the lagged signal $(v(t + \tau))$ has similarity to that of the original signal (v(t)). Autocorrelation function, thus, can be used as an identifier of similarity of the lagged signal. Figure 6 shows an example of autocorrelation function of vibration from a vibration sensor along with rotation of a specific planet gear. In the figure, f_{rs} denotes the number of samples per one rotation of the planet gear, and n_{pr} is the number of rotation of the planet gear relative to the ring gear. As can be seen, the autocorrelation function has multiple peaks at some integer rotation of the planet gear. First peak of autocorrelation function is found at three rotation of planet gear $(n_{pr} = 3)$ which corresponds to Figure 5 (c). At one 95 rotation of the planet gear ($n_{pr} = 95$) which is relevant to Figure 5 (d), the autocorrelation function reveals higher value meaning that much similarity is assured. Based on these findings, it can be said that the similarity of the vibration signal can be assured



Figure 6. Autocorrelation function of vibration signal

when the planet gear of interest is near the vibration sensor, and it gives a guideline for defining range of the window function for TSA.

3.2. ATSA with Autocorrelation-based Window Function

Autocorrelation-based TSA (ATSA) is proposed in this section to take the signals into averaging based on similarity of the vibration. To identify position of the planet gear where the high level of similarity is guaranteed, teeth number of the ring gear is traced when high value of autocorrelation function is measured. For this purpose, teeth sequence of the ring gear should be formulated as a function of rotation of the planet gear as (Samuel, Conroy & Pines, 2004):

$$P_{n,r}(n_{pr}) = \text{mod}(n_{pr}N_{p}, N_{r}) + 1$$
(4)

Where $P_{n,r}(n_{pr})$ is teeth sequence of the ring gear, n_{pr} is the number of rotations of the planet gear which corresponds to

Table 1. Teeth sequence of ring gear corresponding to rotation of planet gear when autocorrelation function is high

n _{pr}	$P_{n,r}$	n_{pr}	$P_{n,r}$	n_{pr}	$P_{n,r}$
0	1	80	11	64	85
46	2	31	12	15	86
92	3	77	13	61	87
43	4	28	14	12	88
89	5	74	15	58	89
40	6	25	16	9	90
86	7	70	81	55	91
37	8	21	82	6	92
83	9	67	83	52	93
34	10	18	84	3	94
				49	95


Figure 7. ATSA with optimized range of window function

x-axis in Figure 6, and N_p and N_r denote the number of teeth on the planet gear and ring gear respectively. At the initial position, teeth sequence is 1 because the planet gear of interest is in mesh with teeth number one of the ring gear under the vibration sensor. Table 1 summarizes teeth sequence of the ring gear when the autocorrelation function has high values. It can be noticed that all of the calculated teeth numbers of the ring gear are around teeth number one of the ring gear ($P_{n,r}=1$) on which vibration sensor is located. Based on this findings, meaningful boundary of the ring gear can be defined as between teeth number 16 and 81 which are highlighted in Table 1. Defined range can provide a guideline for determining range of the window function in TSA.

Tukey window function whose range was optimized based on autocorrelation function is illustrated in Figure 7. Vibration sensor was expressed as circle mark, and boundaries of the defined range was marked as diamonds. Defined window function covers wider range compared to the narrow-ranged window functions but has narrower range compared to the wide-range window function in Figure 3. Defined window function can serve as an extraction tool in TSA procedures which was introduced in Section 2.2. The remaining steps for advanced TSA, which was illustrated in Figure 1, can be conducted to make ATSA signal.

4. DEMONSTRATION

Testbed was designed to simulate large-scale wind turbine consisting of three stage of planetary gear sets. A planetary gearbox with 4.08:1 of gear ratio which corresponds to third stage of the large-scale gearbox is of interest in this study. Before validate the proposed ATSA using test signal, analytic signal was additionally designed to simulate a vibration signal from a planetary gearbox with 4.08:1 of gear ratio. This is for the purpose of verification of the ATSA. For comparison study, recently developed TSA method by employing a Tukey window with 5 teeth range was used (Samuel, Conroy & Pines (2004)).

4.1. Extraction of Health Data

For evaluating performance of the proposed ATSA, some of additional signal processing procedures are required to extract health related data referred to as health data. First, residual signal (RES) can be calculated by removing fundamental gear mesh frequency (GMF) and their harmonics from ATSA signal. RES contains pure sidebands of the GMF and their harmonics. Various health data from RES is very meaningful because a lot of researches about diagnostics of gearboxes have focused on monitoring of the amplitude of sidebands (Samuel & Pines, 2005). As the faults within a gearbox worsen, the magnitude of unexpected frequency out of sidebands can grow. Second, difference signal (DIF) is obtained from RES by excluding sidebands of fundamental GMF and their harmonics as well. If we note that RES is obtained by excluding fundamental GMF and their harmonics, it is clear that DIF ideally should not contain any normal vibration components and should have normal Gaussian distribution when it is in normal condition. As the faults within a gearbox worsen, the magnitude of unexpected frequencies which are from out of sidebands can grow Therefore, diagnostics of a gearbox can be performed by tracking the shape and energy of DIF.

Health data used in this paper are 1) forth moment of residual signal (*M4*) (Zakarjsek, Townsend & Decker, 1993), 2) energy ratio (*ER*) (Samuel & Pines, 2005) which are defined as:

$$M4 = \frac{1}{N} \sum_{i=1}^{N} \left(RES_i - \mu_{RES} \right)^4$$
(8)

$$ER = \frac{RMS(DIF)}{RMS(y_{mesh})}$$
(10)

Where N is the number of samples in a data set, RES_i and DIF_i are i^{th} sample of RES and DIF signal respectively, μ_{RES} is a mean value of RES and y_{mesh} is amplitude of regular meshing components including fundamental meshing frequency and their harmonics. RMS calculates root mean square. As a fault in a gearbox occurs, variance of the sideband can grow which leads to increase in M4 (Zakarjsek, Townsend & Decker, 1993). Moreover, failure of the gearbox can increase the ER which represents magnitude of the unexpected component in vibration signal (DIF) compared to the normal vibration signal (y_{mesh}) (Samuel & Pines, 2005).

4.2. Analytic Signal

An analytical signal was designed for verification of the proposed algorithm. Vibration produced by each planet gear was assumed to be a pure cosine wave, and defined as:

$$v_{pi}(t) = \cos(2\pi f_{rs} N_p t) \tag{5}$$



Figure 8. Design of analytic signal (a) abnormality of teeth number 14 on the first planet gear, (b) Transfer path of the first planet gear

where v_{pi} is vibration signal produced by i^{th} planet gear, f_{rs} is the number of samples per one rotation of the planet gear, and N_p denotes the number tooth of the planet gear which is 31 in this study. It was also assumed that an abnormality can be described as having a higher amplitude than a normal one when the faulty gear tooth meshes with other gears. In this study, abnormality was added to the tooth number 14 of planet 1 (v_{p1}) as shown in Figure 8 (a). There are three planet gears, and all the gears produce the same vibration at each position except for the faulted gear tooth. However, each planet gear has different transfer path. Transfer path of i^{th} planet gear can be defined as:

$$a_{ni} = (1 + \cos(2\pi (f_c t - (i-1)/3)))/2$$
(6)

Where f_c is rotating frequency of the carrier, and *i* is ranging from one to three which is the number of planet gears. Figure 8 (b) shows how the transfer path changes. The *i*th transfer path makes the sensory signal produced by the *i*th planet gear highest when it passes the vibration sensor. Whereas, the magnitude of *i*th transfer path decreases as the *i*th planet gear recedes from the sensor. Moreover, Gaussian noise was added to the signal to consider reality. After all factors are combined, analytic signal can be defined as:

$$v_{analytic} = \frac{1}{3} \sum_{i=1}^{3} \left(v_p a_{pi} + noise_i \right)$$
(7)

Figure 9 and Figure 10 compares the residual signals (RES) came from TSA signal and ATSA signal using 1200 seconds of data and 60 seconds of data respectively. RES were calculated by excluding gear mesh frequencies from the TSA or ATSA. As can be seen from Figure 9, both RESs calculated from TSA and ATSA graphically distinct abnormality of the signal in the teeth domain. When the size of the data decreases, however, abnormality of the planet gear is invisible when the narrow-ranged window function was employed for TSA as shown in Figure 10 (a). In contrary, RES from ATSA reveals abnormality of the gear in teeth domain even if small amount of data was used for signal



(a)
 (b)
 Figure 9. Residual signal using 1200 sec of data (a): TSA with 5 teeth range Tukey window, (b): ATSA with optimized range of Tukey window



Figure 10. Residual signal using 60 sec of data (a): TSA with 5 teeth range Tukey window, (b): ATSA with optimized range of Tukey window

processing as shown in Figure 10 (b). This is because the ATSA employed wider range of extraction window function which lead to efficient use of the vibration data without loss while preventing data distortion.

4.3. Testbed Signal

Absence of normal and abnormal response data from WTs makes it difficult to achieve the objective of this research. Thus, a small-scale wind turbine testbed which has similarity to a 2.5MW WTs was designed for the research outlined in this paper. Gearbox 1, which has 3 stages of planetary gear set can be substituted with combination of gearboxes 2 and 3 which have simpler dynamics characteristics than gearbox 1. Gearbox 3 which has one stage of planetary gear set is of target system in this paper. The main considerations for designing the testbed were as follows. First, the composition is almost identical to that of gearbox in WTs so that the testbed has similarity to the WTs. Moreover the testbed can operate with a closed-loop controller which enables implementation of rotor speed and scaled torque measured from a WT to the testbed. And this testbed was designed to facilitate simple assembly of the gear units with defect into the gearbox. In this case, 1.17mm of crack with 0.05mm of width was machined with wire-cut electro discharge machining as shown in Figure 12 (Jung, Yun, Lee & Fu, 2012), and assembled to the gearbox 3. The gearbox rotated in 1600 rpm at sun gear with 4Nm of torque.



Figure 11. Wind turbine testbed (2kW)



Figure 12. Fault seeding to gearbox

In the testbed, it was difficult to see abnormality in the teeth domain using the residual signal (RES) unlike the case study with the analytic signal. Thus, some of health data, *M4* and *ER*, derived from residual signal (RES) and difference signal (DIF) were used to present the advantage of ATSA.

Figure 13 and Figure 14 show comparison between health data from conventional TSA and ATSA signals. Health data from normal and abnormal gearbox are expressed with circle and cross marks respectively. The results have a common trend that health data from the abnormal system is larger than the health data from the normal system. However, there is no monotonic increase of health data by failure of the system. But combination of the health data enable effective diagnostics of the system. When 60 seconds of operating data were used, health data from normal and abnormal condition have distinct difference in the both TSA and ATSA cases. However, it can be noticed that health data with ATSA have more distinction line than the health data with TSA when the size of data decreases as shown in Figure 14.

5. CONCLUSION

Autocorrelation function was used for in-depth study on characteristics of vibration signal. As a results, it was found that sensory signal from the sensor which is fixed on gearbox housing is dominated by planet gear near the sensor. Autocorrelation function provided significant range in which vibration by the planet gear of interest can be effectively captured with the sensor. Thus, provided significant range



Figure 13. Health data using 60sec of data (a): TSA with 5 teeth range Tukey window, (b): ATSA with optimized range of Tukey window



Figure 14. Health data using 20 sec of data (a): TSA with 5 teeth range Tukey window, (b): ATSA with optimized range of Tukey window

suggested a guideline for defining range of window function for the TSA. TSA with optimized range of window function, referred to as ATSA, was developed to perform an ensemble average of data based on similarity of vibration pattern. The validation study was made by using analytical signal and testbed signals. Among various available health data, forth moment of residual signal (M4), and energy ratio (ER) were employed for the validation study. To produce sample signals for the validation study, the testbed was operated in 1600 rpm at sun gear which corresponds to about 400 rpm at carrier. The test generated 400 carrier cycles for 60 seconds and 144 carrier cycles for 20 seconds. When first stage of the gearbox in WTs is of target for the diagnostics, 25 minutes of rated operation will be required for 400 carrier cycles, which is impractical in real field. The result shown than ATSA had better performance when the size of data was not sufficient for conventional TSA. When ATSA is used, size of data can be reduced to one third for the TSA although some error can be made. This kind of error would be reduced when multiple health data are used for diagnostics.

In the future work, multiple health data should be considered for diagnostics of the gearbox. Furthermore, classification method can be employed to quantitatively evaluate performance of the ATSA compared to the TSA. To effectively verify advantage of the proposed method, quantitative measure for performance of ATSA can be formulated as a function of size of data to define minimum operating duration of WTs necessary for the proposed method.

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References

- Barszcz, T. & Randall, R.B., (2009). Application of spectral kurtosis for detection of a tooth crack in the planetary gear of a wind turbine. *Mechanical Systems and Signal Processing*, 23(4), pp.1352–1365.
- Bendat, J.S. & Piersol, A.G., (2010). *Random Data: Analysis and Measurement Procedures, 4th edition*, Hoboken, NJ: John Wiley & Sons, Inc
- Blough, J.R., (2006). Adaptive Resampling Transforming From the Time to the Angle Domain. 2006 IMAC-XXIV: Conference & Exposition on Structural Dynamics.
- Decker, H.J. & Zakrajsek, J.J., (1999). Comparison of Interpolation Methods as Applied to Time Synchronous Averaging, Cleveland, Ohio: NASA/TM—1999-209086, NASA Glenn Research Center.
- Forrester, B.D., (2001). Method for the separation of epicyclic planet gear vibration signatures. US Patent, US 6,298,725 B1.
- Hochmam, D. & Sadok, M., (2004). Theory of Synchronous Averaging. *IEEE Aerospace Conference Proceedings*. IEEE, pp. 3636–3653.
- Hood, A. & Darryll, P., (2011). Sun Gear Fault Detection on an OH-58C Helicopter Transmission. *American Helicopter Society 67th Annual Forum*. American Helicopter Society, pp. 1664–1690.
- Jung, Y.H. et al., (2012). Mechanical Fault Imbedding Process for Major Mechanical Parts of Offshore Wind Turbine. Proceedings of the Korean Society of Mechanical Engineers 2012 Spring Annual Meeting. pp. 159–160.
- Lewicki, D.G., Ehinger, R.T. & Fetty, J., (2011). Planetary Gearbox Fault Detection Using Vibration Separation Techniques, Cleveland, Ohio: NASA/TM—2011-217127, NASA Glenn Research Center.
- Martin, H.R., (1989). Statistical Moment Analysis as a Means of Surface Damage Detection. *Proceedings of the 7th International Modal Analysis Conference*.
- McFadden, P.D., (1994). Window Functions for the Calculation of the Time Domain Averages of the Vibration of the Individual Planet Gears and Sun Gear in an Epicyclic Gearbox. *Journal of Vibration and Acoustics*, 116(2), pp.179–187.
- McFadden, P.D. & Howard, I.M., (1990). The detection of Seeded Faults in an Epicyclic Gearbox by Signal Averaging of the Vibration, Australia: AR-006-087 / ARL-PROP-R-183, Commonwealth of Australia.

- Samuel, P.D., Conroy, J.K. & Pines, D.J., (2004). *Planetary Transmission Diagnostics*, Cleveland, Ohio: NASA/CR-2004-213068, NASA Glenn Research Center.
- Samuel, P.D. & Pines, D.J., (2005). A review of vibrationbased techniques for helicopter transmission diagnostics. *Journal of Sound and Vibration*, 282(1-2), pp.475–508.
- Yu, J., (2011). Early Fault Detection for Gear Shaft and Planetary Gear Based on Wavelet and Hidden Markov Modeling. Degree of Doctor of Philosophy, University of Toronto.
- Zakarjsek, J.J., Townsend, D.P. & Decker, H.J., (1993). An Analysis of Gear Fault Detection Methods as Applied to Pitting, Cleveland, Ohio: NASA TM-105950 / AVSCOM 92-C-035, NASA Lewis Research Center.

A Similarity-based Prognostics Approach for Remaining Useful Life Prediction

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ABSTRACT

Physics-based and data-driven models are the two major prognostic approaches in the literature with their own advantages and disadvantages. This paper presents a similarity-based data-driven prognostic methodology and efficiency analysis study on remaining useful life estimation results. A similarity-based prognostic model is modified to employ the most similar training samples for RUL estimations on each time instance. The presented model is tested on; Virkler's fatigue crack growth dataset, a drilling process degradation dataset, and a sliding chair degradation of a turnout system dataset. Prediction performances are compared utilizing an evaluation metric. Efficiency analysis of optimization results show that the modified similaritybased model performs better than the original definition.

1. INTRODUCTION

Prognostics is an essential part of condition-based maintenance, described as forecasting the remaining useful life of a system. There are two major prognostics approaches in the literature 1. Physics-based 2. Data-driven models. They both have their own advantages and disadvantages. Data-driven models employ routinely collected condition monitoring data and/or historical event data instead of building a mathematical model based on system physics or human expertise. They attempt to track the degradation of an asset using forecasting or projection techniques (e.g. regression, exponential smoothing, and neural networks), also rely on the past patterns of deterioration to forecast the future degradation. Since datadriven prognostics have no elaborate information related to asset or system, it has been considered as a black-box operation (Zhang et al., 2009). A detailed literature review on data-driven prognostics was conducted by Si et al., (2011) . Artificial Neural Networks (ANN) (Gebraeel and Lawley, 2008), Hidden Markov Models (HMM) and derivations (Camci and Chinnam, 2010), regression models (Guclu et al., 2010), Bayesian & Gaussian Processes (Saha et al., 2010) are employed in order to estimate the remaining useful of a component or system. Similarity-based prognostic approaches can also be categorized in data-driven prognostics. Details of the similarity-based prognostic models are discussed in section 2.4.

Physics-Based Models typically involve describing the physics of the equipment and failure mechanism. Mathematical models are usually employed which is directly tied to health degradation. In order to provide knowledge rich prognostics output; physics-based models attempt to combine defect growth formulas, system specific mechanistic knowledge and condition monitoring data. They assume that an accurate mathematical model for component degradation can be constructed from the first principles. Several examples of degradation modelling and physics-based prognostics, specific to the component or system, are found in the literature (Kacprzynski et al., 2002; Byington et al., 2004; Qiu et al., 2002).

This paper presents a data-driven prognostic methodology. Contribution of the paper is to modify a similarity-based prognostic approach which performs better prognostic results compared to its original definition. Comparison and the efficiency of the remaining useful life estimation results are discussed in the paper. The rest of the paper is organized as follows. In section 2, the details of the used datasets and the methodology are given. The prognostic and optimization results are discussed in section 3. Following that are conclusion and future works.

2. METHODOLOGY

This section provides the datasets used in prognostic modelling, the similarity-based prognostic approach methodology, and the modified version of it.

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2.1. Virkler's Fatigue Crack Growth Dataset

In the structural health management (SHM) field, fatigue cracks are defined as one of the primary structural damage mechanisms caused by cyclic loadings. Cracks at the structure surface grow gradually. Therefore prediction of fatigue life or fatigue crack growth in structures is necessary.

The Virkler fatigue crack growth dataset (Virkler et al., 1979) contains 68 run-to-failure specimens. Each specimen used for the experiments is a center cracked aluminum sheet of 2024-T3. Specimens had a notch of 9mm initial crack and the experiments were stopped once the crack lengths reached around 50mm. Each specimen has 164 crack length observation points. Degradation for all specimens is shown in Figure 1.



Figure 1. Crack length propagation samples under the same loading conditions

2.2. Drill-bit Dataset

Drilling processes are considered to be one of the most commonly used machining processes in industry (Lianyu Fu and Ling, 2002). For instance, up to 50% of all machining operations in the U.S. involve drilling (Furness et al., 1999). Drill bit breakage, excessive wear during the drilling process may cause fatal defects in the product. Drilled surface quality may affect the quality of the product. 60% of rejected parts are often granted to poor surface quality (Ertunc et al., 2001). Therefore, it is important to predict the failure of drill bit for obtaining good products.

The failure prediction for drill bits has been reported in (Camci and Chinnam, 2010; Baruah and Chinnam, 2005). Hidden Markov (HMM) based methods have been used for failure prediction in their methods. The dataset was collected by Chinnam et al., (2003).

Figure 2, shows the data acquisition system for drilling process. The dataset was collected from a HAAS VF-1 CNC machine. They used thin drill-bits to accelerate the aging

process. The drill-bit dataset have twelve run-to-failure samples. The failure for each case is the breakage of the thin drill bit during the penetrating into work piece. Thrust-force and torque signals are collected during the actual drilling process. Concatenated thrust and torque signals, collected during the life of a drill bit, are displayed in Figure 3. In this figure, the degradation of a drill bit from brand new state to the failure state can be observed. This dataset will be used for comparison of the modified data-driven prognostic approach.



Figure 2. Experimental setup for data collection during drilling process (Camci, 2005).



Figure 3. Trust-force and torque data from a drill bit

2.3. Turnout Dataset

Turnout systems are remote controlled electro-mechanical systems enabling trains to change their tracks as displayed in Figure 4. They are considered to be one of the most important components of the railway structure. The standard railway turnout system is a complex device with many potential failure modes. The dataset consist of five different sensors showing the degradation profile of ten different run-to-failure turnout mechanisms (Eker et al., 2011). We utilized the force sensor data among the other sensory information provided since they claimed the force sensor is capable of representing degradation process better than the rest of the sensors (Camci et al., 2014). They employed an exponential degradation model to organize the samples

collected from different discrete health states since there was no prior information about railway turnout degradation. They selected 'dry slide chair' as a failure mode for the turnout system. The dataset will be used for prognostic modelling and comparison. The dataset was collected under the project number '108M275(1001)' supported by TUBITAK (The Scientific and Technological Research Council of Turkey) in Turkey. The dataset is open to public and can be downloaded from their research group website (Camci et al., 2010).



Figure 4. Electro-mechanical turnout system

2.4. Similarity-Based Prognostics (SBP)

Zio and Di Maio, (2010) developed a novel similarity-based prognostics methodology for estimating the remaining useful life components of nuclear systems. Estimations of RUL requires evaluating the similarity between the test sample (i.e. 'q') and the training samples (i.e. 'r = 1: R') as shown in Eq. (2). This is done by calculating the point wise Euclidean distances in between ' $n - \log r'$ sequences of observations. Distance score calculation in between training sample and the test sample at the ith time point shown in Eq. (1). Final RUL estimation of a test sample at a time instance (i.e. 'I') is achieved by taking the similarity weighted sum of training samples' remaining useful life values recorded on the same time instances as shown in Eq. (3).

$$d_{i}^{r} = \sqrt{\sum_{j=1}^{n} \left\| z_{l-n+j}^{q} - z_{i-n+j}^{r} \right\|^{2}}$$
(1)

$$s_i^r = e^{-\frac{(d_i^r)^2}{\lambda}}$$
(2)

$$RUL_{I}^{q} = \frac{\sum_{r=1}^{R} s_{i}^{r} rul_{i}^{r}}{\sum_{r=1}^{R} s_{i}^{r}}$$
(3)

' λ ' is the arbitrary parameter can be set to shape the desired interpretation of similarity whereas 'n' defines the number of latest observations involved in similarity calculations. The smaller is the λ , indicates the stronger the definition of similarity.

2.5. Modified SBP

This subsection discusses in detail the modifications made on the similarity-based prognostic model. The modifications have been made in the RUL estimation (i.e. Eq. (3)), in which the most similar K percent number of the training samples are utilized rather than using whole training set. The most similar K percent of training samples varies for every test sample and even it might vary for every time instance in a test sample. The best number K is required to be optimized by checking an error function, evaluating the prognostics efficiency. We calculated root mean squared error (RMSE) of RUL estimation results for performance evaluation. A genetic algorithm is employed to find the best number 'K' in terms of minimizing the RMSE values out of RUL estimations, shown in Eq. (4). Each K value provides its minimum RMSE value with the optimized 'n' and ' λ ' parameters.

$$\min_{K} RMSE = f(RUL_{K_{\lambda,n}})$$
(4)

Comparison of different 'K' percentage values is discussed in the next section.

3. **RESULTS**

The optimization of K percentage values for their best 'n' and ' λ ' parameters is shown in Table 1. By looking at the table, the lower RMSE from the RUL estimations for the Virkler dataset can be obtained when the most similar 18 numbers of training samples (38%) are utilized whereas this can be achieved in 44% and 100% for Drill-bit and Turnout datasets respectively. RMSE values of different percentage levels are shown in Figure 5. In the figure, K = 100% means all training samples are utilized in RUL calculation where it represents the original definition of the approach in the literature. Improvement in the estimation errors is anticipated as the percentages of training samples involved more in the RUL predictions. However as shown in Virkler's and drill-bit dataset plots in Figure 5 errors start to build up when K is around 40%. Drill-bit and Virkler

datasets show similar profile where the minimum RMSE values are obtained when 40% of the training samples are utilized in similarity weighted sum calculation of RUL values. However, the lowest error for the turnout dataset obtained at 25% and 100% levels.





Figure 5. Optimization of the K percentage for different datasets

4. CONCLUSION & FUTURE WORK

This paper presents a modification on a pure data-driven similarity-based prognostic approach. The original model

modified so that the most similar training samples to the test sample are involved in RUL estimation. Genetic algorithm is applied to optimize the parameters involved in similarity and RUL estimations. Results show that the modifications lessen the root mean squared error of the RUL estimations in two out of three datasets. Future studies will be on integration of a physics-based model with the modified similarity-based approach to achieve improved prediction of remaining useful life. And also the modified model prognostic performance will be compared with other prognostic approaches.

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REFERENCES

- Baruah, P. and Chinnam, R. B. (2005), "HMMs for diagnostics and prognostics in machining processes", *International Journal of Production Research*, vol. 43, no. 6, pp. 1275-1293.
- Byington, C. S., Watson, M., Edwards, D. and Stoelting, P. (2004), "A model-based approach to prognostics and health management for flight control actuators", *IEEE Aerospace Conference Proceedings*, Vol. 6, pp. 3551.
- Camci, F., Eker, O. F., Baskan, S. and Konur, S. (2014), "Comparison of sensors and methodologies for effective prognostics on railway turnout systems", *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit.*
- Camci, F. (2005), Process monitoring, diagnostics and prognostics using support vector machines and hidden Markov models (PhD thesis), Graduate School of Wanye State University, Detroit, Lambert Academic Publishing.
- Camci, F. and Chinnam, R. B. (2010), "Health-state estimation and prognostics in machining processes", *IEEE Transactions on Automation Science and Engineering*, vol. 7, no. 3, pp. 581-597.
- Camci et al., (2010), http://www.aiu.edu.tr/staff/fatih.camci/datasets.html
- Chinnam et al. (2003), Project Name: 'Diagnostic and Prognostic Algorithms for Condition-Based-Maintenance'. Principal investigator: Ratna B. Chinnam, Funded by Advanced Manufacturing Technology Development (AMTD) group of Ford Motor Company for \$65,000, 2003-2004.
- Eker, O. F., Camci, F., Guclu, A., Yilboga, H., Sevkli, M. and Baskan, S. (2011), "A simple state-based prognostic model for railway turnout systems", *IEEE Transactions on Industrial Electronics*, vol. 58, no. 5, pp. 1718-1726.
- Ertunc, H. M., Loparo, K. A., Ozdemir, E. and Ocak, H. (2001), "Real time monitoring of tool wear using multiple modeling method", *Electric Machines and*

Drives Conference, 2001. IEMDC 2001. IEEE International, pp. 687.

- Furness, R. J., Tsu-Chin Tsao, Rankin, J. S.,II, Muth, M. J. and Manes, K. W. (1999), "Torque control for a form tool drilling operation", *Control Systems Technology*, *IEEE Transactions on*, vol. 7, no. 1, pp. 22-30.
- Gebraeel, N. Z. and Lawley, M. A. (2008), "A neural network degradation model for computing and updating residual life distributions", *IEEE Transactions on Automation Science and Engineering*, vol. 5, no. 1, pp. 154-163.
- Guclu, A., Yılboga, H., Eker, O. F., Camci, F. and Jennions, I. (2010), "Prognostics with Autoregressive Moving Average for Railway Turnouts", Annual Conference of Prognostics and Health Management Society, Portland, Oregon, USA, 10-14 October 2010, .
- Kacprzynski, G. J., Roemer, M. J., Modgil, G., Palladino, A. and Maynard, K. (2002), "Enhancement of physics-offailure prognostic models with system level features", *Aerospace Conference Proceedings*, 2002. *IEEE*, Vol. 6, pp. 6-2919.
- Lianyu Fu and Ling, S. -. (2002), "Neural network based online detection of drill breakage in micro drilling process", Neural Information Processing, 2002. ICONIP '02. Proceedings of the 9th International Conference on, Vol. 4, pp. 2054.
- Qiu, J., Seth, B. B., Liang, S. Y. and Zhang, C. (2002), "Damage mechanics approach for bearing lifetime prognostics", *Mechanical Systems and Signal Processing*, vol. 16, no. 5, pp. 817-829.
- Saha, S., Saha, B., Saxena, A. and Goebel, K. (2010), "Distributed prognostic health management with gaussian process regression", *Aerospace Conference*, 2010 IEEE, pp. 1.
- Si, X. -., Wang, W., Hu, C. -. and Zhou, D. -. (2011), "Remaining useful life estimation - A review on the statistical data driven approaches", *European Journal* of Operational Research, vol. 213, no. 1, pp. 1-14.
- Virkler, D. A., Hillberry, B. M. and Goel, P. K. (1979), "The Statistical Nature of Fatigue Crack Propagation", vol. 101, no. 2, pp. 148-153.
- Zhang, H., Kang, R. and Pecht, M. (2009), "A hybrid prognostics and health management approach for condition-based maintenance", *IEEM 2009 - IEEE International Conference on Industrial Engineering and Engineering Management*, pp. 1165.
- Zio, E. and Di Maio, F. (2010), "A data-driven fuzzy approach for predicting the remaining useful life in dynamic failure scenarios of a nuclear system", *Reliability Engineering & System Safety*, vol. 95, no. 1, pp. 49-57.



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BIOGRAPHIES

Evaluation of the Training Process of three different Prognostic Approaches based on the Gaussian Process

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ABSTRACT

Data-driven prognostic approaches like Gaussian Process combined with Unscented Kalman Filter (GPUKF) are promising methods for predicting the Remaining Useful Lifetime (RUL) of a degrading component. Whereas the Gaussian Process (GP) is appropriate to derive a suitable degradation model by means of a set of training data, the Unscented Kalman Filter (UKF) employs this model to determine the prediction and its uncertainty.

Since a degradation process is highly stochastic, it is assumed that by applying more sets of training data the accuracy and precision of the GPUKF is increased. In order to examine the performance enhancement two different approaches are investigated in this paper: First, a single GP is trained with all available data sets. The second approach combines several GPs (each created with a data set of one degradation process) by extending the GPUKF with a Multiple Model Method. The development of a third prognostic approach aims at the investigation of the UKF as a suitable tool for the prognostic algorithm. Therefore, a third method applies a Particle Filter in combination with the GP.

For the evaluation of the aforementioned prognosis algorithms according to their precision and accuracy a set of prevalent performance metrics like the Prognostic Horizon and the Mean Average Percentage Error of a prediction is analyzed. The validity of the determined results is increased by considering the variance of certain metrics over several units under test. Moreover, particular focus is set on the examination of the performance change caused by the use of more training data sets. In order to quantify this process known metrics are extended. The evaluation is based on simulated data sets, which are generated by an exponential degradation model. The analysis of the implemented algorithms indicates that the applied metrics are in a comparable range. However, the three approaches reveal a different behaviour concerning the convergence of the performance values according to the number of training data. In particular cases there is even a decline in accuracy and precision attend by a rising number of training data.

1. INTRODUCTION

In recent years the prognosis of the condition of component parts with a high relevance to safety has become a key technology in Condition-Based Maintenance (CBM), especially in application fields like aerospace or power generation. Although the use of a CBM system is aimed for cost reduction in the overall maintenance cycle, the initial implementation is cost-intensive, since a profound knowledge and observation of the examined element's degradation processes is essential.

Here, data-driven methods can be beneficial, as the origin and the mechanism of a failure is irrelevant for the generation of prognosis models. An additional advantage is the generic coding for possible applications of data-driven algorithms in comparison to model-based methods, which need a specific model for every degradation process. Beside other data-driven methods like the widely spreaded artificial Neuronal Networks or the Support Vector Machine for regression, the Gaussian Process (GP) became a state of the art regression estimator due to its simplicity and the ability to forecast model uncertainties.

The examinations in this paper focus upon the evaluation of three different prognosis methods, which all base on the GP for regression modelling. The first two algorithms use the Unscented Kalman Filter (UKF) for state estimation adapted from the results of (Anger, Schrader, & Klingauf, 2012), whereas the idea to combine a GP with a UKF was first introduced by (Ko, Klein, Fox, & Haehnel, 2007) for an observation model of a robotic blimp. In (Anger et al., 2012) it was proven that the combination of a GP with a UKF (GPUKF) is

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generally capable of predicting even highly stochastic degradation processes using the example of a rolling-element bearing. Additionally, a second concept was introduced by applying several GPUKFs with different models which are connected by a superior algorithm, the Interacting Multiple Model (IMM). By means of the IMM in combination with a GP regression (GPMMM) the robustness of the predictions was significantly increased, since it is able to forecast different damage courses w.r.t. the training data sets. Thus, the central question of this enquiry is, if it is more beneficial to separate the available set of training data into different models or to set up one single model with all data points.

Drawbacks in the prediction uncertainty of the aforementioned GPUKF and GPMMM led to a third algorithm, a combination of a GP regression model with a Particle Filter (GPPF). It is shown that the prognosis of the RUL by means of the GPPF is a more straight forward approach according to the handling of variances. Again the idea of this combination has its seeds in the localization, since Ferris et al. used a similar algorithm for location estimation of people within buildings in (Ferris, Hähnel, & Fox, 2006).

For the evaluation of these different algorithms, performance metrics are necessary. In (Saxena et al., 2008) and (Saxena, Celaya, Saha, Saha, & Goebel, 2009) several metrics concerning the accuracy, precision and robustness of predictive algorithms are summarized. In section 4 well-known metrics like Mean Absolute Percentage Error (MAPE) or Prognostic Precision (PP) are extended by their values w.r.t. the applied number of training data sets. Since one major drawback of data-driven approaches is the need of training data, savings are possible, if these extended metrics do not indicate an increase in the prediction performance after a certain amount of training data.

This paper is divided into six sections: first, the three aforementioned algorithms GPUKF, GPMMM and GPPF are introduced in section 2. After that the model of the simulated degradation data is described, whereupon one major demand was simplicity. The evaluation and especially the applied performance metrics are described in section 4 and the results are summarized in section 5. We conclude in section 6.

2. PROGNOSIS ALGORITHMS

Three different prognostic concepts are compared in this paper, whereupon all base on the Gaussian Process regression modelling. One motivating question for the approaches is: "Is it more beneficial to train one GP with all available data sets or to establish many models by means of every single data set separately?". There are many benefits and drawbacks assumed, such as: If one GP is trained with many data sets, which result from a similar degradation process, the regression model inherits more information about the process and thus is less prone to process noise. On the other hand in case of highly stochastic degradation, the probability to find a match between trained models and tested degradation courses raises, when the regression models are established separately.

Thus, this section starts with the basics of GP regression modelling that was introduced in (Rasmussen, 2006). Afterwards the two algorithms GPUKF and GPMMM are shortly described. Since the UKF shows drawbacks concerning the prognostic uncertainty calculation, a third algorithm based on a Particle Filter is introduced.

2.1. Gaussian Process for regression modelling

Regression modelling tools like the GP enable the opportunity to reproduce processes without the application of any parametric model. Since the GP defines a Gaussian distribution over a function, see (Rasmussen, 2006), the main advantage of regression modelling with a GP is furthermore the potential to identify the model's uncertainty according to the variance of the distribution.

Thus, the aim of the GP regression modelling is to establish a function $f(\mathbf{X})$ so that a noisy process

$$\mathbf{y} = f(\mathbf{X}) + \epsilon, \tag{1}$$

can be described w.r.t a given training data set $D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), ... (\mathbf{x}_n, y_n)\}$, where $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n]^T$ is an $n \times m$ input matrix with m the number of inputs and n the length of the single input vector \mathbf{x}_i . \mathbf{y} is an n-dimensional vector of scalar outputs and ϵ represents a noise term, which is drawn from a Gaussian distribution $\mathcal{N}(0, \sigma^2)$.

A Gaussian distribution can be described by its mean μ and covariance Σ . Thus, the GP defines a prior which is a zeromean Gaussian distribution over the given outputs **y** of the training data *D*, as follows

$$p(\mathbf{y}) = \mathcal{N}(\mathbf{0}; \mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I}).$$
(2)

Here, $\sigma_n^2 \mathbf{I}$ is a Gaussian noise caused by ϵ . The entries of the kernel matrix **K** indicate the deviation of the inputs among each other and are defined by the applied covariance function $k(\mathbf{x}_i, \mathbf{x}_j)$. Although the squared exponential is a standard kernel function, in this paper it is extended by a linear and constant term as follows

$$k(\mathbf{x}_i, \mathbf{x}_j) = \sigma_f^2 \exp(-\frac{1}{2}(\mathbf{x}_i - \mathbf{x}_j)\mathbf{W}(\mathbf{x}_i - \mathbf{x}_j)^T) + \sigma_n^2 \delta_{ij} + \sigma_l \mathbf{x}_i \cdot \mathbf{x}_j + \sigma_c, \quad (3)$$

where σ_f^2 is the signal variance and **W** is a diagonal matrix that contains the distance measure of every input. By means of the other parameters σ_l and σ_c , the linear and constant deviation can be tuned separately.

The mean GP_{μ} and the covariance GP_{Σ} is then expressed for a given test input \mathbf{x}_* and test output y_* w.r.t. the training data D by the following equations

$$GP_{\mu}(\mathbf{x}_{*}, D) = \mathbf{k}_{*}^{T} [\mathbf{K} + \sigma_{n}^{2} \mathbf{I}]^{-1} \mathbf{y}$$
(4)

for the mean and

$$GP_{\Sigma}(\mathbf{x}_*, D) = k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_*^T [\mathbf{K} + \sigma_n^2 \mathbf{I}]^{-1} \mathbf{k}_*$$
 (5)

for the covariance, respectively. For reasons of clarity the abbreviations $\mathbf{K}(\mathbf{X}, \mathbf{X}) = \mathbf{K}$ and \mathbf{k}_* the covariance function between the test input \mathbf{x}_* and the training input vector \mathbf{X} are used. Obviously, the mean prediction in equation 4 is a linear combination of the training output \mathbf{y} and the correlation between test and training input. The covariance is the difference of the covariance function w.r.t. the test inputs and the information from the observation $\mathbf{k}(\mathbf{x}_*, \mathbf{x}_*)$.

All in all, the regression modelling with the applied GP requires the optimization of five so-called hyperparameters $\theta = [\mathbf{W} \sigma_f \sigma_n \sigma_l \sigma_c]$ for the kernel function and the process noise. This can be done by standard optimization algorithms as conjugate gradient descent.

For the purpose of this paper, the degradation of the Unit Under Test (UUT) is considered as a 1-dimensional state specified by x. Using equation 1 a stochastic dynamic degradation process can be written as

$$x_{k+1} = x_k + \Delta x_k + \epsilon_k. \tag{6}$$

The GP regression modelling is then applied on the state transition Δx_k so that the input **X** is the current degradation state x_k and the output **y** is the state transition. With the training data set $D = \{\mathbf{x}, \Delta \mathbf{x}\}$ the next degradation state is written as

$$x_k = x_{k-1} + GP_\mu(x_{k-1}, D) \tag{7}$$

and the covariance $GP_{\Sigma}(x_{k-1}, D)$, both fully describe the Gaussian distribution of the GP. One example of the degradation modelling is given in figure 1.

2.2. Combining GP and an Unscented Kalman Filter

The aforementioned dynamic model of a stochastic degradation process is the basis for the first prognostic algorithm, where one GP is trained with all available training data. Since it is expected that the different degradation courses which have to be forecast are quite similar, the application of all training data in one GP is assumed to be beneficial, as the GP contains more information about the degradation process. Additionally, for uncertainty estimations of the new degradation state w.r.t. measurements and the applied model, an UKF is necessary.

Similar to equation 1, a nonlinear dynamic system in the k^{th} time step can be described as

$$x_k = g(x_{k-1}) + \epsilon_k \tag{8}$$



Figure 1. Example of dynamic degradation modelling using Gaussian Process

with the state transition function g, the 1-dimensional degradation x and an additive Gaussian noise term ϵ drawn from a zero-mean Gaussian distribution $\epsilon \sim \mathcal{N}(0, Q_k)$ with the process noise Q_k as covariance.

The basis of the UKF is the scaled unscented transformation introduced in (Julier, 2002). Instead of a linearization process of the transition function g (as in case of the Extended Kalman Filter), sigma points $\chi^{[i]}$ are defined w.r.t. the covariance Σ and the value of degradation x of the previous time step

$$\begin{aligned} \chi_k^{[0]} &= x_{k-1} \\ \chi_k^{[i]} &= x_{k-1} + (\sqrt{(n+\lambda)\Sigma_{k-1}})_i \quad i = 1, ..., n \end{aligned} (9) \\ \chi_k^{[i]} &= x_{k-1} - (\sqrt{(n+\lambda)\Sigma_{k-1}})_{i-n} \quad i = n+1, ..., 2n, \end{aligned}$$

where λ is a scaling parameter to spread the single sigma points. According to the standard UKF, these sigma points are transformed by the transition function g. Since the applied algorithm plans to use the mean function of the GP (see equation 6), the transformed sigma points are as follows

$$\bar{\chi}_k^{[i]} = \chi_k^{[i]} + GP_\mu(\chi_k^{[i]}, D).$$
 (10)

The mean and covariance of the next time step are then generated by

$$x_k = \sum_{i=0}^{2n} w_m^{[i]} \bar{\chi}_k^{[i]}$$
(11)

$$\Sigma_{k} = \sum_{i=0}^{2n} w_{c}^{[i]} (\bar{\chi}_{k}^{[i]} - x_{k}) (\bar{\chi}_{k}^{[i]} - x_{k})^{T} + GP_{\Sigma}(x_{k}, D)$$
(12)

[0]

with the weights for mean value w_m and covariance w_c , respectively. Instead of the process noise Q_k , the covariance function of the GP is used. Since this algorithm is only employed for prognosis, a correction step as in the standard UKF-algorithm is omitted.

The entire prediction process is sketched in figure 2.



Figure 2. Basic schematic of the GPUKF prognostic approach

2.3. Extension via a Multiple Model Approach

Instead of training one GP with all available data points the second algorithm separates the data sets and creates several trained GPs for degradation prediction. Again, the UKF is used for uncertainty estimation. The superior algorithm that connects the different prognostic models is called Interacting Multiple Model (IMM), which was introduced in (Li & Jilkov, 2003). Since a degradation process is highly stochastic, the prognostic accuracy is expected to increase by the application of various models that could be similar to the tested damage case.

Considering equation 8, the extension to the multiple model approach follows as

$$x_k = g(x_{k-1}, m^i) + \epsilon_k, \tag{13}$$

where additionally m^i is the *i* prognostic model of *M* available models. The first steps of the IMM algorithm consist of a reinitializing step with the calculation of a mode probability

 ξ_{k-1}^i of every i^{th} model

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with the entries $h_{ij} = p \{m_k = m^j | m_{k-1} = m^i\}$ of the transition matrix **H**. The application of the transition matrix **H** prevents the prognostic approach of insisting on one model, as it offers the possibility of a change in the mode probability from model *i* to *j* during every time step. Therefore, the transition matrix **H** describes a Markov chain, whereupon **H** is assumed to be time invariant.

In comparison to other hybrid estimators as the Autonomous Multiple Model the IMM uses the results of every integrated filter by the application of a weighting factor according to

$$\begin{aligned} {}^{\mathcal{J}|i}_{k-1} &= p(m^{i}_{k-1}|y_{1:k-1}, m^{i}_{k}) \\ &= \frac{h_{j|i}\xi^{j}_{k-1}}{\xi^{i}_{k-1}}. \end{aligned}$$
(15)

Herewith an individual reinitializing value for the state for every filter

$$\bar{x}_{k-1}^{i} = E[x_{k-1}|y_{1:k-1}, m_{k}^{i}]$$

$$= \sum_{j=1}^{M} \hat{x}_{k-1}^{j} \xi_{k-1}^{j|i}$$
(16)

and similarly a covariance $\bar{\Sigma}_{k-1}^i$ is computed. W.r.t. these initial values the several models m^i predict the degradation state of the next time step, independently. In the end the results of the *i* filters are fused w.r.t. the model probability ξ_k^i

$$\hat{x}_k = \sum_{i=1}^M \hat{x}_k^i \xi_k^i \tag{17}$$

$$\Sigma_k = \sum_{i=1}^{M} [\Sigma_k^i + (\hat{x}_k - \hat{x}_k^i)(\hat{x}_k - \hat{x}_k^i)^T] \xi_k^i.$$
(18)

The entire algorithm is sketched in figure 3. In comparison to the first algorithm, the GPMMM requires a previous state estimation to identify the model probability ξ_k^i that remains constant during each prediction. According to the likelihood L_k^i , which depends on the residuum $e_k^i = z_k^i - \hat{z}_k^i$ of the measured and estimated state, respectively, the probability that *i* is the correct model is calculated as

$$\xi_k^i = \frac{\xi_{k-1}^i L_k^i}{\sum_{j=1}^M \xi_{k-1}^j L_k^j}$$
(19)

at the beginning of every prediction.



Figure 3. Basic schematic of the GPMMM prognostic approach

One major problem that comes along with the application of the UKF in combination with the model of equation 10 is an observable drift of the sigma points, which can also be identified in several plots concerning the position estimation in (Ko et al., 2007). Consequently, considering equation 12 the covariance of the respective filters rises and the drift is intensified. Since this process is repeated in every time step, the covariance diverges especially in case of early predictions that results in a possible negative degradation, i.e. bettering, of the examined element.

To counteract the drift of the sigma points, the weighting factor $w_c^{[i]}$ was reduced so that the prediction uncertainty remains within an acceptable limit.

2.4. Combining GP and a Particle Filter

The particle filter is established as a flexible mathematical method to represent and manage uncertainties of a long-term prediction, see (Orchard & Vachtsevanos, 2009) or (Saha, Goebel, & Christophersen, 2009). The problems of the afore-

mentioned prognosis approaches in handling the uncertainties of the prediction motivate to combine the GP with a Particle Filter (GPPF). Likewise, the GPPF approach includes various degradation behaviors by means of an arbitrary number of dynamic degradation models, each represented by an individual GP.

In this section only a brief introduction of the operating principle of the particle filter is given. The reader is encouraged to follow (Arulampalam, Maskell, Gordon, & Clapp, 2002) for more detailed information. Differences to the basic filter and enhancements due to the supporting of multiple prognosis models are highlighted.

The essential idea behind the particle filter is to estimate the Probability Density Function (PDF) of the UUT's degradation by means of a weighted set of particles. With an appropriate amount of particles the current and future PDF of the degradation can be estimated. In the suggested approach an individual particle n is characterized by its level of degradation $x_{n,k}$ at time k and a parameter j_n , which is independent of the time and assigns a particle to a i^{th} prognostic model.

Figure 4 illustrates the basic schematic of the implemented prognostic approach. In the initialization step, the degradation $x_{n,0}$ and the parameter j_n of each particle is defined. Given a total amount of N particles and M trained prognostic models each model is equally represented by N/M particles.

During the prediction step each particle is transferred from the state $x_{n,k-1}$ to the state $x_{n,k}$ using the training data set D of the assigned prognostic model j_n . Given the last degradation of a particle $x_{n,k-1}$, the mean function GP_{μ} and covariance function GP_{Σ} the evolution of each particle can be written as:

2

$$\begin{aligned}
x_{n,k} &= x_{n,k-1} + \mathcal{N}(\mu, \Sigma) \\
\mu &= GP_{\mu}(x_{n,k-1}, D) \\
\Sigma &= GP_{\Sigma}(x_{n,k-1}, D).
\end{aligned}$$
(20)

When more information about the degradation of the UUT accumulates over time, the measured degradation z_k is applied to update the weight of each particle $w_{n,k}$ and to determine the model probability ξ_k^i . The weight of a particle is updated by using the normal probability density function and the previous weight:

$$w_{n,k} = w_{n,k-1} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{\left(-\frac{(x_{n,k}-z_k)^2}{2\sigma^2}\right)},$$
 (21)

where σ is a known noise distribution of the measured degradation. After updating all particles the weights are normalized $(\sum_{n=1}^{N} w_{n,k} = 1)$. In order to update the model probabilities ξ_{k}^{i} , the weights of particles assigned to the same model



Figure 4. Basic schematic of the GPPF prognostic approach

i are summarized and normalized

$$\hat{\xi}_{k}^{i} = \xi_{k-1}^{i} \cdot \sum_{n=1}^{N} a(n)
a(n) = \begin{cases} w_{n,k} & j_{n} = i \\ 0 & j_{n} \neq i \end{cases}
\xi_{k}^{i} = \frac{\hat{\xi}_{k}^{i}}{\sum_{m=1}^{M} \hat{\xi}_{k}^{m}}.$$
(22)

One major problem by using a particle filter is that after several iterations all but some particle weights are close to zero. To avoid this situation, the resampling step is executed. A helpful indicator to test whether a resampling of the particles is needed or not is the Effective Sample Size (ESS). Regarding (Arulampalam et al., 2002), ESS can be calculated by

$$ESS = \frac{1}{\sum_{n=1}^{N} w_{n,k}^2}.$$
 (23)

If ESS passes a defined threshold, particles with a low probability are replaced by particles with a high probability. Thereby, it is assured that each model i is still represented by the same amount of particle as before. Consequently, particles of a prognostic model, which inappropriately describes the current degradation behavior, profit from a well matching model. As a result the resampling does not only prevent the degeneration of particles but also the degradation of models.

In cases of long-term prediction is required, the prediction step is executed iteratively until all particles pass a predefined failure threshold of the system. Given the prediction equation 20 and a prognosis model (see figure 1) it is obvious that a particle passes the threshold at some time. In other words, the predicted PDF of the degradation will always indicate a deterioration of the UUT. The problem of a possible negative degradation described in section 2.3 is prevented by using the GPPF approach.

Considering the estimated EoL_n of each particle the expected RUL and their uncertainty limits are determined. The probability of a failure at time k is determined by the probability of the particles, which passed the threshold at this time, and the probability of the assigned prognosis models. Figure 5 illustrates an obtained distribution of the EoL_n using the particle filter approach trained with three training data sets. The estimated and real RUL as well as the upper and lower predicted limits are marked. Since the obtained distribution by means of the expected value and the standard deviation is not appropriate. Instead it is preferred to rely on the median and the percentiles to specify the RUL and uncertainties.



Figure 5. Distribution of the predicted EoL and determination of the estimated RUL including upper and lower limits (GPPF is trained with three data sets)

3. SIMULATED DATA

For a performance investigation of the presented prognostic algorithms, a set of training and test data is needed. This section introduces the developed mathematical model which is applied to generate a data pool containing various degradation courses, each simulating a run-to-failure behavior of an individual UUT. The object of the derived model is to describe an exponential failure process of a UUT including a stochastic part to assure an analogy to reality. Moreover, an important requirement we set up is to keep the mathematical model as simple as possible. This should encourage the reader to rebuild the model and compare the presented results in section 5 with other prognosis algorithms.

The equation of the mathematical model can be written as following:

$$z_{k} = z_{k-1} + \frac{\ln(100)}{100} \cdot e^{(a_{k-1}\cdot k)} + \mathcal{N}(0, b_{k-1})$$

$$a_{k} = a_{k-1} + \mathcal{N}(0, v_{a})$$

$$b_{k} = \frac{z_{k-1}}{b_{S}}.$$
(24)

The course of the degradation z_k is subject to several effects. First, the state *a* influences the exponential course by varying each step according to a noise term, defined by a normal Gaussian distribution with zero mean and variance v_a . Furthermore, the second noise term $\mathcal{N}(0, b_{k-1})$ simulates an instability of the UUT reasoned by the advanced fault, implemented by the dependency of the variance *b* on the degradation.

For the generation of a data pool, the failure threshold is set to a degradation level of 100, the model was designed to reach the limit in approximately 100 time steps. The noise values are defined as $v_a = 8 \cdot 10^{-4}$ and $b_S = 70$, the initial level of the parameter are $y_0 = 1$, $a_0 = 5 \cdot 10^{-2}$ and $b_0 = 1 \cdot 10^{-3}$. Figure 6 shows an example of four obtained UUTs.



Figure 6. Samples of simulated degradation courses generated by the developed mathematical model

4. EVALUATION CONCEPT

During recent years much effort was put into the definition of metrics to assess the performance of prognostic methods and to make them comparable with each other. Since the performance of a data-driven prognostic approach depends on the number of available historical run-to-failure data (Anger et al., 2012), the evaluation should not only consider the individual performance metrics but the change of those metrics when given more training data. It is assumed that not always better results are achieved, when applying more historical data. In some cases, a degradation of the metrics is expected, since inappropriate training data may irritate a prognosis algorithm. However, prognostic methods are rarely investigated regarding their ability in handling various training data. The purpose of the following evaluation concept is to analyse the change of performance metrics according to the number of training data and to figure out an appropriate way to quantify this process.

For the evaluation we included four metrics, namely MAPE, MAD, PH and PP, to cover accuracy as well as precision properties of the three prognosis methods. A brief description of the metrics is given in section 4.1. The procedure of the evaluation is explained in 4.2, whereas a way to quantify the change of the performance is described in section 4.3.

4.1. Performance Metrics

The applied metrics are based on the suggestions given by (Saxena et al., 2008) or (Saxena et al., 2009). Some notations of the metrics domain are given in the following glossary:

P	Time of the first prediction
EoL	End of Life
i	Prediction index $i = 1, 2,, I$
Ι	Total number of predictions
l	UUT index $l = 1, 2,, L$
L	Total number of UUTs
λ	Normed time of the entire range $(EoL - P)$
$r^l(i)$	Estimated RUL of prediction i for the l^{th} UUT
$r^l_*(i)$	Real RUL of prediction i for the l^{th} UUT
$\Delta^l(i)$	Error between predicted RUL and true RUL
	$\Delta^l(i) = r^l_*(i) - r^l(i)$

4.1.1. Mean Average Percentage Error

The Mean Absolute Percentage Error (MAPE) of a prediction testing the l^{th} UUT is specified by

$$MAPE^{l} = \frac{1}{I} \sum_{i=1}^{I} \left| \frac{100 \cdot \Delta^{l}(i)}{r_{*}^{l}(i)} \right|.$$
 (25)

The value of MAPE determines the predicted error w.r.t the real RUL.

4.1.2. Mean Absolute Deviation

The Mean Absolute Deviation (MAD) describes the spread of the prediction error and quantifies the precision of a method. The metric can be written as

$$MAD^{l} = \frac{1}{I} \sum_{i=1}^{I} \left| \Delta^{l}(i) - M^{l} \right|,$$
 (26)

where M is the median of the errors $M^l = median(\Delta^l)$. Using multiple model prognostic methods a high value of MAD indicates that the method does not show a clear tendency towards a prognosis model. When a method changes frequently, the favored model for each prediction the error consequently spreads.

4.1.3. Prognostic Horizon

The Prognostic Horizon (PH) is determined by the time when the predicted RUL remains stable within a given constant error bound. The upper and lower accepted error limit depend on the accuracy value α , therefore, the metric can be written as

$$[1 - \alpha] \cdot r_*^l \le r^l(i) \le [1 + \alpha] \cdot r_*^l.$$
(27)

Figure 7 illustrates the PH. The predicted RUL approaches the true RUL over the time and finally stabilizes for $\lambda \ge 0.6$. The PH is defined by the remaining time until the system failure occurs. In the following evaluation, the PH is expressed as normalized time range. It is clearly visible that the higher the PH the better the performance of a method. Throughout the evaluation the accuracy value was set to $\alpha = 0.1$.

4.1.4. Prognostic Precision

Whereas the PH observes the estimated RUL the Prognostic Precision (PP) considers the uncertainty of the RUL, which is specified by the lower and upper predicted limit of the RUL. The metric is specified by the time the limits remain stable within a constant error bound. Figure 7 shows the determination of PP, the limits of the prediction converge after $\lambda \ge 0.7$. Consequently, the metric allows a statement about how the prognosis method is able to reduce the uncertainty of a forecast as more information accumulates over time.

4.2. Evaluation Procedure

In order to investigate the performance change depending on the number of training data sets, the evaluation of the three methods was organized as follows: By means of the model equations presented in section 3 we generated a data pool of 40 UUTs, which was subdivided in training and test data. The training data contains 15 degradation courses, whereas the test data consists of 25 UUTs.



Figure 7. Illustration of the prognosis horizon and prognosis precision

As a first step, we trained each prognosis method by the first training data set and determined the presented metrics for all 25 test data sets by using the estimated RUL and uncertainties of nine predictions at the time $\lambda = 0.1, 0.2, ..., 0.9$. Then we included the next training data set and tested again all 25 data sets. This procedure was repeated until all 15 training data sets were available for the three prognostic methods. The obtained results for a specific metric, e.g. MAPE, can be summarized as shown in diagram 8.



Figure 8. Course of the MAPE at an increasing number of training data sets (comparison of two prognostic methods)

The results lead to a distribution of the MAPE metric, since the performance naturally varies from one tested UUT to another. The figure illustrates the evolution of this distribution for two prognostic methods. The distribution cannot be considered as a Gaussian distribution. It is helpful to rely on the median and percentiles when discussing the distribution. In the following analysis the 10^{th} and 90^{th} percentile are used. Accordingly, the displayed distribution in the figure covers 80 percent of all predictions or in other words it presents the results of 20 UUTs.

4.3. Enhancement of Metrics

By comparing the courses of the medians in figure 8, method 1 reveals a better performance using less training data sets but is easily outperformed by the second method. Whereas method 2 improves the metrics as more historical data is available, the performance of the first method even deteriorates at the beginning and benefits later from the training data. This deterioration indicates difficulties of method 1 in handling the trained run-to-failure data and selecting the appropriate model for the prediction. According to the course of the median, one tends to rely on the second method since a better performance is reached even with less training data. Involving the distribution in the decision shows that method 2 has a higher range in which the performance is located. This means that the second method reached more often worse performance values by the prediction of the RUL. This motivates to involve the course of the median as well as the distribution in order to assess the performance of prognostic methods.

For further discussion we enhance the aforementioned notations by the following:

N	Total number of training data sets
n	Number of applied data sets for the prediction
$MAPE(n)_m$	Median of the distribution (testing L UUTs)
$MAPE(n)_d$	Difference between the upper and lower
	percentile of the distribution (testing L UUTs)
$MAPE_{m,N}$	Rating of $MAPE(n)_m$ $n = 1, 2,, N$
$MAPE_{d,N}$	Rating of $MAPE(n)_d$ $n = 1, 2,, N$

This is done by the example of the performance metrics MAPE. Of course, this notation can be transferred to other metrics. Instead of taking the MAPE metrics to assess the performance, we examine the obtained values for $MAPE_{m,N}$ and $MAPE_{d,N}$. Thereby, the change of MAPE over the number of training data is taken into account. Moreover, the range within the performance value varies over the number UUTs is considered. In the following, we introduce a straight-forward method to quantify both values. Again, this approach is assignable to other metrics.

In a first attempt to determine the values appropriately, the mean values of $MAPE(n)_m$ and $MAPE(n)_d$ are considered. In this way, all reached performance values are independently of the number of used training data. Thus, deterioration or improvements of the observed metric are not covered by this method. To include the course of the metric, we suggest to calculate the values by means of the weighted mean

value w.r.t the number of training data sets. The equations can be written as:

$$MAPE_{m,N} = \frac{\sum_{i=1}^{N} (i \cdot MAPE(i)_m)}{\sum_{i=1}^{N} i}$$
(28)

$$MAPE_{d,N} = \frac{\sum_{i=1}^{N} (i \cdot MAPE(i)_d)}{\sum_{i=1}^{N} i}.$$
 (29)

Weighting the performance by the number of training data has several effects: First, the performance using less data has a lower influence on the final result. Since the performance at the beginning strongly depends on the order of trained data sets this is a desired consequence. A change in the training order would have a high impact on the determined values. Additionally, with an increasing number of used training data sets a prognosis method should exhibit an improvement or at least a stable behavior of the performance. Therefore, the weighted mean downgrades occurred deterioration in case of more historical data.

Figure 9 illustrates the difference of the results for $PH_{m,N}$ obtained by the mean value and weighted mean value. In the diagram the course of the median $PH(n)_m$ of two prognosis methods is displayed. Whereas the $PH_{m,15}$ value determined by the mean assesses both methods almost similarly, the weighted mean leads to a better distinctness, as the second method shows no stable improvement of the prognosis horizon.



Figure 9. Course of the PH at an increasing number of training data sets (comparison of two prognostic methods)

5. RESULTS AND DISCUSSION

Table 1 summarizes the obtained results of the three prognostic approaches. The performance values are determined by the weighted mean according to the introduced evaluation concept. As we expected, the results show similar values in most categories which is explained by the fact that the three prognostic methods are based on the same regression modelling tool and training data sets. However, since the prognostic approaches manage the trained prognosis models in a different way, it is worth investigating the evolution of the performance according to the available training data sets.

Performance	GPUKF	GPMMM	GPPF
$MAPE_{m,15}$	12.07	13.12	11.80
$MAD_{m,15}$	1.91	3.41	2.34
$PH_{m,15}$	0.88	0.62	0.89
$PP_{m,15}$	0.34	0.66	0.45
$MAPE_{d,15}$	31.60	28.62	27.68
$MAD_{d,15}$	10.21	12.94	11.16
$PH_{d,15}$	0.71	0.71	0.68
$PP_{d,15}$	0.80	0.73	0.64

 Table 1. Enhanced performance metrics of the three prognosis algorithms

Figure 10 shows the improvement of the $MAPE(n)_m$ value over the training data. All prognostic algorithms strongly benefit from the first training data sets and settle down at a similar mean absolute error. It is interesting to note that instead of remaining stable on the achieved performance level, the three methods behave differently with a rising knowledge about the system. Whereas the GPPF is able to further improve the metric, the performance of the GPMMM approach deteriorates. Regarding table 1, this leads to a reduction of $MAPE_{m,15}$ value. The GPMMM also reveals a weakness w.r.t the MAD metric displayed in figure 11. In contrast to the other approaches, the GPMMM exhibits less precision with a raising number of historical data. Given that the MAD value can be considered as an indicator of a prognostic method's tendency towards models, the GPMMM seems to struggle with the selection of a correct prognostic model. Consequently, the MAPE and MAD value of the GPMMM increase. Furthermore, this impact is also observable by looking at the dissatisfactory PH value. One explanation is the applied transition matrix H that - in the case at hand - permits a fast transition from model i to another model j so that GPMMM alternates between several models. The increased system knowledge has less influence on the GPUKF, which is reasoned by the manner the training data is stored. Including an additional training data set does not essentially change the basic orientation of the one applied prognosis model.



Figure 10. Course of the MAPE at an increasing number of training data sets



Figure 11. Course of the MAD at an increasing number of training data sets

It is evident that the GPMMM reveals the best PP value, which indicates that the predicted lower and upper RUL limit enter the defined error bound earlier. This is reasoned by the fact that the variance of the forecast is limited artificially (see section 2.3). Thus, the predicted lower and upper limit of the RUL are close. Hence, we learned that the used evaluation concept lacks of a metric which specifies the quality of the predicted error bound. In the current concept, keeping the variance as low as possible will always end in a good performance. A metric which assesses the meaningfulness of the variance is not implemented.

Another aspect of the evaluation is the investigation of the distribution values in Table 1. As described in section 4.3 the values indicate the range within the corresponding metric over the 25 tested UUTs is spreaded. GPPF reaches better results than the other approaches in three of the four criteria.

Nevertheless, there is no noticeable difference to the other methods and all values show that a considerable part of the tested UUTs is predicted with a deviating performance than indicated by the weighted means of the median's course. In other words, whereas the $PH_{m,15}$ values point to a high accuracy of the methods, the $PH_{d,15}$ values reveal that this performance is not always achieved. Especially considering safety relevant systems, this issue should not be neglected.

6. CONCLUSION AND OUTLOOK

In this paper we have presented three data-driven prognosis algorithms. Each algorithm is based on the Gaussian Process to generate prognosis models by means of training data sets. Nevertheless, the way they rate and select suitable models for the estimation of the RUL differs.

One purpose of this paper was to suggest a method to include the training process of a prognosis algorithm in the evaluation process. A simple way is presented to assess the trend of performance metrics at an increasing number of provided training data sets. Moreover, the presented evaluation concept considers the fact that a prognosis method does not constantly reach the same accuracy and precision by testing several UUTs.

Another purpose was to investigate the training process of three data-driven prognosis methods. The results show that the prognosis methods do not automatically benefit from more knowledge about the degradation processes of a system. A particularly motivation was, whether a single GP approach or a Multiple Model Method is preferable when training an arbitrary number of training data sets. The obtained results indicate that GPUKF reaches slightly better performance, especially since the applied GPMMM approach reveals a weakness by managing a high number of prognosis models. In contrast, the single GP approach converges towards a constant performance. Combining the Gaussian Process with a Particle Filter shows the best results and provides a more straight forward possibility to handle the model uncertainties in comparison to the UKF. Of course, the conclusion are strongly depending on the chosen data pool and evaluation concept.

As a result effort is going to put to an enhancement of the mathematical degradation model and thus to generate various data pools to obtain a more comprehensive fundament for the evaluation. We plan to enhance the presented model by an additional load input and to replace the fixed failure threshold by a hazard model, which simulates varying failure limits of UUTs. Furthermore, in order to increase the informative value of the results, other regression modelling concepts like Relevance Vector Machines etc. will be examined under same conditions.

We do not claim the presented evaluation concept near complete, since there is still enough room for improvement. Focus of future work is to include more performance metrics. Especially, a metric to determine the quality of the predicted uncertainty is required. An emerged drawback is that the assessment of a prognosis method suffers from the increased number of available performance indicators, since one metric value is replaced by two. A further bottleneck of the described evaluation concept is that a comprehensive data pool is necessary. Using simulated data this should be no problem. However, generating such a data pool by means of real data is a long and costly work.

ABBREVIATIONS

CBM	Condition Based Maintenance
ESS	Effective Sample Size
GP	Gaussian Process
IMM	Interacting Multiple Model
MAD	Mean Absolute Deviation
MAPE	Mean Average Percentage Error
MMM	Multiple Model Method
PDF	Probability Density Function
PF	Particle Filter
PH	Prognosis Horizon
PP	Prognosis Precision
RUL	Remaining Useful Lifetime
UKF	Unscented Kalman Filter
UUT	Unit Under Test

REFERENCES

- Anger, C., Schrader, R., & Klingauf, U. (2012). Unscented kalman filter with gaussian process degradation model for bearing fault prognosis. *Proceedings of First European Conference of the Prognostics and Health Management Society 2012*, 202–213.
- Arulampalam, M. S., Maskell, S., Gordon, N., & Clapp, T. (2002). A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking. *IEEE Transactions on Signal Processing*, 50(2), 174–188. doi: 10.1109/78.978374
- Ferris, B., Hähnel, D., & Fox, D. (2006). Gaussian processes for signal strength-based location estimation. In *In proc. of robotics science and systems.*
- Julier, S. J. (2002). The scaled unscented transformation. In American control conference, 2002. proceedings of the 2002 (Vol. 6, pp. 4555–4559).
- Ko, J., Klein, D. J., Fox, D., & Haehnel, D. (2007). Gp-ukf: Unscented kalman filters with gaussian process prediction and observation models. In *Intelligent robots and* systems, 2007. iros 2007. ieee/rsj international conference on (pp. 1901–1907).
- Li, X. R., & Jilkov, V. P. (2003). Survey of maneuvering target tracking. part i. dynamic models. Aerospace and Electronic Systems, IEEE Transactions on, 39(4),

1333-1364.

- Orchard, M. E., & Vachtsevanos, G. J. (2009). A particle-filtering approach for on-line fault diagnosis and failure prognosis. *Transactions of the Institute of Measurement and Control*, *31*(3-4), 221–246. doi: 10.1177/0142331208092026
- Rasmussen, C. E. (2006). Gaussian processes for machine learning.
- Saha, B., Goebel, K., & Christophersen, J. (2009). Comparison of prognostic algorithms for estimating remaining useful life of batteries. *Transactions of the Institute* of Measurement and Control, 31(3-4), 293–308. doi:

10.1177/0142331208092030

- Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., & Schwabacher, M. (2008). Metrics for evaluating performance of prognostic techniques. In *Prog*nostics and health management, 2008. phm 2008. international conference on (pp. 1–17).
- Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2009). Evaluating algorithm performance metrics tailored for prognostics. In *Aerospace conference*, 2009 *ieee* (pp. 1–13).

Statistical Aspects in Neural Network for the Purpose of Prognostics

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ABSTRACT

Neural network (NN) is a representative data-driven method, which is one of prognostics approaches that is to predict future damage/degradation and the remaining useful life of in-service systems based on the damage data measured at previous usage conditions. Even though NN has a wide range of applications, there are a relatively small number of literature on prognostics compared to the usage in other fields such as diagnostics and pattern recognition. Especially, it is difficult to find studies on statistical aspects of NN for the purpose of prognostics. Therefore, this paper presents the aspects of statistical characteristics of NN that are presumable in practical usages, which arise from measurement data, weight parameters related to the neural network model, and loading conditions. The Bayesian framework and Johnson distribution are employed to handle uncertainties, and crack growth problem is addressed as an example.

1. INTRODUCTION

Prognostics illustrated in Figure 1 is to predict future damage/degradation and the remaining useful life (RUL) of in-service systems based on the damage data obtained at previous usage conditions, which facilitate condition-based maintenance known as cost effective maintenance strategy in company with diagnostics. Once a damage model (black solid curve) is determined based on damage data at previous times under a given usage condition (black dots) or under the various usage conditions (grey dots), RUL which is remaining time/cycles before required maintenance can be predicted by progressing the damage state until it reaches the threshold. In general, prognostics methods can be categorized into data-driven (Schwabacher, 2005), physics-based (Luo, Pattipati, Qiao & Chigusa, 2008), and hybrid

(Yan & Lee, 2007) approaches, based on the usage of information. Data-driven approaches use information from collected data to identify the characteristics of damage state without using any specific physical model; physics-based ones combine the physical model describing the behavior of damage with measured data; and hybrid ones integrate the other two methods to improve the prediction performance.

Since the physical model describing the behavior of damage rarely exists, data-driven approaches have a wide range of applications. It includes NN (Chakraborty, Mehrotra, Mohan & Ranka, 1992; Yao, 1999), Gaussian process regression (Seeger, 2004; Mohanty, Teale, Chattopadhyay, Peralta & Willhauck, 2007), relevance vector machine (Tipping, 2001), least square regression (Tran & Yang, 2009), etc. Among these algorithms, NN is a representative data-driven method, in which a network model learns a way to produce a desired output such as future damage level reacting to given inputs such as previous damage level and usage conditions instead of physical model. The learning process is the same as finding weight parameters associated with the network model by minimizing the mean square error between measurement data and network outputs, which is called training process, and the data used for training expressed as dotted markers in Figure 1 is called



Figure 1. Illustration of prognostics.

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training data.

In general, weight parameters are obtained as deterministic values by using an optimization process, and prediction uncertainties are added with confidence bounds based on nonlinear regression and/or the error between NN outputs and training data (Chryssoloiuris, Lee & Ramsey, 1996; Veaux, Schumi, Schweinsberg & Ungar, 1998; Yang, Kavli, Carlin, Clausen & Groot, 2000; Leonard, Kramer & Ungar, 1992). It, however, is difficult to find global optimum of parameters due to measurement noise, a small number of data compared to the number of parameters, and the complexity of damage growth, which can yield a significant error in prediction results. On the other hand, Bayesian NN (BNN) (Freitas, 2003; Neal, 1995) has been proposed to resolve local optimum problem, which provides distribution of prediction results caused by measurement error and uncertainty in parameters that are identified as distributions based on Bayes' theorem instead of deterministic values given by an optimization process. There are no literatures that employ BNN for the purpose of prognostics, though. Liu, Saxena, Goebel, Saha, and Wang (2010) repeated NN process 50 times to predict battery's RUL, which is similar to BNN in a sense of employing randomness of weight parameters.

In addition to general statistical aspects mentioned in the previous paragraph, additional issues that are presumable in practical usages are also addressed. Data used for input variables have mostly been considered as deterministic values, but they can be distributed. In such a case, there are no clear damage indicators, many numbers of damage data are given at the same usage conditions from the same system, and usage conditions such as loading conditions can also have uncertainties and need to be considered as distributions. This case as well as general statistical aspects will be considered with a crack growth example.

The paper is organized as follows: in Section 2, the process of NN is explained for the purpose of prognostics with a crack growth example; and in Section 3, statistical aspects are considered based on the understanding of NN, followed by discussions and conclusions in Section 4.

2. NEURAL NETWORK

2.1. Typical Network Model

A typical architecture of NN is feed-forward neural network (FFNN) (Svozil, Kvasnička & Pospíchal, 1997), which is illustrated in Figure 2. In the figure, circles represent nodes (also called neuron or unit), and each set of nodes in the same column is called a layer. The nodes in the input and output layer, respectively, represent input variables and response variable. Since the given information for data-driven approaches are only measurement data, previous damage data and the current damage data are, respectively, usually employed for input and output variables. And then,

the number of nodes in the hidden layer can be adjusted to properly express the mechanism between input and output by receiving signals from input layers and forwarding them to the output layer. Even though the network model that includes selecting the number of hidden nodes, hidden layers and input nodes has an effect on the prediction results, it is not considered here because the network problem is a different issue from statistical ones as well as trial-and-error methods are often used to determine a suitable network model.

Once the network model is determined, the model is functionalized using transfer functions and weight parameters. Transfer functions characterize the relationship between each layer, and several types of transfer function are available such as sigmoid, inverse, and linear function (Duch & Jankowski, 1999). Usually, the tangent sigmoid and pure linear functions are employed as a common way. Weight parameters include weights for the interconnected nodes and biases that are added to inputs of transfer functions (Liu et al., 2010; Firth, Lahav & Somerville, 2003), which are shown as rectangles and ellipses in Figure 2, respectively. The process of finding the weight parameters is called training or learning, and to accomplish that, usually many sets of training data are required.

In general, FFNN is often called a back-propagation neural network (BPNN) because weight parameters are obtained through the learning/optimization algorithm (Rumelhart, Hinton & Williams, 1986) that adjusts weight parameters through backward propagation of errors between actual output (training data) and the one from the network model based on gradient descent optimization methods. In other words, FFNN and BPNN are, respectively, to calculate the response forward and to update weight parameters based on the response backward. Once the network model learns enough the relationship between inputs and output, it can be used for the purpose of prognosis. In the following, the process of NN-based prognostics becomes specified with crack growth example.

2.2. The Process of NN with a Crack Growth Example

Figure 3 shows an example of NN-based prognostics for a



Figure 2. Illustration of typical network model: FFNN.

crack growth problem. The star markers are assumed as crack growth data measured at every 100 cycles in a fuselage panel under repeated pressurization loadings, which are generated based on Paris model (Paris & Erdogan, 1963) with true damage growth parameters $m_{\rm true} = 3.8$, $C_{\rm true} = 1.5 \times 10^{-10}$, the initial half crack size $a_0 = 10$ mm, load magnitude $\Delta \sigma = 80$ MPa, and random noise that is uniformly distributed between -1.0 mm and +1.0 mm. Note that the true values of parameters are used only for the purpose of generating measurement data in this paper.

The network model is constructed based on aforementioned FFNN with two input nodes, one hidden layer with one node; and thus, the number of total weight parameters become 5 including three weights $(2 \times 1 + 1 \times 1)$ and two biases (1+1). For input variables, damage data (x_{k-2}, x_{k-1}) at the previous two 100 cycles are used, and the current damage data (x_k) becomes the output, k is the current time index. If k = 16 (the current cycle is 1500 cycles), 14 sets of input and output data are available, which are the training data used to obtain weight parameters via optimization process. Then future damages ($x_{k+1}^p, x_{k+2}^p, x_{k+3}^p, \dots$, superscript *p* represents predicted value in opposition to measured one) are predicted based on the obtained weight parameters and the previous damage data, i.e., input variables. According to the previous damage data used as inputs, prediction methods can be divided into short term prediction and long term prediction. Short term prediction is one-step ahead prediction since it uses only measured data for input, e.g., x_{k+1} , x_{k+2} are inputs to predict x_{k+3}^p . On the other hand, long term prediction is multi-step ahead prediction since it utilizes predicted results as inputs, e.g., x_{k+1}^p , x_{k+2}^p are inputs to predict x_{k+3}^p .

Future damage prediction results are shown in Figure 3. In the figure, thick dotted curve and thick dashed curve are, respectively, the median of short term prediction and long



Figure 3. Example of NN-based prognostics with crack growth example.

term prediction obtained by repeating NN 30 times, and their thin curves mean 90% confidence intervals. The wide range of long term prediction interval means that the results become significantly different whenever the NN process is performed due to the local optimum problem, even though the training simulation results shown as circles are close to the training data shown as gray star makers. Nevertheless, NN can be used for the purpose of prognostics by employing proper statistical methods. Although repeating the process to obtain statistical distribution can be a way, a more logical method is introduced in the next section.

3. STATISTICAL ASPECTS IN NN

In the following subsections, different statistical aspects that are presumable in practical usages are considered according to given information.

3.1. Prediction Uncertainty

The first case is a common condition caused by noise in measurement data and parameter identification, and it is to identify the weight parameters as distribution based on Bayesian framework. Bayesian inference is a statistical method in which observations are used to estimate and update unknown parameters such as weight parameters in the form of a probability density function (PDF). Bayesian inference is based on the following Bayes' theorem (Bayes, 1763):

$$p(\boldsymbol{\theta} | \mathbf{z}) \propto L(\mathbf{z} | \boldsymbol{\theta}) p(\boldsymbol{\theta}) \tag{1}$$

where $\boldsymbol{\theta}$ is a vector of unknown parameters, \mathbf{z} a vector of observed data, $L(\mathbf{z} | \boldsymbol{\theta})$ the likelihood, $p(\boldsymbol{\theta})$ the prior PDF of $\boldsymbol{\theta}$, and $p(\boldsymbol{\theta} | \mathbf{z})$ the posterior PDF of $\boldsymbol{\theta}$ conditional on \mathbf{z} . The likelihood is the PDF value of \mathbf{z} conditional on given $\boldsymbol{\theta}$, and the prior information can be given, assumed, or not considered. The reliability of posterior PDF increases as more data are used, which gives more accurate and precise prediction results of damage and RUL.

Figure 4 shows the comparison between repeating NN (RNN) and BNN. Figure 4 (a) and (b) are the same condition as the previous example in Section II.B but with a larger level of noise, ± 5 mm. Figure 4 (c) and (d) are also crack growth problem, but they are based on Huang's model (Huang, Torgeir & Cui, 2008) that express crack growth under variable amplitude loading condition, which is employed to show the case of complex damage model. In both cases, large noise and complex model, BNN outperforms RNN in terms of accuracy and precision of future damage prediction. The two cases means severe prediction conditions, but such conditions are more likely to be in real damage data. If the damage data have small level of noise and the damage growth increase monotonically, it will be more efficient to use RNN as Liu et al. (2010) did. There are two reasons why: (1) the results obtained by repeating NN more than 30 times do not much change with other attempts, which gives more reliable results compared to use NN just one time with confidence bounds, and (2) since it grows hard to identify the distribution of weigh parameters as the number of parameters depending on network model increases, BNN is interrupted to construct



a) RNN with large noise



b) BNN with large noise



c) RNN with complex model



d) BNN with complex model

Figure 4. Comparison example of NN-based prognostics with crack growth example.

network model flexibly.

3.2. Input Variable Uncertainty

Input variables of NN are composed of damage data and usage conditions that are considered as deterministic values, and never considered as distributions. However, input variables can be distributed in such cases: many number of damage data are given at the same usage conditions from the same system, usage conditions such as loading conditions are uncertain, and there are no clear damage indicators. Johnson distribution (Johnson, 1949) having four parameters, four quantiles corresponding to probabilities 0.0668, 0.3085, 0.6915 and 0.9332, is employed to predict future damage distribution. Figure 5 shows examples of Johnson distribution in cases of normal and beta distribution. The black solid curves are exact PDF from each distribution, and the bars are the results from Johnson distribution using four quantiles represented as red star markers. Johnson distribution can express any other distribution types when the four quantiles are correctly given.

The same crack growth example as the previous one is again employed to demonstrate the case of random input variable. Distributed synthetic data are generated from the load magnitude $\Delta \sigma = 78$ MPa, the perturbation of Paris model parameter *m* and small noise level: $m \sim U[3.8-0.027, 3.8+0.027]$, *noise* $\sim U[-1,+1]$ mm , whose result is shown in Figure 6. Each cycle has 5000 samples as the measurement data, whose distribution at 0,



a) standard normal distribution







800, 1500, and 2200 cycles are shown in Figure 6 (b) with their true damage size shown as black squares. It is shown that the shape of distributions is changed as cycle increases. Four quantiles whose example at 2500 cycles is shown as red star markers in Figure 6 (a) are used for input variables. Since there were two input variables and one output variable in the previous study, total number of input and output variables becomes eight and four, respectively.

Figure 7 shows damage prediction results at 1500 cycles. In Figure 7 (a), the median of future damage growth is very close to the true one, and 90% confidence interval also covers damage distribution at every cycle. Figure 7 (b) and (c) show comparison of damage distribution between predicted one and measured one at 1600 and 2400 cycles, and their errors at four quantiles are listed in Table 1. The

Table 1 Errors between prediction results and measurement at 1500 cycles.

Cycles		1600	1800	2000	2200	2400
6.7 %	measurement	0.0186	0.0210	0.0239	0.0276	0.0327
	prediction	0.0186	0.0210	0.0240	0.0279	0.0332
	error (%)	0.03	0.02	0.58	0.95	1.82
30.9 %	measurement	0.0196	0.0221	0.0253	0.0296	0.0354
	prediction	0.0197	0.0225	0.0261	0.0308	0.0374
	error (%)	0.63	1.54	2.89	4.18	5.75
69.1 %	measurement	0.0207	0.0237	0.0278	0.0333	0.0413
	prediction	0.0207	0.0237	0.0276	0.0329	0.0402
	error (%)	0.10	0.01	0.59	1.35	2.66
93.3 %	measurement	0.0218	0.0251	0.0296	0.0363	0.0463
	prediction	0.0218	0.0253	0.0299	0.0363	0.0453
	error (%)	0.32	0.82	0.78	0.09	2.20





c) damage distribution at 2400 cycles Figure 7. Damage prediction results.

maximum magnitude of error is 5.75% at 2400 cycles that is 900 cycles ahead prediction from 1500 cycles. These results show that NN using Johnson distribution is applicable for prediction of damage distribution.

Lastly, Figure 8 shows real measurement data from the bearing provided by the Center for Intelligent Maintenance Systems (Lee, Qiu, Yu, Lin & Rexnord Technical Services, 2007). Vibration signal is monitored using accelerometer during one second with 20 kHz sampling rate at specific intervals. The distributions in Figure 8 (a) and Figure 8 (b) are, respectively, observed from a bearing without failure and a bearing with failure. While the distribution of the case without failure does not changes much, the distribution with failure gets wider and its mode shift to the value greater than zero as cycles increase. Even though it has not been fully explored to consider the change of distribution as the damage indicator (there are no clear criteria of damage threshold yet), the results in this section show that this



method has a possibility to be employed for prognosis when there are no clear damage indicators like this bearing problem.

4. CONCLUSION

The goal of this paper is to address the aspects of statistical aspects in NN that are presumable in practical usages. As the first case, RNN and BNN are compared in terms of prediction uncertainty that is general statistical aspect related with noise in measurement data and weight parameters in NN model. BNN outperforms RNN under severe prediction conditions such as large level of noise in data and complex damage growth. In another case, random input variables are handled by employing Johnson distribution to NN. Future damage distribution are well predicted, and the results show that the method considering the change of distribution has a possibility to be employed for prognosis when there are no clear damage indicators.

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REFERENCES

- Bayes, T. (1763). An essay towards solving a problem in the doctrine of chances. *Philosophical Transactions of the Royal Society of London*, vol. 53, pp. 370-418.
- Chakraborty, K., Mehrotra, K., Mohan, C. K., & Ranka, S. (1992). Forecasting the behavior of multivariate time series using neural networks. *Neural Networks*, vol. 5, pp. 961-970.
- Chryssoloiuris, G., Lee, M., & Ramsey, A. (1996). Confidence interval prediction for neural network models. *IEEE Transactions on Neural Networks*, vol. 7(1), pp. 229-232.
- Duch, W. & Jankowski, N. (1999). Survey of neural transfer functions. *Neural Computing Surveys*, vol. 2, pp. 163-212.
- Firth, A. E., Lahav, O., & Somerville, R. S. (2003). Estimating photometric Redshifts with artificial neural networks. *Monthly Notices of the Royal Astronomical Society*, vol. 339, 1195, DOI: 10.1046/j.1365-8711.2003.06271.
- Freitas, de J. F. G. (2003). *Bayesian methods for neural networks*. Doctoral dissertation. University of Cambridge, UK.
- Huang, X., Torgeir, M., & Cui, W. (2008). An engineering model of fatigue crack growth under variable amplitude loading. *International Journal of Fatigue*, vol. 30(1), pp. 2-10.
- Johnson, N. L. (1949). Systems of frequency curves generated by methods of translation. *Biometrika*, vol. 36, pp. 149-176.
- Lee, J., Qiu, H., Yu, G., Lin, J., & Rexnord Technical Services. (2007). Bearing data set. IMS, University of Cincinnati. NASA Ames Prognostics Data Repository, http://ti.arc.nasa.gov/project/prognostic-data-repository, NASA Ames, Moffett Field, CA.
- Leonard, J. A., Kramer, M. A., & Ungar, L. H. (1992). A neural network architecture that computes its own reliability. *Computers in Chemical Engineering*, vol. 16(9), pp. 819-835.
- Liu, J., Saxena, A., Goebel, K., Saha, B., & Wang, W. (2010). An adaptive recurrent neural network for remaining useful life prediction of lithium-ion batteries. *Annual Conference of the Prognostics and Health Management Society*, October 10-16, Portland, Oregon.
- Luo, J., Pattipati, K. R., Qiao, L., & Chigusa, S. (2008). Model-based prognostic techniques applied to a suspension system. *IEEE Transactions on System, Man* and Cybernetics, vol. 38(5), pp. 1156-1168.
- Mohanty, S., Teale, R., Chattopadhyay, A., Peralta, P., & Willhauck, C. (2007). Mixed Gaussian process and state-space approach for fatigue crack growth prediction. *International Workshop on Structural Heath Monitoring*, vol. 2, pp. 1108-1115.
- Neal, R. M. (1995). Bayesian learning for neural networks. Doctoral dissertation. University of Toronto, Ontario, Canada.

- Paris, P. C. & Erdogan, F. (1963). A critical analysis of crack propagation laws. *Transactions of the ASME*, *Journal of Basic Engineering, Series D*, vol. 85(3), pp. 528-534.
- Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning internal representations by error propagation. *In Parallel Distributed Processing: Ex-plorations in the Microstructure of Cognition*, vol. 1: foundations, MIT Press, pp. 318-362.
- Schwabacher, M. A. (2005). A survey of data-driven prognostics. *AIAA Infotech@Aerospace Conference*, September 26-29, Reston,VA.
- Seeger, M. (2004). Gaussian processes for machine learning. *International Journal of Neural Systems*, vol. 14(2), pp. 69-106.
- Svozil, D., Kvasnička, V., & Pospíchal, J. (1997). Introduction to multi-layer feed-forward neural networks. *Chemometrics and Intelligent Laboratory Systems*, vol. 39, pp. 43-62.
- Tipping, M. E. (2001). Sparse Bayesian learning and the relevance vector machine. *Journal of Machine Learning Research*, vol. 1, pp. 211-244.
- Tran, V. T. & Yang, B. S. (2009). Data-driven approach to machine condition prognosis using least square regression tree. *Journal of Mechanical Science and Technology*, vol. 23, pp. 1468-1475.
- Veaux, R. D., Schumi, J., Schweinsberg, J., & Ungar, L. H. (1998). Prediction intervals for neural networks via nonlinear regression. *Technometrics*, vol. 40(4), pp. 273-282.
- Yan, J. & Lee, J. (2007). A hybrid method for on-line performance assessment and life prediction in drilling operations. *IEEE International Conference on Automation and Logistics*, August 18-21, Jinan, Shandong, China.
- Yang, L., Kavli, T., Carlin, M., Clausen, S., & Groot, P. F. M. (2000). An evaluation of confidence bound estimation methods for neural networks. *European Symposium on Intelligent Techniques 2000*, September 14-15, Aachen, Germany.

Yao, X. (1999). Evolving Artificial neural networks. *Proceedings of the IEEE*, vol. 87(9), pp. 1423-1447.

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Fault Prognosis with Stochastic Modelling on Critical Points of Discrete Processes

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ABSTRACT

The primary role of a machine tool is produce the good quality parts, but a machine tool goes always through a process of degradation and wear which will affect the accuracy and precision of machining and the quality of products. Therefore, monitoring the degradation of machine tool and quantifying its health is very important. The degradation level of a machine can be qualified by an index which is called health indicator (HI). Based on the HI, fault prognosis can provide the Remaining Useful Life (RUL) of machine which is useful for an effective maintenance policy, thus, that helps to increase efficiency of operations and manufacturing. However, the HI is not usually predetermined in most Discrete Manufacturing Processes (DMP). This paper presents a new method of HI extraction based on the degradation reconstruction. The HI is then modeled with a stochastic process. For the online supervision, the RUL is estimated for each inspection time.

1. INTRODUCTION

Fault prognosis of industrial systems is one of central issues of Condition Based Maintenance (CBM). It is important to minimize the downtime of machinery and production, and thus to increase efficiency of operations and manufacturing. Till now, the production units in most DMP use a strategy of Preventive and Corrective Maintenance which is less efficient than the CBM, and few studies are conducted on this subject. There is not yet an efficient method which is capable to extract the underlying state of DMP tools because of their complex processes, which are highly non-linear, time varying and usually exhibit batch-to-batch variation disturbances.

In semiconductor manufacturing, a survey of data-driven prog-

nosis of (Thieullen, Ouladsine, & Pinaton, 2012) shows that, most of the HI are calculated as the values of the indexes such as Squared Prediction Error (SPE), Hotellings T2, Mahalanobis distance, etc. In this paper, the health index is not built from these indexes but from the trend of critical points of sensors. Based on the same principles of reconstructionbased fault identification (Yue & Qin, 2001), (Gang, Qin, Ji, & Zhou, 2010), a method of degradation detection and identification is proposed. The EWMA Hybrid-wise Multiway PCA (E-HMPCA) (Zhang, 2008) which is an extension of Principal Component Analysis (PCA) is used to perform degradation detection and diagnosis for the batch process machine. This is because E-HMPCA combines the advantages of both batch-wise and variable-wise unfolding approaches. Moreover, the EWMA algorithm considers the time dependencies. The index SPE is calculated and is compared to its upper control limit (UCL) to detect the degradation. The significant sensors which carry the degradation information of machine are localized and their critical points are identified based on an optimization algorithm. The HI is then extracted for the failure prognosis.

This paper proposes a new fault prognosis method for DMP tools, as illustrated in the schema of Figure 1. The on-line supervision is supported by the off-line analysis. A degradation reconstruction is executed to determine the set of critical points of processes which are considered representing the tool's underlying state. Then an indicator of degradation is extracted from the evolution of these points and is modelled with an adequate stochastic process to predict the Remaining Useful Life (RUL). In on-line supervision, the value of RUL is updated for each inspection time. A real case application using data collected in STMicroelectronics Rousset is presented to illustrate the efficiency of the proposed method.

The remaining of this paper is organised as follows. Sec-

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Figure 1. Schema of fault prognosis

tion 2 presents the off-line analysis where 2.1 provides the formulation of health index contribution, 2.2 describes the degradation modelling based on an adequate process. The online supervision procedure is proposed in section 3. Section 4 presents a real case application using data collected in STMicroelectronics. Section 5 gives the conclusion.

2. OFF-LINE ANALYSIS

2.1. Heath indicator extraction

2.1.1. Identification of degraded sensors

From the measurement of machine during processing a set of products, a data matrix X of three dimensional matrix $I \times J \times K$ is obtained, respectively I is number of products, J is the number of sensors and K is the number of observations (sampling time).

Suppose that the first n products (n < I) are considered respecting the good quality norm. These n products are thus used to build the degradation detection index.

The data of these n products is unfolded according to batchwise, it is then mean-centered and rearranged in a variablewise structure, it becomes a $((n \times K) \times J)$ matrix. This hybrid-wise unfolding combines the advantages of both batchwise and variable-wise unfolding approaches. Then the algorithm EWMA is employed for considering time dependencies.

After the unfolding step, X $((n \times K) \times J)$ is decomposed by PCA:

$$X = TP^T \tag{1}$$

where T and P are score and loading matrices. n_{pc} is the number of the more significant principal components which are sufficient to explain the variability of data. The matrices of n_{pc} first columns of \mathcal{T} and P are signed respectively $\hat{\mathcal{T}}$ and \hat{P} . \tilde{C} is the projection matrix onto the residual subspace:

$$\tilde{C} = (\mathbb{I} - \hat{P}\hat{P}^T) \tag{2}$$

Call e_k $(J \times n)$ and X_k $(n \times J)$ are respectively the projection on the residual subspace and the data matrix of the k^{th} observation of all the batches. The relation between them is given as:

$$e_k = \tilde{C} X_k^T \tag{3}$$

Signing:

$$X_{E,k} = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} X_j \tag{4}$$

EWMA is used to filter the covariance matrix $S_{E,k}$ and the residual subspaces projection $e_{E,k}$ as:

$$e_{E,k} = \lambda e_k + (1-\lambda)e_{E,k-1} = \lambda \sum_{j=1}^k (1-\lambda)^{k-j} e_j$$
$$= \lambda \sum_{j=1}^k (1-\lambda)^{k-j} \tilde{C} X_j^T$$
$$= \tilde{C} \times \left(\lambda \sum_{j=1}^k (1-\lambda)^{k-j} X_j^T\right) = \tilde{C} X_{E,k}^T$$
(5)

The coefficient λ ($0 \leq \lambda \leq 1$) represents the degree of weighting decrease that determines the weight of older data in the calculation.

Degradation detection indices Call $X_{new,k}$ $(1 \times J)$ is the k^{th} observation of a new batch X_{new} $(K \times J)$. $X_{new,E,k}$ is calculated in the similar way:

$$X_{new,E,k} = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} X_{new,j}$$
(6)

and

$$e_{new,k} = \tilde{C}X_{new,k}^T \tag{7}$$

$$e_{new,E,k} = \lambda e_{new,k} + (1 - \lambda) e_{new,E,k-1}$$
$$= \tilde{C} X_{new,E,k}^T$$
(8)

In E-HMPCA, fault detection is ensured by classical PCA detection index as Squared Prediction Error (SPE) for each observation k:

$$SPE_{E,new,k} = e_{new,E,k}^T e_{new,E,k}$$
 (9)

The process is considered reliable if SPE is under their upper control limit (UCL):

$$UCL_{E,k}^{SPE} = \frac{v_{E,k}}{m_{E,k}} \chi_{2m_{E,k}^2/v_{E,k}}^2$$
(10)

where $m_{E,k}$ and $v_{E,k}$ are the mean and variance of the $SPE_{E,k}$ at the observation k of training data.

Degradation estimation via reconstruction The degradation reconstruction estimates the normal values X^* by eliminating the effect of a degradation direction \mathcal{F}_r on the SPE. A reconstruction $X_{r,k}$ from X_k (k is the index of observation) can be calculated as follows:

$$X_{r,k} = X_k - \Xi_r F_{r,k} \tag{11}$$

where $\hat{F}_{r,k}$ is the estimated degradation magnitude along degradation direction matrix Ξ_r such that $X_{r,k}$ is closest to the normal region. From (Mnassri, El Adel, & Ouladsine, 2013), the $\hat{F}_{r,k}$ and the projection of the reconstructed sample onto SPE-subspace is given:

$$\hat{F}_{r,k} = \left(\Xi_r^T \tilde{C} \Xi_r\right)^{-1} \Xi_r^T \tilde{C} X_k^T \tag{12}$$

$$\tilde{C}^{\frac{1}{2}}X_{r,k}^{T} = \left(\mathbb{I} - \tilde{C}^{\frac{1}{2}}\Xi_{r} \left(\Xi_{r}^{T}\tilde{C}\Xi_{r}\right)^{-1}\Xi_{r}^{T}\tilde{C}^{\frac{1}{2}}\right)\tilde{C}^{\frac{1}{2}}X_{k}^{T} \quad (13)$$

Singular value decomposition of $\tilde{C}^{\frac{1}{2}} \Xi_r$:

$$\tilde{C}^{\frac{1}{2}} \Xi_r = \Xi_r^0 D_r V_r^T \tag{14}$$

Call $e_{r,k}$ is the e_k after reconstruction.

$$e_{r,k} = \tilde{C}X_{r,k}^T$$
$$= (I - \Xi_r^0 \Xi_r^{0T})\tilde{C}X_k^T$$
(15)

After the EWMA filter, the residual subspaces become:

$$e_{r,E,k} = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} e_{r,k} \\ = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} (I - \Xi_{0}^{0} \Xi_{0}^{0}) \tilde{C} X_{k}^{T} \\ = (I - \Xi_{r}^{0} \Xi_{r}^{0}) \tilde{C} X_{E,k}^{T} \\ = (I - \Xi_{r}^{0} \Xi_{r}^{0}) e_{E,k}$$
(16)

The index SPE after reconstruction of a new batch X_{new} at observation k is:

$$SPE_{r,E,new,k} = e_{r,E,new,k}^T e_{r,E,new,k}$$
(17)

The degradation direction matrix Ξ_r is considered the true degradation variables if the SPE is below their new UCL, which are given as follows:

$$UCL_{SPE_{r,E,k}} = \frac{v_{r,E,k}}{m_{r,E,k}} \chi^2_{2m^2_{r,E,k}/v_{r,E,k}}$$
(18)

where $m_{r,E,k}$ and $v_{r,E,k}$ are the mean and variance of the $SPE_{r,E,k}$ at the observation k of training data. Notice that

the subscript r designates one set among the assumed degraded variable sets. The total number of possible sets of J sensors is:

$$C_J^1 + C_J^2 + \dots + C_J^{J-1} = 2^J - 2$$

is really large when $J \ge 8$. To reduce the number of candidate variable sets, an analysis of the SPE-contribution may help. An illustration of this is provided in section 4.

2.1.2. Health indicator extraction

After subsection 2.1.1, the degraded sensors set $\{\mathcal{J}s\} = \{j_1, ..., j_S\}$ is determined where S is the number of sensors. The critical points are then identified via an algorithm with the idea: the critical point of a degraded sensor js is the observation interval k_j at which the variance is the maximum:

$$k_{js} = \arg\max_{k} \{ Var(\tilde{X}_{i,k}^{js}), \quad i = n+1 \to I \}$$
(19)

where $\tilde{X}_{k}^{js} = \frac{X_{i,k}^{js} - m_{k}^{js}}{\sigma_{k}^{js}}$, $X_{i,k}^{js}$ is the measurement of product i at observation k of sensor js; $m_{k}^{js} = mean(X_{i=1\rightarrow n,k}^{js})$, $\sigma_{k}^{js} = standard \ deviation \ (X_{i=1\rightarrow n,k}^{js})$. With this algorithm, the point (js, k_{js}) is considered representing the degradation dynamics of the process. It is because a machine which carries the degradation process, this process will come out in some way of the evolution of the degraded sensors. The variance of the measurement $X_{i,k}^{j}$ from the beginning of degraded batch n+1 (because the first n batches are considered as good quality) to the last batches I is the most logical way which presents this degradation process.

The measure value of them is $X_{i,k_{js}}^{js}$ with $i \in 1, ..., I$. They are then arranged in a new matrix \mathcal{X}_c :

$$\mathcal{X}_{c} = \begin{pmatrix}
X_{n+1,k_{j1}}^{j1} & X_{n+1,k_{j2}}^{j2} & \dots & X_{n+1,k_{jS}}^{jS} \\
X_{n+2,k_{j1}}^{j1} & X_{n+2,k_{j2}}^{j2} & \dots & X_{n+2,k_{jS}}^{jS} \\
\vdots & \vdots & \ddots & \vdots \\
X_{I,k_{j1}}^{j1} & X_{I,k_{j2}}^{j2} & \dots & X_{I,k_{jS}}^{jS}
\end{pmatrix}$$
(20)

 \mathcal{X}_c is then mean-centered and unit-deviation scaled and is decomposed by PCA:

$$\mathcal{X}_c = T_c P_c^T \tag{21}$$

Each point of $\{j_1, ..., j_S\}$ set has a progressively increasing or decreasing evolution, but the increasing is just an inverse trend of decreasing and vice versa. Therefore, the trend of all these points can be presented in a vector, that is the first PC of \mathcal{X}_c , assigned I_0 :

$$I_0 = \mathcal{X}_c P_{c1} \tag{22}$$

where P_{c1} is the first eigenvector of P_c .

2.2. Analysis of health indicator dynamics

Applying the health index extraction presented in the previous section, a *common form* of the indicator is provided in Fig. 2, called I_0 (applied on a real data provided by STMicroelectronics). It is highly noisy with a *large variance* over time. We might think that I_0 can be modelled with the Wiener process, which considers the HI as:

$$I_0(t) = x_0 + \mu t + \sigma B(t)$$
(23)

where x_0, μ, σ are constant, B(t) is the Brownian movement. (23) can be rewritten as followings:

$$I_0(t+1) = I_0(t) + \mu ((t+1) - t) + \sigma B(1)$$

$$\Leftrightarrow I_0(t+1) - I_0(t) = \mu + \sigma B(1)$$
(24)

thus, the variance of $\Delta_t = I_0(t+1) - I_0(t)$ does not depend on t. Figure 3 shows Δ_t of I_0 , which demonstrates that Δ_t is dependent on t. Therefore, the Wiener process is not adequate to modelling this raw HI.



Figure 2. Raw health index I_0



Figure 3. Variation of I_0 between (t + 1) and t

Therefore, it is necessary to choose an another method for HI modelling.

2.2.1. Filtering:

A real health indicator is always *monotonic* over time because we assume that the degradation is not reversible. However,



Figure 4. Health indicator I_1

under the influence of perturbations of machine, of environment and significant disturbances of quality of input products, I_0 is not monotonic. First, a low-pass filter (e.g. an average filter with a window size of 10) is used to eliminate high frequency noises, the result is called I_1 and given in the Fig. 4.

Then, if I_1 *increases* progressively, the higher values reflect the degradation better than their lower neighbour values and inversely if I_1 decreases progressively. Therefore, an algorithm is proposed to eliminate disturbances and to *monotonize* the indicator: I_1 is analysed to structure a *top curve* I_t which is then considered as health indicator if I_1 *increases* or a *bottom-curve* I_b if I_1 decreases. This algorithm is presented for an increasing index as follows (for a decreasing indicator it is the same but replacing "maximum" by "minimum" and replacing the signs by their opposite sign):



2.2.2. Health index modelling

Gamma process is widely used for the deterioration modelling because it is suitable to model gradual damage monotonically accumulating over time such as wear, crack growth, degrading health index, etc. which is presented clearly in a survey of Gamma process (Van Noortwijk, 2009). Therefore, in this work, Gamma process is chosen to model Y. A random quantity Y has a gamma distribution with shape parameter $\nu > 0$ and scale parameter u > 0 if its probability density function is:

$$Ga(y|\nu, u) = \frac{u^{\nu}}{\Gamma(\nu)} y^{\nu-1} exp(-uy), \quad y > 0$$
 (25)

where $\Gamma(a) = \int_{t=0}^{\infty} t^{a-1} e^{-t} dt$. It is assumed that the expected deterioration can be described as a power law between cumulative deterioration and time:

$$E(Y(t)) = \frac{\nu(t)}{u} = \frac{ct^b}{u}$$
(26)

Consider a gamma process with shape function $\nu(t) = ct^b$ and scale parameter u. A data set consists of inspection times t_i , i = 1, ..., n where $0 = t_0 < t_1 < ... < t_n$, and corresponding of the cumulative deterioration y_i , i = 1, ..., n, where $0 < y_0 \le y_1 \le ... \le y_n$.

The parameters (u, c, b) of the gamma process have been estimated by combining the methods of least squared and maximum likelihood (Bakker & van Noortwijk, 2004). First, *b* can be estimated using the least-squares method:

$$b = \frac{\sum_{i=1}^{n} log(\frac{t_i}{t_n}) log(\frac{y_i}{y_n})}{\sum_{i=1}^{n} [log(\frac{t_i}{t_n})]^2}$$
(27)

Then the parameters u and c can be estimated by using the method of moments (Van Noortwijk, 2009)

$$\frac{\hat{c}}{\hat{u}} = \frac{\sum_{i=1}^{n} \delta_i}{\sum_{i=1}^{n} w_i} = \frac{y_n}{t_n^b} = \bar{\delta}$$
(28)

$$\frac{y_n}{\hat{u}}\left(1 - \frac{\sum_{i=1}^n w_i^2}{[\sum_{i=1}^n w_i]^2}\right) = \sum_{i=1}^n (\delta_i - \bar{\delta}w_i)^2 \qquad (29)$$

where $w_i = t_i^b - t_{i-1}^b$, $\delta_i = y_i - y_{i-1}$.

3. ON-LINE SUPERVISION

For on-line supervision: assigning i^n is the index of product. For a new product i^n processed on machine, the obtained data is used to calculate the health indicator and to estimate the RUL. We repeat again that the *time unit* here is the duration of processing a product on machine, thus, it is also the index of product.

3.1. Extraction of HI and filtering

From the equation (22), the value of raw health index at product i^n is calculated as:

$$I_0(i^n) = \mathcal{X}_c(i^n) \times P_{c1} \tag{30}$$

where $\mathcal{X}_{c}(i^{n}) = \begin{pmatrix} \bar{X}_{i^{n},k_{j1}}^{j1} & \bar{X}_{i^{n},k_{j2}}^{j2} & \dots & \bar{X}_{i^{n},k_{jS}}^{jS} \end{pmatrix}$, each value $\bar{X}_{i^{n},k_{js}}^{js}$ is computed from the raw measurement value $X_{i^{n},k_{is}}^{js}$ of online data as follows:

$$\bar{X}_{i^n,k_{js}}^{js} = \frac{X_{i^n,k_{js}}^{js} - m_{k_{js}}^{js}}{d_{k_{is}}^{js}}$$
(31)

 $m_{k_{js}}^{js}, d_{k_{js}}^{js}$ are respectively mean and standard deviation of the critical points (js, k_{js}) of off-line data, P_{c1} is the eigenvector given in subsection 2.1.

The curve I_0 for $1 \to i^n$ is then similarly filtered and the obtained health index called $Y_n(1 \to i_{max}^n)$, see 2.2.1.

3.2. RUL estimation

A failure threshold L is predefined. Supposing that the health index is increasing (if it decreases, the method is the same but with opposite signs). When Y_n exceeds the normal operating threshold T_N , the prognosis model is launched. The cumulative distribution function (cdf) of time to failure (Van Noortwijk, 2009) with the upper threshold L is:

$$F(t) = Pr\{T_L \le t\} = Pr\{X(t) \ge L\}$$
$$= \int_{x=L}^{\infty} f_{X(t)}(x)dx = \frac{\Gamma(\nu(t), Lu)}{\Gamma(\nu(t))}$$
(32)

where $\Gamma(a,x)=\int_{z=x}^\infty z^{a-1}e^{-z}dz$

At the moment t_n , the value of $X(t_n)$ is known as x_n . The definition of the RUL at time t_n can be represented by the first passage time of $\{X(t), t \ge t_n\}$ crossing L as $h_{t_n} = inf\{h_{t_n} : X(t_n + h_{t_n}) \ge L|X(t_n) < L\}$. The cdf of RUL can be written:

$$F(h_{t_n}) = Pr\{X(t_n + h_{t_n}) \ge L\}$$

= $Pr\{X(t_n + h_{t_n}) - X(t_n) \ge L - x_n\}$
= $\int_{x=L-x_n}^{\infty} Ga(\nu(h_{t_n} + t_n) - \nu(t_n), u)dx$
= $\frac{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n), (L - x_n)u)}{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n))}$ (33)

The probability density function (pdf) of RUL is:

$$f(h_{t_n}) = \frac{\delta}{\delta h_{t_n}} \left[\frac{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n), (L - x_n)u)}{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n))} \right]$$
(34)

The expected RUL is:

$$E(h_{t_n}) = \int_{h_{t_n}=0}^{\infty} h_{t_n} f(h_{t_n}) dh_{t_n}$$
(35)

The value of x_n is updated for the online supervision, which updated the RUL estimation.

4. APPLICATION

This section provides the result of application of the proposed method on real industrial data from STMicroelectronics. Measured variables are sampled at 1 second intervals during a process, for 351 observations of totally 19 sensors for one month of production, which represents about 1000 wafers from the first wafer to the last one. The data is preprocessed by Dynamic Time Warping technique to obtain the common length trajectories.

4.1. Off-line analysis

4.1.1. Health indicator extraction

The first two hundred wafers n = 200 are used to build the UCL of SPE. The last batch is considered *bad quality*. Fig. 5 gives the result of degradation detection. The violations before k = 20 are characterized as in short duration, appear on step/phase changes and not repeatable unit-to-unit, therefore, they are spurious violations. Meanwhile, the violations from k = 118 to k = 351 exhibit the drift of machine's quality, this is because of their long durations and their unit-to-unit repeat since the last wafers. The most observation at which the SPE is significant is k = 351. Thus, the contribution of SPE at this observation is investigated. The candidature sensors are 1, 2, 9, 10, 12 and 18.



Figure 5. Degradation detection and SPE contribution

The result of degradation reconstruction on these sensors are given in Fig. 6. We see that there are 4 cases whose reconstruction make SPE under the threshold UCL. The set of *case*

3 is the set which consists the common sensors of the others cases. Thus, the significant sensors are $\{9, 10, 18\}$. The critical point of these sensors are determined as given in Fig. 7. Then the HI extracted from these points are shown in Fig. 2.



Figure 6. Reconstruction of degradation



Figure 7. Variance of observation points of sensors

4.1.2. Analysis of health indicator dynamics

Applying the filtering proposed in 2.2.1, the health index Y is given in Fig. 8. The normal operating threshold is predefined $T_N = -0.5$ and the failure threshold is predefined L = 2.3.

The parameter result of *health indicator modelling* is u = 604.7, c = 0.94 and b = 1.15.



Figure 8. Health indicator

4.2. Online supervision

Assuming that the reference HI represents all the system dynamics of degradation in the considered operating mode; to validate the prognosis model, the online data is generated by a simulator which takes into account the dynamics of historical data. One profile of online HI is given in Fig. 9 compared to the off-line one (shifting forward with n=200). At each inspection time i^n , the available online data is known only for $t = 1, ..., i^n$. When $Y_n(i^n_{max}) > T_N$, (see section 3.1), the degradation alarm launches the prognosis model.



Figure 9. Online data

At each inspection time i^n , the real failure time is 731 thus the real RUL is $(731 - i^n)$. Hence, the estimate RUL (the expected RUL, equation (35)) and the real RUL can be compared as given in Fig. 10. The result shows that the RUL estimation of almost inspection times gives a small error. This error is really small during $i = 260 \rightarrow 430$ and $i = 530 \rightarrow 660$ due to the updating of last value of Y in the equation 33. However, from i = 673, the error becomes larger. The reason for this is found in Fig. 9, that the degradation (Y-online) decelerates during $i = 673 \rightarrow 704$ then it re-accelerates. The degradation is much fluctuating during some small intervals but the average rate of Y-online is generally fitted to Gamma process, that's why the error is smaller before i = 673. This profile is a particular example, which implies that the method adapts to the available data but an improvement of the proposed method is necessary to overcome the influences of local fluctuations.



Figure 10. Estimation error

The *root mean squared error* of RUL estimation is 49 time units (equivalent to the duration of processing 49 wafers or nearly 2 lots in STMicroelectronics manufacturing) is a small error.

5. CONCLUSION

This paper proposed a method of health indicator contribution for discrete manufacturing processes based on degraded sensors identification via degradation reconstruction. The Gamma process is used for HI modelling. An application of the proposed method on a real industrial case shows a small error of RUL estimation for the online supervision. A further improvement of the proposed method is necessary to overcome the influences of local fluctuations of HI in some particular situations.

REFERENCES

- Bakker, J., & van Noortwijk, J. (2004). Inspection validation model for life-cycle analysis. In Bridge maintenance, safety, management and cost, proceedings of the second international conference on bridge maintenance, safety and management (iabmas), kyoto, japan (p. 18-22).
- Gang, L., Qin, S. J., Ji, Y., & Zhou, D. (2010). Reconstruction based fault prognosis for continuous processes. *Control Engineering Practice*, 18(10), 1211-1219.
- Mnassri, B., El Adel, E. M., & Ouladsine, M. (2013). Generalization and analysis of sufficient conditions for pca-

based fault detectability and isolability. Annual Reviews in Control, 37(1), 154-162.

- Thieullen, A., Ouladsine, M., & Pinaton, J. (2012). A survey of health indicators and data-driven prognosis in semiconductor manufacturing process. In 8th ifac symposium on fault detection, supervision and safety of technical processes (safeprocess) (Vol. 8, p. 19-24).
- Van Noortwijk, J. (2009). A survey of the application of gamma processes in maintenance. *Reliability Engi*

neering & System Safety, 94(1), 2-21.

- Yue, H. H., & Qin, S. J. (2001). Reconstruction-based fault identification using a combined index. *Industrial and Engineering Chemistry Research*, 40(20), 4403-4414.
- Zhang, Y. (2008). Improved methods in statistical and first principles modeling for batch process control and monitoring (PhD dissertation). University of Texas, Austin.
Uncertainty in Prognostics and Health Management: An Overview

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ABSTRACT

This paper presents an overview of various aspects of uncertainty quantification in prognostics and health management. Since prognostics deals with predicting the future behavior of engineering systems and it is almost practically impossible to precisely predict future events, it is necessary to account for the different sources of uncertainty that affect prognostics, and develop a systematic framework for uncertainty quantification and management in this context. Researchers have developed computational methods for prognostics, both in the context of testing-based health management and conditionbased health management. However, one important issue is that, the interpretation of uncertainty for these two different types of situations is completely different. While both the frequentist (based on the presence of true variability) and Bayesian (based on subjective assessment) approaches are applicable in the context of testing-based health management, only the Bayesian approach is applicable in the context of condition-based health management. This paper explains that the computation of the remaining useful life is more meaningful in the context of condition-based monitoring and needs to be approached as an uncertainty propagation problem. Numerical examples are presented to illustrate the various concepts discussed in the paper.

1. INTRODUCTION

Prognostics is the art of predicting the future behavior of engineering systems, analyzing possible failure modes, and estimating the remaining useful life (RUL) of such systems. Since it is practically impossible to precisely predict future events and future behavior, it is imperative for an efficient and accurate Prognostics and Health Management (PHM) system to account for the different sources of uncertainty that are associated with system behavior and quantify the combined effect of these sources of uncertainty on prognostics and remaining useful life prediction in order to facilitate riskinformed decision-making.

Existing methods for prognostics and health management can be broadly classified as being applicable to two different types of situations: testing-based prognostics and condition-based prognostics. Methods for testing-based prognostics are based on rigorous testing before and/or after operating an engineering system (offline), whereas methods for condition-based prognostics are based on monitoring the performance of the engineering system during operation (online). Researchers have developed computational methods for both testing-based and condition-based prognostics and health management. Both data-driven methods and model-based approaches been pursued for these purposes. While some of the initial research efforts did not explicitly account for the effects of uncertainty, some of the later efforts have exclusively focused on uncertainty quantification and management in prognostics.

Several researchers have developed methods for uncertainty quantification in crack growth analysis (Sankararaman, Ling, Shantz, & Mahadevan, 2011; Sankararaman, Ling, & Mahadevan, 2011), structural damage prognosis (Farrar & Lieven, 2007; Coppe, Haftka, Kim, & Yuan, 2010), electronics (Gu, Barker, & Pecht, 2007), and mechanical bearings (Liao, Zhao, & Guo, 2006), primarily in the context of offline testing. Such approaches may be applicable to smaller components since it is possible and affordable to perform laboratory tests until these components fail. However, it may not practically feasible to extend this approach to large scale expensive systems that cannot be tested. Further, the estimation of remaining useful life is more significant in an online health monitoring context where the performance of a system under operation needs to be monitored and its remaining useful life needs to be calculated. Engel et. al (Engel, Gilmartin, Bongort, & Hess, 2000) discuss several issues involved in the estimation of remaining useful life in online prognostics and health monitoring. Though some of the initial studies on remaining useful life prediction lacked uncertainty mea-

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sures (Celaya, Saxena, Kulkarni, Saha, & Goebel, 2012), researchers have recently started investigating the impact of uncertainty on estimating the remaining useful life. For example, there have been several efforts to quantify the uncertainty in remaining useful life of batteries (Saha & Goebel, 2008) and pneumatic valves (Daigle & Goebel, 2010) in the context of online health monitoring. Different types of sampling techniques (Daigle, Saxena, & Goebel, 2012) and analytical methods (Sankararaman, Daigle, Saxena, & Goebel, 2013) have been proposed to predict the uncertainty in the remaining useful life.

A review of the aforementioned articles reveal that there exist several challenges in applying uncertainty quantification methods for prognostics. The primary challenge lies in the understanding the philosophical differences between testingbased health management and condition-based health management, since these differences significantly influence the interpretation of uncertainty (Sankararaman & Goebel, 2013c; Celaya, Saxena, & Goebel, 2012). Such interpretation is key to guide different types of decision-making activities during the operation of engineering systems.

The paper focuses on providing an overview of the state-ofthe-art in the topic of uncertainty quantification and management in prognostics and health monitoring. To begin with, the significance of uncertainty in prognostics is explained in detail in Section 2. Then, the various aspects of uncertainty in testing-based health management and condition-based health management are discussed in detail in Section 3 and 4, and the differences between these two approaches are clearly explained. It is also explained that the prediction of remaining useful life is more meaningful only in the context of conditionbased health management, and this topic is discussed in further detail. Numerical examples are presented in Sections 3 and Section 4, to illustrate the various concepts discussed in this paper. Finally, conclusions are presented in Section 5.

2. SIGNIFICANCE OF UNCERTAINTY IN PROGNOSTICS

In an ideal scenario, it would be possible to perfectly and precisely predict the behavior of engineering systems and facilitate decision-making with a significant amount of trust and confidence. However, this is not possible in practical engineering applications. First of all, it is almost impossible to be able to accurately predict the operating conditions and environmental conditions under which the system operates. Further, the future loading demands on the system cannot be precisely known in advance; for example, the future behavior of a simple electric vehicle depends upon several factors such as the driving terrain, climatic conditions, desired speed and acceleration, characteristics, properties, and parameters of the internal batteries, remaining charge, etc. While some factors are internal to the engineering system, other factors are external to the system. In order to be able to account for all of these factors and perform prognostics, it is necessary to acknowledge the presence of uncertainty in all of these factors and develop a systematic framework in order to account for these uncertainties in prognostics.

When information regarding uncertainty is used for decisionmaking, it can lead quantifying the amount of risk involved in different types of decisions. Risk consists of two important components: the likelihood of occurrence of adverse events and the cost associated with the occurrence of adverse events. While the latter can be easily quantified by analyzing the different types of losses that occur due to such occurrence of adverse events, the former can only be quantified by rigorously accounting for the different sources of uncertainty in prognostic and decision-making activities.

It is a common misconception that the effect of uncertainty can be included at latter stages of the analysis when the fundamental deterministic problem has been solved without accounting for uncertainty. It is necessary to account for uncertainty right from the initial stages of system-level conception through analysis, design, testing, and operations. During these stages, there are several types of activities that need to be performed in order to accurately account for the effect of uncertainty in prognostics.

In the context of prognostics and health management, uncertainties have been discussed from representation, quantification, and management points of view (Hastings, D. and Mc-Manus, H., 2004; Orchard, Kacprzynski, Goebel, Saha, & Vachtsevanos, 2008; Tang, Kacprzynski, Goebel, & Vachtsevanos, 2009). While these three are different processes, they are often confused with each other and interchangeably used. In this paper, the various tasks related to uncertainty quantification and management are classified into four, as explained below. These four tasks need to performed in order to accurately estimate the uncertainty in the RUL prediction and inform the decision-maker regarding such uncertainty.

Uncertainty Representation and Interpretation: The 1. first step is uncertainty representation and interpretation, which in many practical applications, is guided by the choice of modeling and simulation frameworks. There are several methods for uncertainty representation that vary in the level of granularity and detail. Some common theories include classical set theory, probability theory, fuzzy set theory, fuzzy measure (plausibility and belief) theory, rough set (upper and lower approximations) theory, etc. Amongst these theories, probability theory has been widely used in the PHM domain (Celaya, Saxena, & Goebel, 2012); even within the context of probabilistic methods, uncertainty can be interpreted and perceived in two different ways: frequentist (classical) versus subjective (Bayesian). While the former interpretation of uncertainty implies that uncertainty exists only when there is natural randomness across multiple nominally identical experiments, the latter facilitates associating uncertainty even with events that are not random and such uncertainty is simply reflective of the analyst's regarding the occurrence or non-occurrence of such events.

- Uncertainty Quantification: The second step is uncer-2. tainty quantification, that deals with identifying and characterizing the various sources of uncertainty that may affect prognostics and RUL estimation. It is important that these sources of uncertainty are incorporated into models and simulations as accurately as possible. The common sources of uncertainty in a typical PHM application include modeling errors, model parameters, sensor noise and measurement errors, state estimates (at the time at which prediction needs to be performed), future loading, operating and environmental conditions, etc. The goal in this step is to address each of these uncertainties separately and quantify them using probabilistic/statistical methods. The Kalman filter is essentially a Bayesian tool for uncertainty quantification, where the uncertainty in the states is estimated continuously as a function of time, based on data which is also typically available continuously as a function of time.
- Uncertainty Propagation: The third step is uncertainty 3. propagation and is most relevant to prognostics, since it accounts for all the previously quantified uncertainties and uses this information to predict (1) future states and the associated uncertainty; and (2) remaining useful life and the associated uncertainty. The former is computed by propagating the various sources of uncertainty through the prediction model. The latter is computed using the estimated uncertainty in the future states along with a Boolean threshold function which is used to indicate end-of-life. In this step, it is important to understand that the future states and remaining useful life predictions are simply dependent upon the various uncertainties characterized in the previous step, and therefore, the distribution type and distribution parameters of future states and remaining useful life should not be arbitrarily chosen. Sometimes, a normal (Gaussian) distribution has been assigned to the remaining useful life prediction; such an assignment is erroneous and the true probability distribution of RUL needs to be estimated though rigorous uncertainty propagation of the various sources of uncertainty through the state space model and the EOL threshold function, both of which may be non-linear in practice.
- 4. Uncertainty Management: The fourth and final step is uncertainty management, and it is unfortunate that, in several articles, the term "Uncertainty Management" has been used instead of uncertainty quantification and/or propagation. As a result, there are few publications that directly address the issue of uncertainty management. In general, uncertainty management is a term used to refer

to different activities which aid in managing uncertainty in condition-based maintenance during real-time operation. There are several aspects of uncertainty management. One aspect of uncertainty management attempts to answer the question: "Is it possible to improve the uncertainty estimates?" The answer to this question lies in identifying which sources of uncertainty are significant contributors to the uncertainty in the RUL prediction. For example, if the quality of the sensors can be improved, then it may be possible to obtain a better state estimate (with lesser uncertainty) during Kalman filtering, which may in turn lead to a less uncertain RUL prediction. Another aspect of uncertainty management deals with how uncertainty-related information can be used in the decision-making process. Future research needs to significantly focus on the different aspects of uncertainty management and develop computational methods for this purpose.

Most of the research in the PHM community pertains to the topics of uncertainty quantification and propagation; few articles have directly addressed the topic of uncertainty management. Even within the realm of uncertainty quantification and propagation, the estimates of uncertainty have sometimes been misinterpreted. For example, when statistical principles are used to estimate a parameter, there is an emphasis on calculating the estimate with the minimum variance. When this principle is applied to RUL estimation, it is important not to arbitrarily reduce the variance of RUL itself. Celaya et al. (Celaya, Saxena, & Goebel, 2012) explored this idea and explained that the variance of RUL needs to be carefully calculated by accounting for the different sources of uncertainty. The calculation of RUL is, arguably, the most important component of a prognostics and health management system, and this topic of discussed in detail, in the rest of this paper. Though the majority of this paper focuses on calculating RUL in the context of condition-based monitoring, some fundamental principles of testing-based health management are discussed, particularly from the perspective of uncertainty quantification, in order to explain the philosophical differences between these two approaches.

3. TESTING-BASED HEALTH MANAGEMENT

In testing-based prognostics (referred to as "reliability-based testing" in some publications), the remaining useful life is typically calculated by testing multiple nominally identical specimens of the engineering component/system. It may be noted that the term "remaining" in "remaining useful life" may not be applicable to all types of testing. This is because, testing is typically carried out before the engineering system is under operation. The term "time-to-failure" is more appropriate for testing-based health management. It is important not to confound "time-to-failure" and "remaining useful life". The appropriate interpretation of the latter will be clarified

in the next section, while discussing about condition-based health management.

Assume that a set of run to failure experiments have been performed with high level of control, ensuring same usage and operating conditions. The time to failure for all the n samples $(r_i; i = 1 \text{ to } n)$ are measured. It is important to understand that *different* time-to-failure values are obtained due to inherent variability across the n different specimens, thereby confirming the presence of physical probabilities or true randomness. The various factors that contribute are:

- 1. Inherent variability in properties and characteristics of the nominally identical specimens
- 2. Inherent variability across the loading conditions experienced by each of the individual specimens
- 3. Inherent variability in operating and environmental conditions for each of the individual specimens

Assume that these random samples belong to an underlying probability density function (PDF) $f_R(r)$, with expected value $E(R) = \mu$ and variance $Var(R) = \sigma^2$. The goal of uncertainty quantification is to characterize this probability density function based on the available n data. Theoretically, an infinite amount of data is necessary to accurately estimate this PDF; however, due to the presence limited data, the estimated PDF is not accurate. Hence, lack of infinite data adds some additional uncertainty to the aforementioned list of sources of uncertainty. Statistical approaches, both frequentist and subjective, express uncertainty regarding the estimate itself. However, frequentist and subjective analysts quantify and express this uncertainty in completely different ways. The following discussion is based on the assumption that the underlying PDF $f_R(r)$ is Gaussian, since closed form expressions for uncertainty are readily available for this case. Whenever appropriate and necessary, remarks are provided for non-Gaussian distributions.

3.1. Confidence Intervals: Frequentist Approach

Since R is Gaussian, estimating the parameters μ and σ is equivalent to estimating the PDF. In the context of physical probabilities (frequentist approach), the "true" underlying parameters μ and σ are referred to as "population mean" and "population standard deviation" respectively. Let \bar{x} and s denote the mean and the standard deviation of the available ndata. As stated earlier, due to the presence of limited data, the sample parameters $(\bar{x} \text{ and } s)$ will not be equal to the corresponding population parameters (μ and σ). The fundamental assumption in this approach is that, since there are true but unknown population parameters, it is meaningless to talk about the probability distribution of any population parameter. Instead, the sample parameters are treated as random variables, i.e., if another set of n data were available, then another realization of \bar{x} and s would have been obtained. Using the sample parameters (μ and σ) and the number of data available (n), frequentists construct confidence intervals on the population parameters.

Confidence intervals can be constructed for both μ and σ (Haldar & Mahadevan, 2000). Consider multiple nominally identical specimens of an engineering component. The term "nominally identical" implies that there is inherent variability in the properties and behavior of these specimens. Suppose that these specimens have been subjective to failure analysis, and their time-to-failure times are available. If the true probability distribution of time-to-failure across multiple specimens is *assumed* to be Gaussian, the $(1 - \alpha)\%$ confidence interval of the mean run-to-failure time can be calculated as:

$$\left[\bar{x} - t_{\frac{\alpha}{2}} \frac{s}{\sqrt{n}}, \bar{x} + t_{\frac{\alpha}{2}} \frac{s}{\sqrt{n}}\right],$$

where \bar{x} , s, and n denote the sample mean, sample standard deviation, and number of samples respectively. If the runto-failure times are given by {100, 105, 98, 110, 92, 97, 85, 120, 93, 101}, then $\mu = 100.10$, s = 9.87, n = 10, and the 95% confidence interval on the mean run-to-failure is given by [93.98, 106.22]. Using the properties of the chi-square distribution (χ^2), the confidence interval on the variance can be calculated as:

$$\frac{(n-1)s^2}{\chi^2_{1-\frac{\alpha}{2}}}, \frac{(n-1)s^2}{\chi^2_{\frac{\alpha}{2}}}$$

For this numerical example, the corresponding confidence interval on the standard deviation is given by [6.79, 18.02]. While the above expressions for confidence intervals on mean and standard deviation are applicable only to Gaussian distributions, similar confidence intervals can also be constructed for other types of distributions; in general, it is easier to construct confidence intervals for mean than it is for standard deviation (or equivalently, variance).

Nevertheless, it is important that these confidence intervals be interpreted correctly. To begin with, the above confidence intervals will decrease as more data is available; therefore, the width of these confidence intervals is simply related to the number of data. The actual uncertainty in the run-to-failures times is given only by the estimate of the standard deviation, and this uncertainty is the result of variability (in material properties, operating conditions, etc.) across all the nominally identical specimens. Further, as stated earlier, the interpretation of confidence intervals may be confusing and misleading. A 95% confidence interval on μ does not imply that "the probability that μ lies in the interval is equal to 95%"; such a statement is wrong because μ is purely deterministic and physical probabilities cannot be associated with it. The random variable here is in fact \bar{x} , and the confidence interval is calculated using \bar{x} . Therefore, the correct implication is that "the probability that the estimated confidence interval contains the true population mean is equal to 95%". Thus, it is easy to understand that, the width of the confidence intervals is indicative of lack of infinite data and the actual value of the standard deviation is indicative of the uncertainty in *R*.

A practical challenge is that, in many applications, it may not be possible to know what type of probability distribution (for example, Gaussian distribution had been "assumed" in the above discussion) needs to be assumed to in order to calculate the above confidence intervals; obviously, the procedure for calculation of confidence intervals depends on the choice of distribution type (Gaussian, Weibull, lognormal, etc.), and the presence of such distribution type uncertainty further adds to the confusion regarding the interpretation of confidence intervals. As the sample size increases, the confidence intervals for the mean and standard deviation may get narrower. This may be misleading since the confidence intervals should be interpreted only based on the underlying assumption of distribution type (which might have been wrong to begin with). Computational methods are being developed to deal with distribution type uncertainty (Sankararaman & Mahadevan, 2013a), however they have not been implemented in prognostics and health management applications.

3.2. Probability Distribution: Bayesian Approach

Alternatively, it is also possible to address the problem of computing $f_R(r)$ purely from a subjective (Bayesian) point of view. One important difference now is that the Bayesian approach does not clearly differentiate between "sample parameters" and "population parameters". The probability distribution of μ is directly computed using the available data (recall that this was impossible in the frequentist approach since μ is the underlying mean that is precise but unknown), and this uncertainty is referred to as the analyst's degree of belief for the underlying true parameter μ . Similarly, the probability distribution of σ can also be computed using Bayes' theorem.

Consider a set of time-to-failure times, given by r_i (i = 1 to n). In order to compute the probability distribution of μ and σ , the first step is construct their joint likelihood as (Sankararaman & Mahadevan, 2011):

$$L(\mu,\sigma) \propto \prod_{i=1}^{m} f_R(r_i|\mu,\sigma)$$
(1)

The maximum likelihood estimate of the parameters P can be calculated by maximizing the above expression. Instead of maximizing the likelihood, the entire likelihood function can be used to construct the PDF of the distribution parameters. Further, sometimes time-to-failure data may also be available in terms of intervals. For example, intermittent inspections may be performed to check whether failure has occurred in a specimen; if failure is found to have occurred between 10 minutes and 11 minutes, the resultant time to failure is actually an interval. The above likelihood-based approach can also be extended to account for interval data, in order to compute the uncertainty in the distribution parameters.

This approach is generally applicable for any type of parametric probability distribution, where the probability density function (PDF) can be expressed as $f_R(r|P)$. If R is Gaussian, then P represents the vector of mean and standard deviation. Let f(P) denote the joint PDF of the distribution parameters P. It is easy to apply Bayes theorem, choose uniform prior density (f'(P) = h), and calculate the joint PDF as:

$$f(\mathbf{P}) = \frac{hL(\mathbf{P})}{\int hL(\mathbf{P})d\mathbf{P}} = \frac{L(\mathbf{P})}{\int L(\mathbf{P})d\mathbf{P}}$$
(2)

Note that the uniform prior density function can be defined over the entire admissible range of the parameters P. For example, the mean of a normal distribution can vary in $(-\infty, \infty)$) while the standard deviation can vary in $(0, \infty)$ because the standard deviation is always greater than zero. Both these prior distributions are improper prior distributions because they do not have finite bounds.

For the above numerical example, i.e., if the run-to-failure times are given by {100, 105, 98, 110, 92, 97, 85, 120, 93, 101}, the probability distribution of μ and σ can be calculated as shown in Figs. 1 and 2.



Recall that one realization of the parameters (μ and σ) uniquely define the PDF $f_R(r)$. However, since the parameters are themselves uncertain, R is now represented by a family of distributions (Sankararaman & Mahadevan, 2011, 2013b). This family of distributions will shrink to the true underlying PDF as the number of available data increases, and asymptotic PDF (as the number data increases) is simply reflective of the variability (in material properties, operating conditions, etc.) across all the nominally identical specimens. Alternative to the family of PDFs approach, a single unconditional PDF of X, which includes both the variability in X and the uncertainty in the distribution parameters P, as:

$$f'_{R}(r) = \int f_{R}(r|\boldsymbol{P})f(\boldsymbol{P})d\boldsymbol{P}$$
(3)



Note that the RHS of Eq. 3 is not conditioned on *P* anymore. Some researchers refer to this PDF $f'_R(r)$ as the predictive PDF (Kiureghian, 1989) of R. The predictive PDF for the above numerical example is shown in Fig. 3.





Note that the predictive PDF $f'_R(r)$ will indicate the presence of larger uncertainty in R than the original PDF $f_R(r)$, because the former accounts for the lack of infinite data. As the number of data increases, $f'_R(r)$ will tend towards $f_R(r)$. Of course, this is true only when the correct distribution type was assumed for R; in many cases, the choice of distribution type (referred to as "statistical model" by some researchers) is a challenge by itself, and contributes to additional uncertainty (Sankararaman & Mahadevan, 2013a).

4. CONDITION-BASED HEALTH MANAGEMENT

Most of the discussion pertaining to testing-based prognostics is not applicable to condition-based monitoring and prognostics. The distinctive feature of condition-based monitoring is that each component/subsystem/system is considered by itself, and therefore, "variability across specimens" is nonexistent. Any such "variability" is spurious and must not be considered. At any generic time instant t_P at which prognostics needs to be performed, the component/subsystem/system is at a specific state. The actual state of the system is purely deterministic, i.e., the true value of each state is completely precise, however unknown. Therefore, if a probability distribution is assigned for this state, then this distribution is simply reflective of the analyst's knowledge regarding this state and cannot be interpreted from a frequentist point of view. Thus, by virtue of definition of condition-based monitoring, physical probabilities are not present here, and a subjective (Bayesian) approach is only suitable for uncertainty quantification.

The goal in condition-based prognostics is, at any generic time instant t_P , to predict the remaining useful life of the component/subsystem/system as condition-based estimate of the usage time left until failure. Such computation needs to be, ideally, performed in real-time. In other words, the performance of the system during its operation needs to be analyzed, possible failure modes and future degradation needs to be prediction, and the remaining useful life needs to be computed while the system is under operation. These calculations help in operational decision-making activities such as path planning, mission routing, etc.

The following prognostics architecture can be used to achieve these goals. First, measurements until time t_P are used to estimate the state at time t_P . Then, using a degradationprediction model (that may be model-based or data-driven), future state values (corresponding to time instants greater than t_P) are computed, and the first time time instant at which a failure threshold is true is calculated; this information is then used to calculate the remaining useful life. In order to forecast future state values, it is also necessary to assume future loading conditions (and operating conditions), and this is a major challenge in condition-based prognostics. Typically, the analyst subjectively assumes statistics for future loading conditions based on past experience and existing knowledge; thus, the subjective interpretation of uncertainty is clearly consistent across the entire condition-based monitoring procedure, and therefore, inferences made out of condition-based monitoring also need to be interpreted subjectively. The prediction of degradation (forecasting of future state values) is stopped when failure is reached, as indicated by a boolean threshold function that checks whether failure has occurred or not. This indicates the end-of-life (EOL) and the EOL can be directly used to compute the remaining useful life (RUL) prediction. Note that it is important to interpret the uncertainty in EOL and RUL subjectively.

4.1. Illustrative Example

Consider a generic engineering component whose health state at any time instant is given by x(t). Consider a simple degradation model, where the rate of degradation of the health state (that decreases with time, due to the presence of damage) is proportional to the current health state. This can be mathematically expressed as:

$$\dot{x}(t) \propto x(t),$$
 (4)

where the constant of proportionality is a negative number. Since differential equations are usually solved by considering discrete time instants, the above equation can be rewritten as:

$$x(k+1) = a.x(k) + b,$$
 (5)

where k represents the discretized time-index. The condition that "the constant of proportionality in Eq. 4 is negative" is equivalent to the condition that "a < 1 in Eq. 5". For the sake of illustration, let a denote the loading on the system, b denote the model of the degradation model above, and let a and b be constant and time-invariant. In practical examples, more than one variable may be necessary to represent the loading conditions and there may be multiple model parameters and state variables; further, the loading variables and model parameters may also be time-varying, just like the state x.

In order to compute the remaining useful life, it is necessary to chose a threshold function that defines the occurrence of failure. Since x(k) is a decreasing function, the threshold function will indicate that failure occurs when the state value x becomes smaller than a critical lower bound (l), and the first time instant at which this event occurs indicates the end of life, and this time instant can be used to calculate the RUL. Therefore, the remaining useful life (r, an instance of the random variable <math>R) is equal to the smallest n such that x(n) < l. Therefore RUL can be calculated as

$$r = \inf\{n : x(n) < l\},\tag{6}$$

For a given value of x(0) (or $x(t_P)$, where t_P denotes the time at which prediction needs to be performed), a, b, it possible to calculate the end-of-life and remaining useful life using the above set of equations. However, in practical conditions, all of these are uncertain. However, note that the uncertainty in x(0), a, b are related only to the knowledge regarding this particular unit and not an ensemble of units; recall that an ensemble of nominally identical units was considered earlier in Section 3. The presence of these uncertainties leads to uncertainty in the RUL prediction. This leads to the obvious question: How to compute the uncertainty in RUL? Prior to answering this question, the next subsection lists the different sources of uncertainty in generic condition-based prognostic applications.

4.2. Sources of Uncertainty

Typically, researchers have classified the different sources of uncertainty into different categories in order to facilitate uncertainty quantification and management. While it has been customary to classify the different sources of uncertainty into aleatory (arising due to physical variability) and epistemic (arising due to lack of knowledge), such a classification may not be suitable for prognostics in the context of conditionbased monitoring and RUL prediction because, as mentioned earlier, "true variability" is not present in condition-based monitoring. A completely different approach for classification, particularly applicable to condition-based monitoring, is proposed in this paper.

- 1. Present uncertainty: Prior to prognosis, it is important to be able to precisely estimate the condition/state of the component/system at the time at which RUL needs to be predicted. Typically, damage (or faults) are expressed in terms of states, and therefore, estimating the state is equivalent to estimating the extent of damage (or fault). This is related to state estimation and is commonly addressed using filtering. Output data (usually collected through sensors) is used to estimate the state and many filtering approaches (Kalman filtering, particle filtering, etc.) are able to provide an estimate of the uncertainty in the state. In the illustrative example, the state uncertainty is equal to the uncertainty associated with x(0). Practically, it is possible to improve the estimate of the states and thereby reduce this uncertainty, by using better sensors and improved filtering approaches. It is important to understand that the system is at particular state at any time instant, and the aforementioned uncertainty simply describes the lack of knowledge regarding the "true" state of the system.
- 2. Future uncertainty: The most important source of uncertainty in the context of prognostics is due to the fact that the future is unknown, i.e. the loading, operating, environmental, and usage conditions are not known precisely, and it is important to assess this uncertainty before performing prognosis. In the illustrative example, the future uncertainty is equal to the uncertainty regarding the loading value, i.e., *a*, from the time of prediction until the time of failure. If there is no uncertainty regarding the future, then there would be no uncertainty regarding the *true* remaining useful life of the engineering component/system. However, this true RUL needs to be estimated using a model; the usage of a model imparts additional uncertainty as explained below.
- 3. **Modeling uncertainty:** It is necessary to use a functional degradation model in order to predict future state behavior, i.e. model the response of the system to anticipated loading, environmental, operational, and usage conditions. Further, the end-of-life is also defined using a Boolean threshold functional model, that is used to indicate whether failure has occurred or not. These two models are jointly used to predict the RUL, and they may either be physics-based or data-driven. It may be practically impossible develop models that accurately predict the underlying reality. Modeling uncertainty represents

the difference between the predicted response and the true response (that can neither be known nor measured accurately), and comprises of several parts: model parameters, model form, and process noise. While it may be possible to quantify these terms until the time of prediction, it is challenging to know their values at future time instants. In the illustrative example, Eq. 5 represents the degradation model, x(n) < l represents the Boolean threshold function that indicates failure, b is a model parameter, and the uncertainty in b corresponds to one aspect of modeling uncertainty. Another aspect is the choice of the "linear" form of the model in Eq. 5; the underlying physical phenomena may differ from this assumption.

4. Prediction method uncertainty: Even if all the above sources of uncertainty can be quantified accurately, it is necessary to quantify their combined effect on the RUL prediction, and thereby, quantify the overall uncertainty in the RUL prediction. It may not be possible to do this accurately and this leads to additional uncertainty. For example, when sampling-based approaches are used for prediction, the use of limited number of samples causes uncertainty regarding the estimated probability distribution.

4.3. Computing Uncertainty in RUL

The goal in condition-based prognostics is to meaningfully integrate the degradation equation along with the failure threshold equation, and account for the different sources of uncertainty in x(0), a, and b, and thereby, estimate the uncertainty in the remaining useful life. For any given realization of x_0 , a, and b, it is possible to compute the first time instant (indicates the end-of-life) at which the failure threshold criteria will be valid, i.e., calculate the smallest value of n at which x(n) < l. The challenge is to compute the combined effect of uncertainty in x(0), a, and b on RUL, and estimate the probability distribution of RUL.

It can be easily demonstrated that the state value at any future time instant can be expressed as a function of the initial state x(0), as:

$$x(n) = a^{n} \cdot x(0) + \sum_{j=0}^{j=n-1} a^{j}b$$
(7)

Note that that x(n) is decreasing and failure happens when x < l. Therefore, the remaining useful life (r, an instance of the random variable <math>R) is equal to the smallest n such that x(n) < l. Therefore RUL can be calculated as

$$r = \inf\{n : a^n \cdot x(0) + \sum_{j=0}^{j=n-1} a^j b < l\},$$
(8)

Assuming that the chosen time-discretization level is infinites-

imally small, it is possible to directly estimate the RUL by solving the equation:

$$a^{r}.x(0) + \sum_{j=0}^{j=r-1} a^{j}.b = l.$$
 (9)

The above equation calculates the RUL (r) as a function of the initial state x(0), a and b. Even if the only considered source of uncertainty is the state estimate x(0) (that is, a and b are constants), RUL R follows a Gaussian distribution if and only if it is linearly dependent on x(0). In other words, R follows a Gaussian distribution if and only if Eq. 9 can be rewritten as:

$$\alpha . r + \beta . x(0) + \gamma = 0 \tag{10}$$

for some arbitrary values of α , β , and γ . If it were possible to estimate such values for α , β , and γ , the distribution of RUL can be obtained analytically.

In order to examine if this is possible, rewrite Eq. 9 as:

$$x(0) = \frac{1}{a^r} \left(l - \sum_{j=0}^{j=r-1} a^j b\right)$$
(11)

While x(0) is completely on the left hand side of this equation, r appears not only as an exponent in the denominator but is also indicative of the number of terms in the summation on the right hand side of the above equation. Therefore, it is clear that the relationship between r and x(0) is not linear. Therefore, even if the initial state (x(0), a realization of X(0)) follows a Gaussian distribution, the RUL $(r, a \text{ real$ $ization of } R)$ does not follow a Gaussian distribution. Furthermore, it is not even possible to analytically estimate the distribution of RUL. Thus, it is clear that even for a simple problem consisting of linear state models, an extremely simple threshold function, and only one uncertain variable that is Gaussian, the calculation of the probability distribution of Ris neither trivial nor straightforward.

Practical problems in the prognostics and health management domain may consist of:

- 1. Several non-Gaussian random variables that affect the RUL prediction,
- 2. A non-linear multi-dimensional state space model,
- 3. Uncertain future loading conditions
- 4. A complicated threshold function that may be defined in multi-dimensional space.

The fact that the distribution of RUL simply depends on quantities such as degradation model and model parameters, threshold function, state estimate, future loading conditions, etc., implies that it is technically inaccurate to artificially assign the probability distribution type (or any statistic such as the mean or variance) to RUL. It is important to understand that RUL is a dependent quantity and that the probability distribution of RUL needs to be accurately estimated using computational approaches. It has been illustrated the the problem of computing the uncertainty in the RUL prediction can be posed as an uncertainty propagation problem (Sankararaman & Goebel, 2013b), and therefore, it may be helpful to investigate statistical uncertainty propagation techniques in order to accomplish this goal.

4.4. Uncertainty Propagation Methods

The most commonly used uncertainty propagation technique is Monte Carlo sampling (Caflisch, 1998), which is based on drawing random samples of independent quantities, and computing corresponding realizations of the dependent quantity (in this case, the RUL). For instance, in the conceptual example, if x(0) follows a Gaussian distribution (with mean and standard deviation equal to 975 and 50 respectively), a follows a uniform distribution (with lower and upper bounds of 0.990 and 0.995), and b follows a uniform distribution (with lower and upper bounds of -0.005 and 0 respectively), then the RUL (defined by Eq. 6, where l = 50) can calculated as a probability distribution, using Monte Carlo sampling. Using unit discretization (i.e., the time interval between the k^{th} and $(k+1)^t h$ instants is equal to one second) for solution, the resultant probability density function (PDF) is shown in Fig. 4. It is clear that this distribution is not a typical parametric distribution (such as normal, lognormal, etc.) and that is why rigorous uncertainty propagation methods are necessary to accurate estimate this PDF.



While Monte Carlo sampling can be accurate, it is computationally expensive and time-consuming, and therefore, researchers have focused on developing advanced methods that are computationally cheaper. These approaches include Latin hypercube sampling (Loh, 1996), adaptive sampling (Bucher, 1988), importance sampling (Glynn & Iglehart, 1989), unscented transform sampling (Van Zandt, 2001), etc. Alternatively, there are analytical methods such as the first-order second moment method (Dolinski, 1983), first-order reliability method (Hohenbichler & Rackwitz, 1983; Sankararaman & Goebel, 2013a), second-order reliability method (Der Ki-

ureghian, Lin, & Hwang, 1987), etc. In addition, there are also methods such as the efficient global reliability analysis (Bichon, Eldred, Swiler, Mahadevan, & McFarland, 2008) method which involve both sampling and the use of analytical techniques. All of these methods empirically calculate the probability distribution of RUL; while some of these methods calculate the PDF ($f_R(r)$) of RUL, some other methods calculate the CDF ($F_R(r)$), and some other methods directly generate samples from the desired probability density function $(f_R(r))$. Due to some limitations of each of these methods, it may not be possible to accurately calculate the actual probability distribution of R. Accurate calculation is possible only by using infinite samples for Monte Carlo sampling. Any other method (for example, the use of a limited, finite number of samples) will lead to uncertainty in the estimated probability distribution, and this additional uncertainty is referred to as prediction-method uncertainty. It is possible to decrease (and maybe eventually eliminate) this type of uncertainty either by using advanced probability techniques or powerful computing power.

It is necessary to further investigate the aforementioned uncertainty propagation methods, and identify whether they can be applied to prognostics health monitoring. Some earlier publications have investigated the use of certain methods such as Monte Carlo sampling, unscented transform sampling, firstorder reliability methods, etc. in this regard.

5. CONCLUSION

This paper presented an overview of uncertainty quantification in prognostics and health management in engineering systems. First, the significance of the uncertainty in prognostics was explained, and the need for a systematic approach to account for uncertainty in prognostics was discussed. It was explained that four different activities - uncertainty representation and interpretation, uncertainty quantification, uncertainty propagation, and uncertainty management — need to be performed in order to rigorously include the effects of uncertainty in prognostics and provide useful information for decision-making under uncertainty. Researchers have pursued two different approaches for prognostics, and these two approaches are based on testing and condition-based assessment. The philosophical differences between these two approaches were explained and it was demonstrated that the concept of remaining useful life is more meaningful in the context of condition-based assessment since the engineering system is under operation. Further, these differences are used to analyze the interpretation of uncertainty in prognostics.

Probability and uncertainty can be interpreted in two ways. The frequentist interpretation of uncertainty is applicable in the presence of true randomness, as is the case in testingbased health management. The Bayesian (subjective) interpretation of uncertainty is applicable even while talking about events that may not be random, and therefore, this interpretation is applicable for both testing-based health management and condition-based health management. In fact, only the Bayesian interpretation of uncertainty is applicable in conditionbased health management. Techniques such as Kalman filtering, particle filtering, etc. that are commonly used in conditionbased prognostics are collectively known as Bayesian tracking algorithms, not only because they use Bayes theorem but also because they are based on the subjective interpretation probability. Numerical examples were discussed in order to illustrate the effects of uncertainty interpretation on prognostics.

The final goal of this paper was to investigate methods for computation of remaining useful life, in the context of conditionbased prognostics. It was illustrated that it is not possible to analytically calculate the uncertainty in the remaining useful life prediction even for certain simple problems involving Gaussian random variables and linear state-prediction models. Therefore, it is necessary to resort to computational methodologies for such uncertainty quantification and compute the probability distribution of remaining useful life prediction. While different types of uncertainty quantification methodologies were discussed, there are still several challenges that exist in this regard (Sankararaman & Goebel, 2014), and further research is necessary to investigate the applicability of these methods to prognostics and health monitoring applications.

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REFERENCES

- Bichon, B., Eldred, M., Swiler, L., Mahadevan, S., & McFarland, J. (2008). Efficient global reliability analysis for nonlinear implicit performance functions. *AIAA journal*, 46(10), 2459–2468.
- Bucher, C. G. (1988). Adaptive samplingan iterative fast monte carlo procedure. *Structural Safety*, *5*(2), 119–126.
- Caflisch, R. E. (1998). Monte carlo and quasi-monte carlo methods. *Acta numerica*, 1998, 1–49.
- Celaya, J., Saxena, A., & Goebel, K. (2012). Uncertainty representation and interpretation in model-based prognostics algorithms based on kalman filter estimation. In *Proceedings of the Annual Conference of the PHM Society* (pp. 23–27).

- Celaya, J., Saxena, A., Kulkarni, C., Saha, S., & Goebel, K. (2012). Prognostics approach for power MOSFET under thermal-stress aging. In *Reliability and Maintainability Symposium (RAMS)*, 2012 Proceedings-Annual (pp. 1–6).
- Coppe, A., Haftka, R. T., Kim, N. H., & Yuan, F.-G. (2010). Uncertainty reduction of damage growth properties using structural health monitoring. *Journal of Aircraft*, 47(6), 2030–2038.
- Daigle, M., & Goebel, K. (2010). Model-based prognostics under limited sensing. In *Aerospace Conference*, 2010 *IEEE* (pp. 1–12).
- Daigle, M., Saxena, A., & Goebel, K. (2012). An efficient deterministic approach to model-based prediction uncertainty estimation. In *Annual conference of the prognostics and health management society* (pp. 326–335).
- Der Kiureghian, A., Lin, H.-Z., & Hwang, S.-J. (1987). Second-order reliability approximations. *Journal of Engineering Mechanics*, 113(8), 1208–1225.
- Dolinski, K. (1983). First-order second-moment approximation in reliability of structural systems: critical review and alternative approach. *Structural Safety*, *1*(3), 211– 231.
- Engel, S. J., Gilmartin, B. J., Bongort, K., & Hess, A. (2000). Prognostics, the real issues involved with predicting life remaining. In *Aerospace Conference Proceedings*, 2000 IEEE (Vol. 6, pp. 457–469).
- Farrar, C. R., & Lieven, N. A. (2007). Damage prognosis: the future of structural health monitoring. *Philosophi*cal Transactions of the Royal Society A: Mathematical, *Physical and Engineering Sciences*, 365(1851), 623– 632.
- Glynn, P. W., & Iglehart, D. L. (1989). Importance sampling for stochastic simulations. *Management Science*, 35(11), 1367–1392.
- Gu, J., Barker, D., & Pecht, M. (2007). Uncertainty assessment of prognostics of electronics subject to random vibration. In AAAI fall symposium on artificial intelligence for prognostics (pp. 50–57).
- Haldar, A., & Mahadevan, S. (2000). *Probability, reliability, and statistical methods in engineering design.* John Wiley & Sons, Incorporated.
- Hastings, D. and McManus, H. (2004). A framework for understanding uncertainty and its mitigation and exploitation in complex systems. In *Engineering Systems Symposium MIT* (p. 19). Cambridge MA..
- Hohenbichler, M., & Rackwitz, R. (1983). First-order concepts in system reliability. *Structural safety*, *1*(3), 177– 188.
- Kiureghian, A. D. (1989). Measures of structural safety under imperfect states of knowledge. *Journal of Structural Engineering*, 115(5), 1119–1140.
- Liao, H., Zhao, W., & Guo, H. (2006). Predicting remaining useful life of an individual unit using proportional haz-

ards model and logistic regression model. In *Reliability* and *Maintainability Symposium*, 2006. *RAMS'06*. Annual (pp. 127–132).

- Loh, W.-L. (1996). On latin hypercube sampling. *The annals* of statistics, 24(5), 2058–2080.
- Orchard, M., Kacprzynski, G., Goebel, K., Saha, B., & Vachtsevanos, G. (2008, oct.). Advances in uncertainty representation and management for particle filtering applied to prognostics. In *Prognostics and Health Management, 2008. PHM 2008. International Conference* on (p. 1 -6). doi: 10.1109/PHM.2008.4711433
- Saha, B., & Goebel, K. (2008). Uncertainty management for diagnostics and prognostics of batteries using Bayesian techniques. In *Aerospace Conference*, 2008 IEEE (pp. 1–8).
- Sankararaman, S., Daigle, M., Saxena, A., & Goebel, K. (2013). Analytical algorithms to quantify the uncertainty in remaining useful life prediction. In *Aerospace Conference*, 2013 IEEE (pp. 1–11).
- Sankararaman, S., & Goebel, K. (2013a). A novel computational methodology for uncertainty quantification in prognostics using the most probable point concept. In *Annual conference of the prognostics and health management society.*
- Sankararaman, S., & Goebel, K. (2013b). Remaining useful life estimation in prognosis: An uncertainty propagation problem. In 2013 aiaa infotech@ aerospace conference.
- Sankararaman, S., & Goebel, K. (2013c). Why is the remaining useful life prediction uncertain? In Annual conference of the prognostics and health management society.
- Sankararaman, S., & Goebel, K. (2014). Uncertainty in prognostics: Computational methods and practical challenges. In *Aerospace Conference*, 2014 IEEE (pp. 1– 9).
- Sankararaman, S., Ling, Y., & Mahadevan, S. (2011). Uncertainty quantification and model validation of fatigue crack growth prediction. *Engineering Fracture Mechanics*, 78(7), 1487–1504.
- Sankararaman, S., Ling, Y., Shantz, C., & Mahadevan, S. (2011). Uncertainty quantification in fatigue crack growth prognosis. *International Journal of Prognostics and Health Management*, 2(1), 15 pages.
- Sankararaman, S., & Mahadevan, S. (2011). Likelihoodbased representation of epistemic uncertainty due to sparse point data and/or interval data. *Reliability En*gineering & System Safety, 96(7), 814–824.
- Sankararaman, S., & Mahadevan, S. (2013a). Distribution type uncertainty due to sparse and imprecise data. *Mechanical Systems and Signal Processing*, 37(1), 182– 198.

- Sankararaman, S., & Mahadevan, S. (2013b). Separating the contributions of variability and parameter uncertainty in probability distributions. *Reliability Engineering & System Safety*, 112, 187–199.
- Tang, L., Kacprzynski, G., Goebel, K., & Vachtsevanos, G. (2009, march). Methodologies for uncertainty management in prognostics. In *Aerospace conference*, 2009 *IEEE* (p. 1 -12).
- Van Zandt, J. R. (2001). A more robust unscented transform. In *International symposium on optical science and technology* (pp. 371–380).

BIOGRAPHIES



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Quantification of Signal Reconstruction Uncertainty in Fault Detection Systems

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ABSTRACT

In Condition-Based Maintenance (CBM), Fault Detection (FD) systems monitor the health state of the components and aid the operator to decide whether a maintenance intervention is necessary. A FD system is a decision-aid tool typically based on i) a reconstruction model that estimates (reconstructs) the values of measurable signals in normal conditions, and ii) an analyzer of the differences (residuals) between the measured and reconstructed values: abnormal conditions are detected when residuals are statistically significant. The performance of the reconstruction model is influenced by several sources of uncertainty which can influence the operator decision: 1) measurement errors, 2) intrinsic stochasticity of the physical process, 3) uncertainty on the settings of the model parameters, and 4) uncertainty on the model output due to incompleteness of the training data. The objective of the present work is the quantification overall uncertainty affecting the of the model reconstructions. The proposed novel approach for uncertainty quantification relies on the estimation of Prediction Intervals (PIs) by using Order Statistics (OS) for a pre-defined confidence level. The proposed approach is verified with respect to an artificial case study; the obtained results show that the approach is able to guarantee the desired level of confidence on the correctness of the detection and provide the decision maker with the required information for establishing whether a maintenance intervention is necessary.

Keywords: Signal Reconstruction, Fault Detection, Uncertainty, Prediction Intervals, Auto-Associative Kernel Regression, Order Statistics, Scale Factor.

1. INTRODUCTION

Recent developments in data processing and computational capabilities are encouraging industries such as nuclear, oil and gas, chemical, automotive and aerospace to apply Condition-Based Maintenance (CBM) (Campos, 2009) for increasing system availability, reducing maintenance costs, minimizing unscheduled shutdowns and increasing safety (Thurston & Lebold, 2001).

A typical scheme of CBM can be described as follows: a Fault Detection (FD) system continuously collects information from sensors mounted on the component of interest (Ahmad & Kamaruddin, 2012; Montes de Oca, Puig & Blesa, 2012) and delivers a decision regarding its health state (either normal or abnormal conditions). In case of abnormal conditions, an alarm is triggered and the decision maker decides whether it is necessary to perform a maintenance action or it is possible to postpone it. In this work, we consider a FD system architecture based on an empirical reconstruction model and a decision tool.

Different empirical models have been used with success to estimate (reconstruct) the expected values of the signals in normal conditions. Typical examples include Artificial Neural Networks (ANNs) (Hines, Wrest & Uhrig, 1997; Safty, Ashour, Dessouki & Sawaf, 2004; Rahman, 2010), Auto-Associative Kernel Regression (AAKR) (Chevalier, Provost & Seraoui, 2009; Baraldi, Canesi, Zio, Seraoui & Chevalier, 2010; Baraldi, Di Maio, Pappaglione, Zio & Seraoui, 2012), Evolving Clustering Method (ECM) (Zhao, Baraldi & Zio, 2011), Principal Component Analysis (PCA) (Garcıa-Alvarez, 2009; Baraldi, Zio, Gola, Roverso & Hoffmann, 2011), Independent Principal Component

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Analysis (Ding, Hines & Rasmussen, 2003), Support Vector Machines (SVMs) (Zavaljevski & Gross, 2000; Batur, Zhou & Chan, 2002; Laouti, Sheibat-Othman & Othman, 2011) and Fuzzy Similarity (Baraldi, Di Maio, Genini & Zio, 2013).

The decision tool is typically constructed on the analysis of the differences (residuals) between the measured and the reconstructed values of the *n* signals at time *t*, $\bar{x}^{test}(t)$ and $\vec{x}^{test}(t)$, respectively, in order to decide whether the component is in normal or abnormal conditions (Figure 1). In practice, two possible cases may arise at time t: a) reconstructions are similar to measurements. $\vec{x}^{test}(t) \simeq \vec{x}^{test}(t)$ b) reconstructions are different from measurements, $\vec{x}^{test}(t) \neq \vec{x}^{test}(t)$. In the former case, the component is recognized to be in normal conditions (nc) and the alarm is not triggered, whereas in the latter case abnormal conditions (ac) are detected and the alarm is triggered.



Figure 1. Traditional FD system.

Independently from the choice of the reconstruction model and of the method adopted to analyze the residuals, different sources of uncertainty may influence the performance of the FD system and can cause false or missing alarms (Helton, 1994; Zheng & Frey, 2005; Aven & Zio, 2012).

In this context, the present work focuses on the analysis of the uncertainty in the signal reconstruction phase of the FD process. In particular, we consider the following sources of uncertainty: 1) the measurement errors, 2) the inherent variability (stochasticity) of the physical process, 3) the uncertainty on the settings of the reconstruction model parameters, and 4) the uncertainty on the reconstruction model output due to incompleteness of the training data. The objective is the quantification of the overall uncertainty which the reconstructions provided by the empirical model are subject to. To this aim, we propose a novel method based on the estimate of Prediction Intervals (PIs) by using Order Statistics (OS) theory. For illustration purposes, we adopt the AAKR technique to build the reconstruction model, but the approach proposed is general and can be applied to any other techniques for developing the reconstruction model.

The method for the quantification of the uncertainty on the signal reconstructions is verified with respect to an artificial case study representing the behavior of a component during operational transients. This situation, characterized by a non-stationary behavior of the signals, has been chosen due to the criticality of the FD task during operational transients (Baraldi et al. 2012). In particular, the time evolution of 4 signals during various start-up transients have been simulated and used to assess the performance of the method in the quantification of the uncertainty on the reconstructions. Artificial data have been used in order to allow testing the approach on a large number of different simulated transients and, thus, to evaluate its capability of correctly quantify the uncertainty on the reconstruction.

The remaining of this paper is organized as follows; in Section 2, a description of the four sources of uncertainty to which a FD system is subject is provided. In Section 3, a reconstruction model for signal reconstruction during operational transients is developed, and a method for estimating the PIs of the reconstruction is proposed. In Section 4, an artificial case study representing the component behavior during typical start-up transients is introduced and, in Section 5, the results of the application of the proposed method are discussed. Finally, some conclusions are proposed in Section 6.

2. Sources of uncertainty in FD systems

The reconstructions provided by an empirical model, e.g., AAKR (Chevalier et al., 2009; Baraldi et al., 2010; Baraldi et al., 2012), are subject to the following 4 sources of uncertainty (Lin & Stadtherr, 2008; Baraldi et al., 2011; Ramuhalli, Lin, Crawford, Konomi, Braatz, Coble, Shumaker & Hashemian, 2013):

- 1. the measurement errors, which can be due to systematic or random errors of the sensors;
- 2. the inherent variability (stochasticity) of the physical process, which causes different evolutions of the signal during identical operational transients: e.g., during two different start-up transients of the same component in the same environmental and operational conditions, different signal evolutions are observed.
- 3. the uncertainty on the correct setting of the AAKR-built model parameters. In practice, according to the AAKR method, signal reconstructions are built on the basis of a measure of similarity between the test pattern and "neighbouring" training patterns (Appendix A.1). The computation of the similarity measure is based on a kernel function characterized by a parameter, called bandwidth, whose value is typically set by following a trial and error procedure on some validation data.
- 4. the uncertainty caused by the incompleteness of the training data. The performance of an empirical signal

reconstruction model built by AAKR is remarkably influenced by the quality and quantity of the training patterns (Appendix A.1).

3. RECONSTRUCTION MODEL AND UNCERTAINTY QUANTIFICATION

A typical reconstruction model receives in input at time *t* a vector $\vec{x}^{test}(t) = [x^{test}(t,1), x^{test}(t,j), ..., x^{test}(t,n)]$ containing the test measurements of *n* signals, *j*=1,...,*n*. On the basis of historical measurements performed in normal conditions, the reconstruction model produces in output a vector $\vec{x}^{test}(t) = [\hat{x}^{test}(t,1), \hat{x}^{test}(t,j), ..., \hat{x}^{test}(t,n)]$ containing the values of the input signals expected in case of normal conditions at the present time *t*. For the sake of simplicity, the signal index *j* will be omitted from the notations $x^{test}(t,j)$ and $\hat{x}^{test}(t,j)$, and will be used only when strictly required.

3.1. Reconstruction of operational transients

In Baraldi et al. (2012), different approaches to the problem of signal reconstruction during operational transients have been compared. The obtained results have shown that in order to reduce the computational efforts and to increase model reconstruction accuracy, it is useful to develop a final reconstruction model made by several reconstruction models, each one dedicated to a different operational zone of the component. To this aim, the training patterns are split into different sets, according to the different operational zones. Then, for each operational zone, a dedicated AAKR model is built using the corresponding training set. Once the reconstruction model has been built, it can be used on line for the signal reconstruction task by sending the test pattern, $\vec{x}^{test}(t)$, to the corresponding reconstruction model (Figure

2). In this case, looking at the signal value it is possible to select the corresponding AAKR model. However, for more complex case studies, where discontinuity of the reconstructed variable should be avoided when the model change, one can rely on other algorithms like Takagi-Sugeno concept and Bayes approaches for AAKR model averaging.



Figure 2. Scheme of AAKR model selection.

It is worth mentioning that abrupt signal changes that might be induced by AAKR model switching have been accommodated in our approach because different models have different thresholds on detection and triggering the alarm.

3.2. Uncertainty quantification using PIs

The uncertainty on the signal reconstruction provided by an empirical model can be quantified by using PIs. With respect to a component in normal conditions, a PI with confidence level $1-\sigma$ is defined as an interval, $\left[\hat{x}^{lower}(t), \hat{x}^{upper}(t)\right]$, such that the probability that the measurement of signal *j* at time *t*, $x^{test}(t)$, falls within the interval is equal to $1-\sigma$ (Eq. (1)) (Office of Nuclear Regulatory Research, 2007; Rasmussen, Wesley Hines & Gribok, 2003). In other words, assuming that the component is in normal conditions:

$$p\left(x^{test}\left(t\right)\in\left[\hat{x}^{lower}\left(t\right),\hat{x}^{upper}\left(t\right)\right]\right)=1-\sigma \qquad (1)$$

In order to assess the correctness and effectiveness of the estimated prediction intervals, two indicators are usually considered: the coverage, i.e., the fraction of patterns in a validation set which actually fall within the prediction interval and the prediction interval width. Desiderata are that a PI with confidence $1-\sigma$ has coverage of at least $1-\sigma$ and width is as small as possible.

Satisfactory PI estimates of time series data have been obtained by using nonlinear regression techniques such as Artificial Neural Networks (ANN), Neural Network Partial Least Squares (NNPLS), Kernel Regression (KR) and Evolving Clustering Method (ECM)) (Rasmussen et al., 2003; Zhao et al., 2011; Ak, Li, Vitelli & Zio, 2013; Zhao, Tao, Ding & Zio, 2013). In applications developed for the nuclear industry, PIs associated to normal component operations have been calculated, using Eq. (2) (Rasmussen et al., 2003; Office of Nuclear Regulatory Research, 2007):

$$\hat{x}^{upper,lower}(t) = \hat{x}^{test}(t) \pm t_N^{\sigma/2} \sqrt{A + B}$$

$$A = var\left(\hat{x}^{val}(t_{m=1,\dots,N_{val}})\right)$$

$$B = \sum_{m=1}^{N_{val}} \left(\hat{x}^{val}(t_m) - x^{val}(t_m)\right)^2 / N_{val}$$
(2)

where, $x^{val}(t_m)$ is the value of signal *j* measured at time t_m after the beginning of the transient of a validation set, $\hat{x}^{val}(t_m)$ is the signal reconstruction value of signal *j* provided by the empirical model at time t_m of a validation set, N_{val} is the number of patterns in a validation set

containing time series measurements performed in normal conditions, N is the number of training patterns used to train the empirical model, $1-\sigma$ is the confidence level ($0 \le \sigma \le I_{1}$).

 $t_N^{\sigma/2}$ is the *t*-distribution value for a given σ and number of training patterns.

It is important to mention that the patterns in the validation set are different from those in the training set, the former being used to optimize the kernel bandwidth parameter (see Appendix A.3 for more details) and to calculate the PIs, and the latter to train the reconstruction model, and that the quantity $\sqrt{A+B}$ is typically referred to as prediction

error. In this work, it is denoted as ε .

In this work, a confidence level, $1-\sigma$ equals to 95% is considered. It is worth mentioning that this latter value has been chosen as per the Nuclear Regulatory Commission guidelines that require using the 95th percentile largest uncertainty estimate (Office of Nuclear Regulatory Research, 2007; Denning, Aldemir & Nakayama, 2012). However, setting up the confidence level depends upon the industrial application. In that case, the value of $t_N^{\sigma/2}$ for N>30 is close to 2. Notice that from the point of view of the FD, the higher is the confidence level, $1-\sigma$, the larger is the obtained prediction interval and the lower is the expected false alarm rate (γ). On the other side, the larger is the prediction interval, the higher is the expected missing alarm rate (β) and the longer is the detection delay time.

A drawback of performing PIs quantification using Eq. (2) is that the prediction interval width is independent from the test patterns, $\vec{x}^{test}(t)$. This is not satisfactory since the empirical model performance may vary in different zones of the training space, according to the density and information content of the training patterns available to build the model. Thus, prediction interval widths are expected to be different for different patterns $\vec{x}^{test}(t)$, with smaller PI width when the test pattern is in a zone characterized by a high density of training patterns.

Furthermore, when the AAKR is applied to the reconstruction of operational transients, Eq. (2) typically leads to very large PIs for all measurements. This is due to the term $\operatorname{var}(\widehat{x}^{val}(t_{m=1,\dots,N_{val}}))$ which, even in the case of reconstructions very close to the signal measurements, can be large due to the variability of the patterns in the validation set.

To overcome these limitations, in the present work we propose to:

1. reduce the variability of the patterns in the validation set by considering, for the computation of the PI at time t_k , $k=1,...,N_p$, only the reconstructions in the validation

set performed at time t_k after the beginning of the transient, with N_p equals to the number of patterns in each test, validation and training transients. Thus, instead of considering, as in Eq. (2), the variance of all the N_{val} reconstructions of the validation set, the variance is computed by considering the $NV < N_{val}$ reconstructions referring to patterns measured only at time t_k .

2. replace $t_N^{\sigma/2}$ with a scaling parameter called scale factor (α) which is used to rescale the prediction error ε , so that, at each time t_k it yields a PI with a specified coverage and with an acceptable width (Bouckaert, Frank, Holmes & Fletcher, 2011). The proper number *NV* of measurements to estimate the PIs with a given coverage 1- σ is selected relying on Order Statistics (OS), according to Secchi, Zio and Di Maio (2008). In this regard, using the 95% confidence level; the number *NV* of measurements used to estimate the PIs at each time t_k is estimated and is equal to 59.

In practice, at time t_k after the beginning of the transient, for a reconstructed signal j, $\hat{x}^{test}(t_k)$, Eq. (2) becomes (for large values of NV):

$$\hat{x}^{upper,lower}(t) = \hat{x}^{test}(t) \pm \alpha \sqrt{C + D}$$
(3)

$$C = var\left(\hat{x}_{i=1,\dots,NV}^{val}(t_k)\right)$$

$$D = \sum_{i=1}^{NV} \left(\hat{x}_i^{val}(t_k) - x_i^{val}(t_k)\right)^2 / NV$$

The method goes along the following steps. It entails an offline procedure for quantifying the scale factor α , and an online procedure for FD.

Step 1: Offline signal reconstruction. Using N training data, the AAKR-built model provides the reconstruction $\hat{x}_{i}^{val}(t_{k})$ of signal *j* in the *i*-th validation transient of length N_{p} , *i*=1,...,NV, (*i.e.*, $N=N_{p}*NT$, where NT is the number of training transients each of length N_{p}). These historical measurements are collected into the matrix \overline{X} whose generic element $x(t_{k,j})$ is the measured value of signal *j* at time t_{k} , $k=1,...,N_{p}$.

Step 2: Residual calculations. At each k-th time, the absolute difference between the measured value and its reconstruction of signal j is calculated as $e_i(t_k) = \left| \hat{x}_i^{val}(t_k) - x_i^{val}(t_k) \right|$ of the *i*-th validation transient, i=1,...,NV.

Step 3: *Prediction error calculations.* At each time k, the prediction error of signal j is calculated as

$$\varepsilon(t_k) = \sqrt{\operatorname{var}_k\left(\hat{x}^{\operatorname{val}}\left(t_k\right)\right) + \operatorname{bias}_k\left(\hat{x}^{\operatorname{val}}\left(t_k\right)\right)} \qquad \text{by}$$

calculating the variance $\operatorname{var}_{k}\left(\widehat{x}^{val}\left(t_{k}\right)\right)$ (Eq. (4)) and the bias $bias_{k}\left(\widehat{x}^{val}\left(t_{k}\right)\right)$ (Eq. (5)) of the *NV* reconstructions of signal *j* (for large values of *NV*):

$$\operatorname{var}_{k}\left(\hat{x}^{val}(t_{k})\right) = \frac{\sum_{i=1}^{NV} \left(\hat{x}_{i}^{val}(t_{k}) - \sum_{i=1}^{NV} \left(\hat{x}_{i}^{val}(t_{k})\right) / NV\right)^{2}}{NV}$$
(4)

$$bias_{k}\left(\hat{x}^{val}(t_{k})\right) = \frac{\sum_{i=1}^{NV} \left(\hat{x}_{i}^{val}(t_{k}) - x_{i}^{val}(t_{k})\right)^{2}}{NV}$$
(5)

Step 4: Scale factor calculations. At each time k, α is calculated as the 95th percentile of the $NV \alpha_i(t_k)$, i=1,...,NV where $\alpha_i(t_k)=e_i(t_k)/\varepsilon(t_k)$. The coverage capability depends on the number of the NV validation transients used. The advantages of using the scale factor are: 1) the trade-off between the coverage and the width is satisfied; 2) the technique is independent from the reconstruction method applied (Bouckaert et al., 2011); and 3) α deals with the uncertainty caused by the AAKR-built model. In practice, at each time k, if the AAKR reconstructions are inaccurate,

then, the α values are large (i.e., $e_i(t_k) = \left| \hat{x}_i^{val}(t_k) - x_i^{val}(t_k) \right|, i = 1, ..., NV$ is large) in order to achieve the desired coverage level (1- σ), and vice versa.

In order to guarantee a certain coverage $1-\sigma$ (i.e., $(1-\sigma)$ of the measurements $x^{lest}(t_k)$ of signal *j* in normal conditions are within the PI at each time *k*), we need to find a scale factor such that $(1-\sigma)$ of the $\alpha_i(t_k)$ are lower and the remainder higher than α . This value is denoted as $\alpha^S(t_k)$ where *S* stands for "Sorted" and is found by sorting the *NV* available $\alpha_i(t_k)$ (Bouckaert et al., 2011), where *NV* is properly defined by OS (Wald, 1947; Secchi et al., 2008). For $\sigma = 0.05$; the correct scale factor may be denoted as $\alpha^{95 percentile}(t_k)$.

Finally, within the online FD, for any test measurement $x^{test}(t_k)$ of a given signal *j* at each time *k*, Eq. (3) can be rewritten as:

$$\hat{x}^{upper,lower}(t) = \hat{x}^{test}(t) \pm \alpha^{95\,percentile}(t)\varepsilon(t) \qquad (6)$$

4. CASE STUDY

In this work, an artificial case study has been designed to generate transients representative of the start-up behavior of a component (Baraldi, Di Maio & Zio, 2013). Each transient, $f_i(x(t, 1),...,x(t, 4))$, is four-dimensional (i.e., n = 4

signals) and has a time horizon of $N_p=101$ time steps, in arbitrary units of measurements.

With respect to normal conditions, 5500 transients representing the start-up of the component have been simulated. The signal evolutions are characterized by a sigmoid behavior $x_i^{nc}(t_k)$, k=1,...,101, i=1,...,5500 given by Eq. (7):

$$x_{i}^{nc}(t_{k}) = 2a\left(1 + erf\left\{\frac{t_{k} - \mu}{\sqrt{2}}\right\}\right) + 10^{-3\zeta}$$
 (7)

where α , μ and ζ are random parameters in arbitrary units. In practice, the simulations have been performed by sampling random values of the parameter ζ from a Gaussian distribution $\zeta \sim N(0,1)$ and of the parameters α , μ from uniform distribution functions with lower and upper bounds reported in Table 1.

Figure 3 shows the obtained evolutions of the four signals in the 5500 transients, $\vec{x}_{i=1:5500}^{nc}(t_k)$.



Figure 3. Simulated time evolution in normal conditions of the 4 signals in 5500 start-up transients.

Among them, we have used *NT*=300 transients to train the AAKR-built model, *NV*=59 transients as validation set to optimize the value of the model parameter, i.e., the kernel bandwidth h, and for calculating the scale factors $\alpha_i(t_k)$. The remaining transients are used to verify the performance of the proposed method.

Furthermore, 50 additional abnormal conditions transients (Eq. (8)) have been simulated in order to reproduce the signal behaviours in abnormal conditions (Figure 4) by assuming a different time evolution for one signal randomly chosen among the four available. It is worth mentioning that this situation, characterized by assuming only one signal in abnormal conditions to create the abnormal transients has been chosen due to the criticality of the FD task under this assumption, i.e., this situation is considered the most challenging case.

$$x_{i}^{ac}(t_{k}) = a_{\ell}t_{k} + 10^{-3\zeta}$$
(8)

where a_{ℓ} is a random parameter whose values are sampled from a uniform distribution with lower and upper limits reported in Table 1.

Table 1. Limits of the uniform	a distributions from which the
parameters in Eq. (7) and I	Eq. (8) have been sampled.

Parameter	Lower bounds	Upper bounds
а	0.45	0.55
μ	2.2	2.7
a_{ℓ}	0.3	0.4



Figure 4. Simulated time evolution in abnormal/normal conditions of signal 1 and the other three signals, respectively, in 50 start-up transients.

4.1. Reconstruction model

The final model for the reconstruction of signals during start-up transients is made by R = 5 AAKR-built reconstruction models, each one dedicated to a different operational zone. The different operational zones are defined according to the time elapsed from the start of the transient and are reported in Table 2. In order to develop the overall reconstruction model, the training patterns are split into different sets, according to the time at which they have been measured. Then, for each operational zone, an AAKR model is built using the corresponding training set. Once the FD system has been built, it can be used on line for the signal reconstruction task by sending the test pattern to the corresponding reconstruction model.

 Table 2. Definition of the five operational zones and their optimal h values for the four signals.

Zone	Time	Operative conditions	h
#	period	Operative conditions	values
1	1-20	Slow start up	0.05
2	21-40	Fast start up	0.05
3	41-60	Start converging to a steady state	0.01
4	61-80	Almost steadiness	0.009
5	81-101	Steady state (nominal value)	0.005

The AAKR models have been trained and their parameters optimized as described in Appendix A.3. In particular, the parameter h values have been identified by optimizing the

accuracy of the signal reconstructions in normal conditions and their robustness in abnormal conditions. The obtained optimal values of parameter h in the different operational zones are reported in Table 2.

5. VERIFICATION OF THE PROPOSED METHOD FOR UNCERTAINTY QUANTIFICATION

In this Section, the results obtained by applying the method for PI estimation to the case study of Section 4 are presented. In Subsection 5.1 the PIs obtained by applying a traditional approach for PI estimation, based on a single AAKR-built reconstruction model and Eq. (2), are compared to those obtained by using the proposed method. Subsection 5.2 presents the results of an extensive test performed in order to understand whether the obtained PIs with confidence level 95% provide satisfactory coverage levels, i.e., the fraction of patterns in a validation set that actually falls within the quantified prediction interval is at least equal to 95%, whereas in Subsection 5.3 the ability of the method to properly represent the four sources of uncertainty affecting the signal reconstructions (namely, measurement errors, intrinsic stochasticity of the physical process, uncertainty on the correct setting of the AAKR parameter, and uncertainty caused by the incompleteness of the training data) is discussed.

5.1. PI estimation

The PIs obtained in the reconstructions of signal 1, $x^{test}(t_k, 1)$, of a test transient by considering a single AAKR-built reconstruction model and Eq. (2), are shown in Figure 5. Notice that, as expected, the obtained PI widths are constant and very large. This is due to the fact that, according to Eq. (2), the PI widths are independent from the test patterns, $x^{test}(t_k, 1)$, and are computed by considering the variance, $var(\hat{x}^{val}(t_{m=1,...,N_{val}}, 1))$, of the reconstructions of patterns taken in different zones of the operational transients, and

thus characterized by an high variability of signal values.



Figure 5. PIs of the reconstruction of 21 patterns obtained using Eq. (2).

Figure 6 shows the results obtained by applying the procedure of Section 3 to a similar transient. Notice that the

PI widths are variable during the time evolution and with a reduced width with respect to those obtained in Figure 5.



Figure 6. PIs of the reconstruction of 21 patterns obtained using the proposed method.

It is worth noticing that the PI widths of the reconstructions in zone 1 (time from 1 to 20) are smaller than those obtained in zone 3 (time from 41 to 60). This is due to the variability of the training patterns used to train the AAKR-built reconstruction model, which is lower at the beginning of the transient.

5.2. Verification of the prediction interval coverage

In order to verify whether the coverage of the obtained prediction intervals with confidence level 95% is satisfactory, i.e., of at least 95%, we have performed an extensive test using 5000 normal conditions test transients. Figure 7 shows the coverage of the obtained prediction intervals for the first signal, $x^{test}(t_k, 1)$, at different times after the beginning of the transient. The test has been performed using *NV* value equal to 59. In practice, we have counted how many times the signal measurement falls within the prediction interval at the different times.



Figure 7. Coverage of the PI with a level of confidence 95% at different times considering 59 validation transients.

Notice that the obtained coverage values are, as expected, close to the confidence level 95%, as it is confirmed by the overall coverage throughout all the transient length which is equal to 94.6%.

To investigate the impact of the number of validation transients to the overall coverage, the same test has been performed with a random number of validation transients, NV=20, lower than 59. As expected, the overall coverage drops down to 88% (Figure 8). This is indeed due to the inadequate use of OS. If the number NV had been taken larger than 59, the overall coverage would be exceed the 95%.





5.3. PI capability of quantifying the different uncertainty sources

In this Subsection, without any loss of generality, we focus on the signal reconstruction problem during the first operational zone of the component transient. The evolutions of the NT=300 training transients used to train the AAKR model in zone 1 are shown in Figure 9.

In order to verify the capability of the PI estimates of properly quantifying the effect of different sources of uncertainty, we have performed the following experiments:

- 1) variation of the measurement error
- 2) variation of the intrinsic stochasticity of the physical process
- 3) variation of the AAKR bandwidth parameter value
- 4) variation of the number of transients used to train the AAKR model.

Experiments 1), 2), and 4) require generating new sets of transients, whereas in experiment 3) different AAKR-built models are generated and trained using the same set of transients illustrated in Section 4.



Figure 9. Training transients of signal 1 (zone 1).

5.3.1. Variation of the measurement error

Five different sets of transients characterized by different values of the measurement error have been simulated. In practice, a noise characterized by different standard deviations has been added to the signals generated according to Eq. (7) and Eq. (8). Table 3 reports the five levels of standard deviation considered. The simulated transients have been used to train the AAKR model, to find the prediction intervals according to the proposed method and to compute the overall coverage of the prediction intervals. For each level of noise, we have repeated the AAKR development of the model and the PI estimation five times using different random partitions of the available transients in training, test and validation sets. The same cross-validation procedure is applied also in Subsections 5.2.2, 5.2.3 and 5.2.4. In what follows, we present the average of the five obtained coverage values and their standard deviations.

Table 3. Five levels of standard deviation characterizing the noise in the signals generated by Eq. (7) and Eq. (8).

Noise Levels	Standard Deviations values
1	0.5
2	1
3	1.5
4	2
5	2.5

Figure 10 (top) shows the overall coverage obtained considering the different measurement noise levels. Notice that the obtained coverage values are close to 95% and that the coverage is not influenced by the measurement error. Figure 10 (bottom) shows the average width of the prediction interval. As expected, the higher is the measurement noise, the larger is the prediction interval width. This experiment confirms the ability of the proposed method to properly quantifying the effect of the measurement error on the PI estimate: the method is able to achieve the desired coverage level regardless of the level of the noise, by adjusting the PI width.



Figure 10. Overall mean coverage (top) and PI width (bottom), considering different measurement noise levels.

5.3.2. Variation of the intrinsic stochasticity of the physical process

In the considered artificial case study, the stochasticity of the physical process is represented by the variation of the parameters α , μ , and a_{ℓ} in Eq. (7) and Eq. (8), which determines the transients behaviour. In order to simulate different levels of stochasticity in the process, we have sampled the values of these parameters from different probability distributions. Table 4 reports the considered distributions in the four cases: the larger is the range of the uniform distributions, the higher is the stochasticity of the process.

Table 4. Distributions from which the parameters of Eq. (7) and Eq. (8) are sampled, in the considered four cases characterized by different levels of process stochasticity.

Case #	a	μ	a_ℓ
1	U(0.48,0.53)	U(2.33, 2.58)	U(0.33,0.375)
2	U(0.45,0.55)	U(2.2, 2.7)	U(0.3,0.4)
3	U(0.435,0.58)	U(2.08, 2.835)	U(0.28,0.425)
4	U(0.4,0.6)	U(1.95, 2.95)	U(0.25,0.45)

The overall coverage obtained in the four cases is shown in Figure 11 (top): the model achieves satisfactory coverage values regardless the level of stochasticity of the process. As in the previous case, this is obtained by adjusting the PI width (Figure 11 (bottom)): the wider the range of the uniform distributions of the parameters of the equations governing the transients behaviour, i.e., the higher the level of stochasticity in the process, the wider the width of the PIs.





5.3.3. Variation of the AAKR bandwidth parameter value

In this experiment, the same set of transients illustrated in Section 4 have been used to train eight different AAKR models characterized by different values of the bandwidth parameter, h, (h = 0.005, 0.009, 0.02, 0.05, 0.3, 0.5, 0.9, 1.5).

The overall coverage of the prediction intervals with confidence 95% obtained by the eight different AAKR models is shown in Figure 12 (top). Notice that the obtained coverage values are close to the target of 95%. Figure 12 (bottom) shows that very small and very large values of h are characterized by large PI widths. This is due to the fact that the corresponding reconstruction models are characterized by bad performances and, thus, in order to obtain the desired coverage, the prediction interval is enlarged. Furthermore, it is interesting to observe that the PI width is minimum for the value of h=0.05, which minimizes the reconstruction error (see Appendix A.3).



Figure 12. Overall mean coverage (top) and PI width (bottom), considering different AAKR-built models characterized by different values of the bandwidth parameter.

5.3.4. Variation of the number of transients used to train the AAKR model

In order to investigate the effect of the uncertainty caused by the incompleteness of the training data, different AAKR models have been developed using different numbers of training transients. In particular, we have trained three AAKR models based on 100, 300 and 500 training transients, *NT*. In each case, the optimal h value has been identified by considering the Mean Squared Error, *MSE* (see Appendix A.3).

The overall coverage obtained in the three cases is shown in Figure 13 (top). As expected, the coverage is close to the target value of 95% and the PI width tends to decrease as the number of training transients increases (Figure 13 (bottom)). This latter effect is due to the fact that model accuracy tends to increase with the number of patterns used to train the empirical model (see Appendix A.1).



Figure 13. Overall mean coverage (top) and PI width (bottom), considering different number of training transients.

6. CONCLUSIONS

In this work, a novel method to quantify the uncertainty to which signal reconstructions are subject has been developed. Uncertainties are quantified in the form of prediction intervals which have been estimated using Order Statistics (OS) theory. The capability of the methods to deal with measurement errors, intrinsic stochasticity of the physical process, uncertainty on the settings of the model parameters and uncertainty on the signal reconstructions due to incompleteness of the training data has been shown with respect to an artificial case study regarding the monitoring of a component during start-up transients.

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References

- Ahmad, R., & Kamaruddin, S. (2012). An overview of timebased and condition-based maintenance in industrial application. *Computers & Industrial Engineering*, 63(1), 135–149. doi: 10.1016/j.cie.2012.02.002
- Ak, R., Li, Y. F., Vitelli, V., & Zio, E. (2013). A Genetic Algorithm and Neural Network Technique for Predicting Wind Power under Uncertainty. *Prognostics* and System Health Management Conference PHM-2013 (1-6), September 9-11, Milan, Italy. doi: 10.3303/CET1333155
- Aven, T., & Zio, E. (2012). Foundational issues in risk assessment and risk management. *Risk Analysis*, 32(10), 1647-1656. doi: 10.1111/j.1539-6924.2012.01798.x
- Baraldi, P., Canesi, R., Zio, E., Seraoui, R., & Chevalier, R. (2010). Signal Grouping for Condition Monitoring of

Nuclear Power Plants Components. *Control and Human-Machine Interface Technologies*.

- Baraldi, P., Zio, E., Gola, G., Roverso, D., & Hoffmann, M. (2011). Signal reconstruction by a GA-optimized ensemble of PCA models, *Nuclear Engineering and Design*, 241, 301-309. doi: 10.1016/j.nucengdes.2010.10.012
- Baraldi, P., Canesi, R., Zio, E., Seraoui, R., & Chevalier, R. (2011). Genetic Algorithm-based Wrapper Approach for Grouping Condition Monitoring Signal of Nuclear Power Plant Components. *Integrated Computer-Aided Engineering*, 18(3), 221-234. doi: 10.3233/ICA-2011-0375
- Baraldi, P., Di Maio, F., Pappaglione, L., Zio, E., & Seraoui, R. (2012). Condition monitoring of electrical power plant components during operational transients. *Proceedings of the Institution of Mechanical Engineers, Part O, Journal of Risk and Reliability*, 226(6), 568–583. doi: 10.1177/1748006X12463502
- Baraldi, P., Di Maio, F., Genini, D., & Zio, E. (2013). A Fuzzy Similarity Based Method for Signal Reconstruction during Plant Transients. *Prognostics* and System Health Management Conference PHM-2013 (889-894), September 9-11, Milan, Italy. doi: 10.3303/CET1333149
- Baraldi, P., Di Maio, F., & Zio, E. (2013). Unsupervised Clustering for Fault Diagnosis in Nuclear Power Plants Components. *International Journal of Computational Intelligence Systems*, 6(4), 764-777. doi: 10.1080/18756891.2013.804145
- Batur, C., Zhou, L., & Chan, C. C. (2002). Support vector machines for fault detection. *In Decision and Control, Proceedings of the 41st IEEE Conference on* (1355-1356), December 10-13, Las Vega, Nevada USA. doi: 10.1109/CDC.2002.1184704
- Bouckaert, R. R., Frank, E., Holmes, G., & Fletcher, D. (2011). A Comparison of Methods for Estimating Prediction Intervals in NIR Spectroscopy: Size Matters. *Chemometrics and Intelligent Laboratory Systems*, 109(2), 139-145. doi: 10.1016/j.chemolab.2011.08.008
- Campos, J. (2009). Development in the application of ICT in condition monitoring and maintenance. *Computers in Industry*, 60(1), 1-20. doi: 10.1016/j.compind.2008.09.007
- Chevalier, R., Provost, D., & Seraoui, R. (2009). Assessment of statistical and Classification model for monitoring EDF's assets. *Control and Human-Machine Interface Technologies*.
- Denning, R. S., Aldemir, T., & Nakayama, M. (2012). The use of latin hypercube sampling for the efficient estimation of confidence intervals, in Proceedings of the International Congress on Advances in Nuclear Power Plants (ICAPP '12), Chicago, Ill, USA.
- Di Maio, F., Baraldi, P., Zio, E., & Seraoui, R. (2013). Fault Detection in Nuclear Power Plants Components by a

Combination of Statistical Methods, *IEEE Transaction* on *Reliability*, Vol. 62(4), 833 - 845. doi: 10.1109/TR.2013.2285033

- Ding, J., Hines, J.W., & Rasmussen, R. (2003). Independent component analysis for redundant sensor validation. *Proceedings of the 2003 Maintenance and Reliability Conference (MARCON 2003), Knoxville, TN.*
- Garcia-Alvarez, D. (2009). Fault detection using principal component analysis (PCA) in a wastewater treatment plant (WWTP). *In Proceedings of the International Student's Scientific Conference.*
- Helton, J. C. (1994). Treatment of uncertainty in performance assessments for complex systems, *Risk analysis*, 14(4), 483-511.
- Hines, J.W., Wrest, D.J., & Uhrig, R.E. (1997). Signal validation using an adaptive neural fuzzy inference system, *Nuclear Technology*, 119, 181–193.
- Laouti, N., Sheibat-Othman, N., & Othman, S. (2011). Support vector machines for fault detection in wind turbines. *In Proceedings of IFAC World Congress* (7067-7072), August 28th – September 2nd, Milan, Italy.
- Lin, Y., & Stadtherr, M. A. (2008). Fault detection in nonlinear continuous-time systems with uncertain parameters. AIChE journal, 54(9), 2335-2345.
- Montes de Oca, S., Puig, V., & Blesa, J., (2012). Robust fault detection based on adaptive threshold generation using interval LPV observers, *International Journal of Adaptive Control and Signal Processing*, Vol. 26(3), 258-283. doi: 10.1002/acs.1263
- Office of Nuclear Regulatory Research. (2007). Technical Review of On-Line Monitoring Techniques for Performance Assessment, 2 Theoretical Issues, ORNL/TM-2007/188, NUREG/CR-6895.
- Rahman, S. A. S. A. (2010). Application of Artificial Neural Network in Fault Detection Study of Batch Esterification Process. *International Journal of Engineering and Technology IJET-IJENS*, 10(3).
- Ramuhalli, P., Lin, G., Crawford, SL., Konomi, A., Braatz, BG., Coble, JB., Shumaker, BD., Hashemian, HM., (2013). Uncertainty Quantification Techniques for Sensor Calibration Monitoring in Nuclear Power Plants, Pacific Northwest National Laboratory.
- Rasmussen, B., Wesley Hines, J., & Gribok, A. V. (2003). An Applied Comparison of the Prediction Intervals of Common Empirical Modeling Strategies. *Proceedings* of the 2003 Annual Maintenance and Reliability Conference, Knoxville, TN.
- Safty, S. M. E., Ashour, H. A., Dessouki, H. E., & Sawaf, M. E. (2004). Online fault detection of transmission line using artificial neural network. *IEEE International Conference on Power System Technology* (1629-1632), November 21-24, Singapore. doi: 10.1109/ICPST.2004.1460264
- Secchi, P., Zio, E., & Di Maio, F. (2008). Quantifying uncertainties in the estimation of safety parameters by

using bootstrapped artificial neural networks. *Annals of Nuclear Energy*, 35(12), 2338-2350. doi: 10.1016/j.anucene.2008.07.010

- Thurston, M., & Lebold, M. (2001). Standards Developments for Condition-Based Maintenance Systems. Ft. Belvoir Defense Technical Information Center, Applied Research Laboratory, Penn State University.
- Wald, A. (1947). Sequential Analysis. John Wiley & Sons, New York, NY.
- Zavaljevski, N., & Gross, K.C. (2000). Support vector machines for nuclear reactor state estimation. *Proceedings of the ANS Topical Meeting on Advances in Reactor Physics and Mathematics and Computation into the Next Millennium*, Pittsburgh, Pennsylvania, USA.
- Zhao, W., Baraldi, P., & Zio, E. (2011). Confidence in Signal Reconstruction by the Evolving Clustering Method. *IEEE Prognostics and System Health Management Conference* (1-7), May 24-25, Shenzhen, China. doi: 10.1109/PHM.2011.5939535
- Zhao, W., Tao, T., Ding, Z. S., & Zio, E. (2013). A dynamic particle filter-support vector regression method for reliability prediction. *Reliability Engineering and System Safety*, 119, 109–116.
- Zheng, J., & Frey, H. C. (2005). Quantitative analysis of variability and uncertainty with known measurement error: methodology and case study. *Risk Analysis*, 25(3), 663-675. doi: 10.1111/j.1539-6924.2005.00620.x

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APPENDIX

Appendix A.1 Auto-associative Kernel Regression (AAKR)

Auto-associative kernel regression (AAKR) is a nonparametric, empirical modelling technique that relies on historical measurements of the signals taken during normal conditions of the component to predict (reconstruct) the current signal measurements vector at a given time t, $\vec{x}^{test}(t) = [x^{test}(t, 1), x^{test}(t, j), ..., x^{test}(t, n)], j=1,...,n;$ where n is the number of measured signals e.g., pressure, temperature, vibration, etc. as a weighted sum of those historical observations. The historical measurements performed at past time t_k , k=1,...,N are collected into the matrix \overline{X} whose generic element $x(t_k, j)$ is the measured value of signal j at time t_k (Baraldi et al. 2012; Baraldi, Canesi, Zio, Seraoui & Chevalier, 2011; Di Maio, Baraldi, Zio & Seraoui, 2013).

AAKR technique requires three different sets of data:

1. **Historical data (often called training data)** which are historical measurements of the signals taken during

normal conditions of the component used to train/develop the model for accurate reconstructions.

- 2. Validation data which are historical measurements of the signals taken during normal/abnormal conditions of the component used to optimize the model parameters, such as the kernel bandwidth h, as we shall show in the following.
- 3. **Test data** which are the measurements taken at current time *t* to perform a real-time health assessment of the component.

In Figure 14, a sketch of the procedure for predicting one test measurement at time t: $\vec{x}^{test}(t) = [x^{test}(t, 1), x^{test}(t, 2)]$ is provided. Historical data which fall within the bandwidth *h* have a large impact on the reconstructed values $\hat{x}(t)$.



Figure 14. AAKR basic principle.

In more details (Baraldi et al. 2011), the *j*-th component at time *t* of $\hat{x}^{test}(t, j)$ is given by Eq. (9):

$$\hat{x}^{test}(t,j) = \frac{\sum_{k=1}^{N} w(t_{k}) x(t_{k},j)}{\sum_{k=1}^{N} w(t_{k})}$$
(9)

Weights $w(t_k)$ are similarity measures obtained by computing the Euclidean distance between the current sensor measurement $x^{test}(t, j)$ and the *k*-th observation of $\overline{\overline{X}}$ Eq. (10):

$$d^{2}(t_{k}) = \sum_{k=1}^{N} \left(x^{test}(t,j) - x(t_{k},j) \right)^{2}$$
(10)

and inserting it in the Gaussian kernel Eq. (11):

$$w(t_k) = \frac{1}{\sqrt{2\pi}h} e^{\frac{-d^2(t_k)}{2h^2}}$$
(11)

where h is the Gaussian kernel bandwidth.

In order to provide in Eq. (10) a common scale across the different signals measuring different quantities, it is necessary to normalize their values. In the present work, the signal values at time *t* are normalized according to Eq. (12):

$$x^{test-normalized}(t,j) = \frac{x^{test}(t,j) - \mu(j)}{\sigma(j)}$$
(12)

Where, $x^{test}(t, j)$ is a generic measurement of signal j, $\mu(j)$ and $\sigma(j)$ are the mean and the standard deviation of the *j*-th signal in $\overline{\overline{X}}$:

$$\mu(j) = \frac{\sum_{k=1}^{N} x(t_k, j)}{N},$$

$$\sigma(j) = \sqrt{\frac{\sum_{k=1}^{N} (x(t_k, j) - \mu(j))^2}{N}}$$
(13)

A.2 Performance Metrics

In order to evaluate the performance of AAKR model, the following criteria should be considered (Baraldi et al. 2011):

1. The accuracy which is the ability of the model to correctly and accurately reconstruct the signal values of a component in normal conditions: An accurate Fault Detection (FD) system allows reducing the number of false alarms (γ). The accuracy metric is typically defined as the Mean Squared Error (*MSE*) between the model reconstructions and the signal measured values.

Let \overline{X}_{nc} be a matrix of measured data whose generic element $x_{nc}^{test}(t_k, j)$ represents the *k*-th time measurement, $k=1,...,N_p$, of the *j*-th measured signal, j=1,...,n, taken during normal conditions, and $\widehat{x}^{test}(t_k, j)$ its reconstruction in nc; then, the *MSE* with respect to signal *j* is given by Eq. (14):

$$MSE_{j} = \frac{\sum_{k=1}^{N_{p}} (x_{nc}^{test}(t_{k}, j) - \hat{x}^{test}(t_{k}, j))}{N_{p}}$$
(14)

A global accuracy measure that takes into account all the monitored signals and test patterns is defined by Eq. (15):

$$MSE = \frac{\sum_{k=1}^{n} \frac{\sum_{k=1}^{N_{p}} (x_{nc}^{test}(t_{k}, j) - \hat{x}^{test}(t_{k}, j))^{2}}{n}}{n} = \frac{\sum_{j=1}^{n} MSE_{j}}{n}$$
(15)

Notice that, although the metric is named accuracy, it is actually a measure of error and, thus, a low value is desired.

2. The robustness which is the ability of the model to reconstruct the signal values of a component in abnormal conditions: a robust AAKR model reconstructs the value of a measured signal as if the component is in normal

conditions thus, allows reducing the number of missing alarms (β). The robustness metric is here defined as the *MSE* between the model reconstructions and the mean of the historical data $\overline{\overline{X}}$.

Let \overline{X}_{ac}^{test} be a matrix of measured data whose generic element $x_{ac}^{test}(t_k, j)$ represents the k-th time measurement, t_k , $k=1,...,N_p$, of the j-th measured signal, j=1,...,n, taken during abnormal conditions, and $\widehat{x}^{test}(t_k, j)$ its reconstruction in nc and let \overline{X} be a mean matrix of the NT training transients, with length N_p , computed at each time t_k , $k=1,...,N_p$ whose generic element $x^{mean}(t_k, j)$ represents the mean of the k-th time observations performed at t_k , $k=1,...,N_p$, of the j-th measured signal, j=1,...,n, taken during normal conditions; then, the robustness MSE with respect to signal j is given by Eq. (16):

$$MSE_{ac,j} = \frac{\sum_{k=1}^{N_{p}} (\hat{x}^{test}(t_{k}, j) - x^{mean}(t_{k}, j))^{2}}{N_{p}}$$
(16)

A.3 Kernel's Bandwidth (h) Optimization

The value of the kernel bandwidth has to be optimized to have a balance between the AAKR accuracy and robustness. That is, the optimum bandwidth h value that minimizes the product (Eq. (17)) between the global model accuracy, MSE, and the global model robustness, MSE_{ac} :

$$Objective \ Function = MSE \ x MSE_{ac}$$
(17)

Without loss of generality, the optimization of the AAKR model parameter, i.e., the kernel bandwidth h, is hereafter presented with respect to only the operational zone "1". A cross-validation approach can serve the scope of optimizing the objective function; for the sake of saving computational time, in this work a large set of data of the training and validation transients have been used, i.e., we have used NT=300 transients to train the AAKR-built model and NV=59 transients as validation set to optimize the value of the model parameter, h. Figure 15 shows the objective function (Eq. (17)) obtained when 11 potential settings of h (0.005, 0.007, 0.009, 0.01, 0.05, 0.09, 0.10, 0.15, 0.20, 0.25, 0.30) are used. It is worth noticing that the optimal bandwidth value for the first operational zone is close to 0.05. The optimum h values of the remaining four operational zones are estimated using the same procedure. The obtained optimal values of parameter h of the five operational zones are reported in Table 2.



Figure 15. Reconstruction error (objective *MSE* function) versus kernel's bandwidth (*h*) values.

A local optimum value of h and a misleading setting of h may lead to inaccurate reconstructions that have to be tackled by properly quantifying the reconstructions model uncertainty. As an example, in Figure 16 it can be seen that with a small bandwidth (h = 0.2) large weights (similarities) are assigned to historical data whose distance is very close to zero, whereas with a larger bandwidth (h = 1.5), the weight assignment is less specific (Office of Nuclear Regulatory Research, 2007).



Figure 16. Gaussian Kernel Function with two h values.

A General Framework for Uncertainty Propagation Based on Point Estimate Methods

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ABSTRACT

A general framework to approach the challenge of uncertainty propagation in model based prognostics is presented in this work. It is shown how the so-called Point Estimate Methods (PEMs) are ideally suited for this purpose because of the following reasons: 1) A credible propagation and representation of Gaussian (normally distributed) uncertainty can be done with a minimum of computational effort for non-linear applications. 2) Also non-Gaussian uncertainties can be propagated by evaluating suitable transfer functions inherently. 3) Confidence intervals of simulation results can be derived which do not have to be symmetrically distributed around the mean value by applying PEM in conjunction with the Cornish-Fisher expansion. 4) Moreover, the entire probability function of simulation results can be reconstructed efficiently by the proposed framework. The joint evaluation of PEM with the Polynomial Chaos expansion methodology is likely to provide good approximation results. Thus, non-Gaussian probability density functions can be derived as well. 5) The presented framework of uncertainty propagation is derivativefree, i.e. even non-smooth (non-differentiable) propagation problems can be tackled in principle. 6) Although the PEM is sample-based the overall method is deterministic. Computational results are reproducible which might be important to safety critical applications. - Consequently, the proposed approach may play an essential part in contributing to render the prognostics and health management into a more credible process. A given study of a generic uncertainty propagation problem supports this issue illustratively.

This work includes unpublished elements of the Ph.D.-Thesis (Schenkendorf, 2014).

1. INTRODUCTION

Model based approaches in fault diagnosis and identification (FDI) have become quite popular in last decades. The value,

however, of any derived mathematical model is directly linked to its predictive power. That is, to describe the essential features of interest as credibly as possible. In consequence of a potential model misspecification and measurement uncertainties the statistics of model based results has to be taken into account adequately. This is especially true in the field of prognostics and health management. For instance, the derived remaining useful life (RUL) of an analyzed device might suffer in its significance without any information of its credibility. The underlying problem of uncertainty propagation, however, is challenging for many real life applications. In this paper it is demonstrated how Point Estimate Methods (PEMs) are ideally suited to tackle the problem of uncertainty propagation efficiently, i.e. utilizing a minimum of computational effort but ensuring a good approximation power even for highly non-linear applications - which is usually the case in RUL calculation.

The remainder of this paper is organized as follows. In Section 2 the general problem of uncertainty propagation is addressed. In Section 3 the basics of the Point Estimate Methods are summarized. Moreover, it is discussed how non-Gaussian uncertainties can be considered in the PEM framework. Global sensitivities are addressed in 4. The proposed framework of uncertainty propagation is illustrated in Section 5. Finally, the conclusion is given in Section 6.

2. UNCERTAINTY PROPAGATION

The continuously rising number of articles devoted to problems of uncertainty propagation/management in the field of PHM (Saha, Goeble, Poll, & Christophersen, 2009; Daigle & Goebel, 2010; Daigle, Saxena, & Goebel, 2012; Lapira, Brisset, Davari, Siegel, & Lee, 2012; Williard, He, Osterman, & Pecht, 2013; Sankararaman & Goebel, 2013; Sankararaman, Daigle, Saxena, & Goebel, 2013; Daigle & Sankararaman, 2013; Kulkarni, Biswas, Celaya, & Goebel, 2013; X. Zhang & Pisu, 2014) is an excellent indicator for the significance of this topic but highlights that there are still unsolved issues to the same extent. Before introducing the PEM framework as

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a versatile tool for uncertainty propagation, general problems in uncertainty propagation are briefly summarized.

To a certain extent, variability exists in any physical system. The uncertainty quantification as well as its adequate representation might be challenging in itself. Thus, to have a starting point only problems are going to be analyzed which act in the probabilistic framework exclusively. In general, the probability theory provides a comprehensive framework which, however, may suffer in practicability in the presence of nonlinearity. Consequently, there is a keen demand in a credible determination of probability density functions (PDFs) which are associated to computational results in PHM. The concepts of uncertainty propagation can be divided into analytical and in approximate methods, respectively. Analytical approaches might be suitable to illustrate the general concept of uncertainty propagation for deliberately chosen problems, but they suffer from practicability to the most real life applications.

2.1. Analytical Expressions

In general, the uncertainty propagation describes how a random variable, ξ , is transferred by a (non)-linear function, $g(\cdot)$, to the quantity of interest, η , according to

$$\eta = g(\xi) \tag{1}$$

Occasionally, ξ and η are referred to as the input and the output of an uncertainties propagation problem. For the purpose of readability, the proposed methodologies are introduced without loss of generality for 1-dimensional problems, i.e., $\xi \in \mathcal{R}^1$ and $\eta \in \mathcal{R}^1$. Additionally, unless otherwise specified, a standard Gaussian distribution of ξ is assumed, $\xi \sim \mathcal{N}(0, 1)$. One possible way to represent the uncertainty about η consists in calculating the associated probability density function, pdf_{η} . Assuming a monotonic function, $g(\cdot)$, an analytical solution of the resulting PDF can be derived in principle (Breipohl, 1970; Hines, Montgomery, Goldsman, & Borror, 2003)

$$pdf_{\eta} = pdf_{\xi} \left(g^{-1}(\eta) \right) \left| \frac{dg^{-1}(\eta)}{d\eta} \right|$$
(2)

Any non-monotonic function has to be split up into monotonic sub-parts that are transferred separately (Breipohl, 1970; Hines et al., 2003).

Another point of interest might be in characteristic quantities of the associated PDF, i.e, statistical moments of pdf_{η} can be used as an alternative to characterize the induced uncertainty about η (Kay, 1993; Hines et al., 2003). For instance, the mean, $E[g(\xi)]$, and the related variance, σ_{η}^2 , are frequently analyzed and can be determined by

$$E[g(\xi)] = \int_{\Omega} g(\xi) p df_{\xi} d\xi$$
(3)

$$\sigma_{\eta}^2 = \int_{\Omega} \left[g(\xi) - E\left[g(\xi)\right] \right]^2 p df_{\xi} d\xi \qquad (4)$$

Here, Ω represents the integration domain, i.e., in case of probability theory it is equivalent to the sample space (Maitre & Knio, 2010). Throughout this work, also higher statistical moments are applied, e.g., the third, μ_3 , and the fourth central moment, μ_4 , are considered as well and expressed by

$$\mu_{3} = \int_{\Omega} \left(g(\xi) - E[g(\xi)] \right)^{3} p df_{\xi} d\xi$$
 (5)

$$\mu_4 = \int_{\Omega} \left(g(\xi) - E\left[g(\xi)\right] \right)^4 p df_{\xi} d\xi \tag{6}$$

Unfortunately, the proposed analytical solutions of the PDF and/or statistical moments of η can be solved only for a limited number of uncertainty propagation problems (Breipohl, 1970; Stengel, 1994; Hines et al., 2003). In practice, however, approximate methods have to be applied. Here, the Taylor series expansion and sample-based approaches are of current interest and reviewed subsequently.

2.2. Basic Approaches in Approximate Methods

In real life, the complexity of $g(\cdot)$ - if at all available explicitly - prohibits results in closed-form. Consequently, approximate methods aim: (1) to replace $g(\cdot)$ by handy surrogate functions, $\hat{g}(\cdot)$, which facilitate closed-form solutions of Eq. (2)-(6). Or alternatively (2), to solve these integral expressions by numerical routines approximately.

2.2.1. Taylor Series Expansion

To solve equations similar to Eq. (2)-(6) in closed-form the mapping function, $g(\cdot)$, is approximated by a surrogate function, $\hat{g}(\cdot)$, first. Here, the most common approach is the Taylor series expansion. Under the assumption that $g(\cdot)$ is sufficiently differentiable, the uncertainty propagation function can be expressed by a superposition of Taylor terms:

$$\eta \approx \hat{g}(\xi) = \sum_{i=0}^{N} \left. \frac{\partial^{i}g}{\partial\xi^{i}} \right|_{\xi = E[\xi]} \frac{(\xi - E[\xi])^{i}}{i!} \tag{7}$$

Generally, this sum is limited to a certain extent, $N \ll \infty$, which may introduce an approximation error but ensures a manageable computation demand. In the field of uncertainty propagation, therefore, the first-order Taylor expansion can be considered as a standard approach with good reasons. According to Eq. (1), the first-order Taylor series approximation is expanded at $\overline{\xi} = E[\xi]$ as shown below assuming without loss of generality a one-dimensional problem.

$$\eta \approx \hat{\eta} = g(\overline{\xi}) + \left. \frac{\partial g}{\partial \xi} \right|_{\xi = \overline{\xi}} (\xi - \overline{\xi}) \tag{8}$$

Here, the resulting function, $\hat{\eta}$, acts as a surrogate of the original function, η . Now, by evaluating $\hat{\eta}$ instead of η , the determination of statistical moments can be performed easily. For instance, the resulting mean $E[\hat{\eta}]$ is expressed by

$$E[\hat{\eta}] = g(E[\xi]) \tag{9}$$

In addition, the expectation of the squared difference of Eqs. (8) and (9) results into the variance expression of $\hat{\eta}$ according to

$$\sigma_{\hat{\eta}}^2 = \left(\left. \frac{\partial g}{\partial \xi} \right|_{\xi = \overline{\xi}} \right)^2 \sigma_{\xi}^2 \tag{10}$$

Obviously, the statistics about η is approximated by a linearization scheme and, therefore, only valid under serious constraints:

"The Taylor series will be a good approximation if $g(\cdot)$ is not too far from linear within the region that is within one standard deviation of the mean." *A. M. Breipohl (Breipohl, 1970)*

Naturally, the utilization of higher-order terms in the Taylor series expansion improves the accuracy gradually. For instance, it has been shown that even an incorporation of a moderate number of higher-order terms leads to a significant improvement in accuracy (Xue & Ma, 2012), but ...

"In practice, even the second order approximation is not commonly used and higher order approximations are almost never used." *U. N. Lerner (Lerner, 2002)*

The same is true, in case of non-Gaussian distributions and/or correlated random variables, see (Kay, 1993; J. Zhang, 2006; Mekid & Vaja, 2008; Anderson, 2011; Mattson, Anderson, Larson, & Fullwood, 2012) and references therein.

Additionally, the Taylor series is limited to problems of differentiable transfer functions, $g(\cdot)$. At first, that means, the transfer function has to be known explicitly. Therefore, blackbox type functions cannot be addressed immediately. Secondly, even in case of explicit expressions, functions might be non-differential at all, e.g, the maximum function belongs to those terms. Hence, the Taylor series is likely to suffer in precision as well as in applicability.

3. POINT ESTIMATE METHODS

The method of Unscented Transformation (UT), which had been introduced by Julier and Uhlmann in 1994 (Julier & Uhlmann, 1994), have become quite popular in non-linear filter theory over the last two decades. The mathematical basics of UT, however, date back approximately 60 years in time (Tyler, 1953) to the so-called Point Estimate Methods. Formulas had been of interest to solve multi-dimensional integration problems over symmetrical regions, e.g., symmetric probability functions (Evans, 1967, 1974). Due to this symmetry, numerical integration techniques can be derived which at best scale linearly to an n-dimensional integration problem. The general basics of PEMs are shortly summarized below following the annotations given in (Tyler, 1953; Lerner, 2002).

In Point Estimate Methods, the fundamental idea is to choose sample points, ξ_i , and associated weights, w_i , in relation to the first raw moments of the random input variable, ξ . Here, the so-called Generator Function, $GF[\cdot]$, (Tyler, 1953; Lerner, 2002) is of vital importance. A GF describes how sample points are directly determined in \mathcal{R}^n by permutation and the change of sign-combinations. For instance, the first three GFs are illustrated with a problem in \mathcal{R}^3 :

$$GF[0] = \{(0,0,0)^T\}$$
(11)

$$GF[\pm\vartheta] = \{(\vartheta, 0, 0)^T, (-\vartheta, 0, 0)^T, (0, \vartheta, 0)^T, (0, -\vartheta, 0)^T, (0, -\vartheta, 0)^T, (0, 0, -\vartheta)^T, (0, 0, -\vartheta)^T\}$$
(12)

$$GF[\pm\vartheta,\pm\vartheta] = \{(\vartheta,\vartheta,0)^T, (-\vartheta,-\vartheta,0)^T, (\vartheta,-\vartheta,0)^T, (-\vartheta,\vartheta,0)^T, (-\vartheta,\vartheta,0)^T, (-\vartheta,0,\vartheta)^T, (-\vartheta,0,-\vartheta)^T, (-\vartheta,0,\vartheta)^T, (-\vartheta,0,\vartheta)^T, (-\vartheta,-\vartheta)^T, (0,-\vartheta,-\vartheta)^T, (0,-\vartheta,-\vartheta)^T, (0,-\vartheta,\vartheta)^T\}$$

$$(13)$$

Here, the scalar parameter, ϑ , controls the spread of the sample points, ξ_i , in \mathcal{R}^n . Generally, for the purpose of solving a n-dimensional integration problem, the idea is to use a weighted superposition of function evaluations at GF-based sample points, $g(\xi_i)$, according to

$$\int_{\Omega} g(\xi) p df_{\xi} d\xi \approx w_0 g(GF[0]) + w_1 \sum_{n \text{ times}} g(GF[\pm\vartheta]) + \dots + w_n \sum_{n \text{ times}} g(GF[\underline{\pm}\vartheta, \pm\vartheta, \dots, \pm\vartheta])$$
(14)

In practical applications, however, a balance has to be found between the total number of used sample points and the resulting precision in calculation. As only a finite number of raw moments of the input random variable, ξ , is considered, the transfer function, $g(\cdot)$, is approximated by monomials of finite degree (Evans, 1967; Lerner, 2002). For instance, by taking account for the first two non-zero raw moments of ξ (still assuming a standard Gaussian distribution), the related monomials of the transfer function, $g(\cdot)$, are $g(\xi) = 1$ and $g(\xi) = \xi[i]^2$ (any element of the random vector, $i \in$ $\{1,\ldots,n\}; \ \xi \in \mathcal{R}^n$, could be evaluated due to symmetry, $\xi[i] = \xi[j] \sim \mathcal{N}(0,1); \ i, j \in \{1, \dots, n\}; \ \xi \in \mathcal{R}^n$. Thus, the transfer function is approximated correctly for monomials of order three. This approximation scheme is labeled as PEM3 in what follows. Remember that any odd power term is zero in association to Gaussian distributions. In this particular case, only the first two Generator Functions, $GF[0] \cap$ $GF[\pm \vartheta]$, can be parametrized by solving the following equation system

$$w_0 + 2nw_1 = \int_{\Omega} 1p df_{\xi} d\xi = 1$$
 (15)

$$2w_1\vartheta^2 = \int_{\Omega} \xi[i]^2 p df_{\xi} d\xi = 1$$
 (16)

In consequence, for $\vartheta \neq 0,$ the related weights can be calculated via

$$w_0 = 1 - \frac{n}{\vartheta^2} \tag{17}$$

$$w_1 = \frac{1}{2\vartheta^2} \tag{18}$$

As shown in (Julier & Uhlmann, 2004) higher-order moments of the analyzed PDF can be used for the quantification of ϑ additionally. For instance, considering the 4'th raw moment of the standard Gaussian distribution leads to

$$2w_1\vartheta^4 = \int_{\Omega} \xi[i]^4 p df_{\xi} d\xi = 3 \tag{19}$$

Therefore, applying $\vartheta = \sqrt{3}$ might be an optimal choice in case that the probability distribution of η is close to the normal distribution, but different values might be appropriate as well depending on the problem at hand.

After a proper selection of points, $\eta_i = g(\xi_i)$, and associated weights, $w_0 \& w_1$, the mean and the variance of η can be determined approximatively according to

$$E[\eta] \approx \overline{\eta} = w_0 \eta_0 + w_1 \sum_{i=1}^{2n} \eta_i \tag{20}$$

$$\sigma^{2}(\eta) \approx w_{0}(\eta_{0} - \overline{\eta})(\eta_{0} - \overline{\eta})^{T} + w_{1} \sum_{i=1}^{2n} (\eta_{i} - \overline{\eta})(\eta_{i} - \overline{\eta})^{T}$$

$$(21)$$

In the same manner also higher order moments of η can be approximated according to

$$\mu_{3} \approx w_{0}(\eta_{0} - \overline{\eta})(\eta_{0} - \overline{\eta})^{T}(\eta_{0} - \overline{\eta}) + w_{1} \sum_{i=1}^{2n} (\eta_{i} - \overline{\eta})(\eta_{i} - \overline{\eta})^{T}(\eta_{0} - \overline{\eta})$$

$$(22)$$

$$\mu_4 \approx w_0(\eta_0 - \overline{\eta})(\eta_0 - \overline{\eta})^T(\eta_0 - \overline{\eta})(\eta_0 - \overline{\eta})^T + w_1 \sum_{i=1}^{2n} (\eta_i - \overline{\eta})(\eta_i - \overline{\eta})^T(\eta_0 - \overline{\eta})(\eta_0 - \overline{\eta})^T$$
(23)

Naturally, the general precision of the PEM approach can be increased gradually by considering higher order raw moments of ξ . For instance, an approximation scheme can be applied which represents monomials of $g(\cdot)$ correctly up to the precision of 5 via

$$E[g(\xi)] = \int_{\Omega} g(\xi) p df_{\xi} d\xi \approx w_0 g(GF[0]) + w_1 g(GF(\pm\vartheta)) + w_2 g(GF(\pm\vartheta,\pm\vartheta))$$
(24)

This approximation scheme is labeled as PEM5 subsequently. In this case, the number of generated sample points, ξ_i , correlates to $2n^2 + 1$ for a n-dimensional integration problem. Here, for the purpose of parametrization of w_i and ϑ an equation system can be derived taking into account monomials of degree 5 or less

$$w_0 + 2nw_1 + 2n(n-1)w_2 = \int 1p df_{\xi} d\xi = 1 \qquad (25)$$

$$2w_1\vartheta^2 + 4(n-1)w_2\vartheta^2 = \int \xi[i]^2 p df_{\xi} d\xi = 1$$
 (26)

$$2w_1\vartheta^4 + 4(n-1)w_2\vartheta^4 = \int \xi[i]^4 p df_\xi d\xi = 3$$
 (27)

$$4w_2\vartheta^4 = \int \xi[i]^2 \xi[j \neq i]^2 p df_\xi d\xi = 1$$
 (28)

Therefore, the four unknowns can be uniquely determined by

the previous equation system as

$$\vartheta = \sqrt{3}$$
 (29)

$$w_0 = 1 + \frac{n^2 - 7n}{18} \tag{30}$$

$$w_1 = \frac{4-n}{18}$$
(31)

$$w_2 = \frac{1}{36}$$
 (32)

Obviously, in case of an 1-dimensional input problem, $\xi \in \mathcal{R}^1$, the PEM3 and PEM5 scheme become equivalent for $\vartheta = \sqrt{3}$. In this very special constellation the PEM3 scheme has the same precision as PEM5. This might be one reason why the approximation potential of PEM3 is sometimes overrated in n-dimensional input problems. Alternatively, the following considerations may provide an assessment of the associated approximation power in a readily comprehensible manner.

First, the Eq. (21) is reformulated according to

$$\sigma_{\eta}^{2} \approx \left(w_{0}g(\xi_{0})^{2} + w_{1}\sum_{i=1}^{2n}g(\xi_{i})^{2} \right) - \overline{g}(\xi)^{2} \quad (33)$$

$$\sigma_{\eta}^{2} \approx \overline{g(\xi)^{2}} - \overline{g}(\xi)^{2} \quad (34)$$

Obviously, by calculating the variance, σ_{η}^2 , any sample-based approach has to provide a good approximation of $q(\cdot)$ - but of $q(\cdot)^2$, too. Here, the Taylor expansion is in favor as it is sufficient to represent $g(\cdot)$ appropriately. This issue is illustrated in Fig.(1) by an generic 2-dimensional problem, $g(\xi) =$ $\xi[1]^{c_1}\xi[2]^{c_2}$. In case of, $g(\xi)^2 = \xi[1]^{2c_1}\xi[2]^{2c_2}$, monomials of order 4 and higher show up for $c_i > 1$, $\forall i = 1, 2$. Thus, the application of PEM3, which is correct up to monomials of order 3, suffers in precision. In summary, only the PEM5 scheme outperforms the 2. Order Taylor expansion for multi-dimensional input problems and is applied in subsequent considerations for this very reason. (Technical Remark: The same is true when applying PEM3 and PEM5 as an inherent part of Kalman Filtering. Only PEM5 is likely to outperform a so-called second-order Extended Kalman Filter.)

3.1. Non-Gaussian Inputs

So far only the standard Gaussian distribution has been considered. In principle, the PEM concept can be applied for any symmetric distribution. That means, distribution specific sample points and weights can be determined by adapting Eq. (15)-(16) and Eq. (25)-(28), respectively.

In most practical applications, however, one is usually inter-

ested in an easy to implement, robust, as well as efficient algorithm. Therefore, a more practicable framework might be desirable. Instead of adapting the weights and sample points according to the distribution at hand, $pdf_{\xi'}$, a (non)linear transfer function can be derived, $q(\cdot)$, which renders a standard Gaussian distribution into the desired distribution, $\xi' = q(\xi)$. Here, the inverse Rosenblatt transformation (Lee & Chen, 2007) is applied to represent given PDFs associated to ξ' by random variables of standard Gaussian distributions, ξ . Generally, the transformation can be expressed by

$$\xi' = q(\xi) = F^{-1}(\Phi(\xi))$$
(35)

Here, $F^{-1}(\cdot)$ represents the inverse of the cumulative distribution function (CDF) of the desired random variable ξ' , and $\Phi(\cdot)$ denotes the CDF of the standard Gaussian random variable ξ . In the same manner even correlated random variables can be transformed into independent standard Gaussian representatives (Mandur & Budman, 2012). Moreover, empirical (data driven) probability density functions might be incorporated as well, see (Schöniger, Nowak, & Franssen, 2012) for details. In conclusion, the PEM becomes applicable for correlated non-Gaussian random variables. For example, in Tab. 1 some resulting transformation functions are given for frequently used PDFs. Additional transformation formulas can be found in (Isukapalli, 1999).

Type of $pdf_{\xi'}$	Transformation: $q(\xi) =$
Normal (μ, σ)	$\mu + \sigma \xi$
Uniform(a, b)	$a + (b - a) \left(\frac{1}{2} + \frac{1}{2} \operatorname{erf}(\xi \sqrt{2})\right)$
Log-normal(μ, σ)	$\exp(ilde{\mu}+ ilde{\sigma}\xi)$
Gamma(a, b)	$ab\left(\xi\sqrt{rac{1}{9a}}+1-rac{1}{9a} ight)^3$
Exponential(λ)	$-\frac{1}{\lambda}\log\left(\frac{1}{2}+\frac{1}{2}\operatorname{erf}\left(\frac{\xi}{\sqrt{2}}\right)\right)$

Table 1. Probability density function transformation formulas adapted from (Isukapalli, 1999). Here, the term *erf* means the error function.

Obviously, in most cases, the transformation function, $q(\cdot)$, is a non-linear expression. Hence, as an inherent part of the original uncertainty propagation problem, $\eta = g(q(\xi))$, the overall non-linearity may become more severe. That means, PEMs may suffer in precision to a certain extent additionally. In many practical applications, however, this precision flaw might be acceptable in the light of the easiness in implementation. The numerical results given in Sec. 5 confirm the usefulness of the transformation approach convincingly.

3.2. Non-Gaussian Outputs

The problem of an adequate representation of the resulting output uncertainty, η , is addressed in this subsection. As shown previously, an approximation of the mean, $E[\eta]$, and the vari-



Figure 1. Benchmark of approximate methods: light gray circles represent the approximation power of the method given in the caption of the sub-figures. Dark gray circles represents the approximation power of PEM5, which is considered as the gold standard. In general, a high number of circles indicates a good approximation power, i.e., the associated monomial, $\eta = \xi[1]^{c_1}\xi[2]^{c_2}$, is approximated correctly. First row is devoted to the mean approximation. Here, the best performance shows the PEM5 approach followed by PEM3, 2. Order Taylor, and, 1. Order Taylor expansion. Second row is devoted to the variance approximation. Here, the best performance shows the PEM5 approach followed by 2. Order Taylor, PEM3, and, 1. Order Taylor expansion.

ance, σ_{η}^2 , can be determined by PEM. Commonly, a Gaussian PDF associated to the simulation result is parameterized by these two quantities. In cases, however, where the actual distribution of η diverges strongly in comparison to a Gaussian PDF misleading inferences might be expected. Here, the additional information of higher order moments of η , e.g., skewness, μ_3 , and the kurtosis, μ_4 , provided by PEM (Eq. (22)-(23)) might be used as correction factors. For instance, by considering confidence intervals related to η the Cornish-Fisher expansion might be put in operation according to

$$q_p^{cf} = q_p + \frac{(q_p^2 - 1)\mu_3(\eta)}{6\sigma^3(\eta)} + \frac{(q_p^3 - 3q_p)\mu_4(\eta)}{24\sigma^4(\eta)} - \frac{(2q_p^3 - 5q_p)\mu_3^2(\eta)}{36\sigma^6(\eta)}$$
(36)

Here, q_p^{cf} is a corrected confidence limit associated to a confidence level p, for more details see (Usaola, 2009) and references therein.

Moreover, the entire PDF of η can be reconstructed efficiently by combining PEM with the Polynomial Chaos Expansion (PCE) concept. In uncertainty analysis, PCE has become quite popular in the last two decades. The essential idea is to represent a random variable, η , by a weighted superposition of an infinity number of basis functions, $\Psi_i(\cdot)$, (Maitre & Knio, 2010) according to

$$\eta = g(\xi) = \sum_{i=0}^{\infty} a_i \Psi_i(\xi) \tag{37}$$

Similar to the Taylor series expansion computational feasibility has to be addressed. Therefore, the expansion in Eq. (37) is implemented in a truncated form

$$\hat{\eta} = \sum_{i=0}^{l_{pree}} a_i \Psi_i(\xi) \tag{38}$$

By a proper choice of basis functions, $\Psi_i(\cdot)$, the determination of the unknown coefficients, a_i , can be simplified. In particular, different sets of orthogonal basis functions are provided depending on the associated PDF of the random input variable, ξ . For instance, Hermite polynomials are utilized in case of a Gaussian distribution. In literature, different approaches are known to determine the coefficients, a_i , see (Templeton, 2009; Maitre & Knio, 2010) and references therein. Here, the focus is on the least-square approach solely as PEM can be utilized here, too. In practical implementations, a residual, $r(\xi)$, emerges due to the truncation of PCE terms, $l_{pce} << \infty$,

$$r(\xi) = g(\xi) - \sum_{i=0}^{l_{pce}} a_i \Psi_i(\xi)$$
(39)

Now, the expected sum of squared errors can be defined as a suitable cost function

$$J_{PCE} = \int_{\Omega} [r(\xi)]^2 p df_{\xi} d\xi \tag{40}$$

The additivity of the expectation operator enables the following reordering

$$J_{PCE} = \int_{\Omega} g(\xi)^2 p df_{\xi} d\xi - 2 \int_{\Omega} g(\xi) \sum_{i=0}^{l_{pce}} a_i \Psi_i(\xi) p df_{\xi} d\xi + \int_{\Omega} \left(\sum_{i=0}^{l_{pce}} a_i \Psi_i(\xi) \right)^2 p df_{\xi} d\xi$$
(41)

The minimum of this cost function can be found by differentiation of Eq. (41) with respect to a_i , and by setting the resulting derivative equal to zero. Here, due the orthogonality of Ψ_i the mathematical expression results in

$$\frac{\partial J_{PCE}}{\partial a_i} = -2 \int_{\Omega} g(\xi) \Psi_i(\xi) p df_{\xi} d\xi + 2a_i \int_{\Omega} \Psi_i(\xi)^2 p df_{\xi} d\xi \stackrel{!}{=} 0$$

$$\tag{42}$$

Therefore, the i^{th} coefficient can be calculated according to

$$a_{i} = \frac{\int_{\Omega} g(\xi) \Psi_{i} \, p df_{\xi} \, d\xi}{\int_{\Omega} \Psi_{i}(\xi)^{2} \, p df_{\xi} \, d\xi} \tag{43}$$

In case of Hermite polynomials, the denominator can be determined immediately, see (Maitre & Knio, 2010) for details. The numerator of Eq. (43), however, has to be derived numerically. Obviously, instead of solving one of the original integrals, Eq. (2)-(6), a modified integration problem has to be tackled. Here, a proper quantification of the coefficients, a_i , ensures an optimal parametrization of PCE, Eq. (38). By combining PCE with PEM5 an overall number of $2n^2 + 1$; ($\xi \in \mathbb{R}^n$) function evaluations has to be performed. Subsequently, associated moments of $\hat{\eta}$ can be calculated analytically, e.g., the mean and the variance are determined by

$$E[\hat{\eta}] = a_0 \tag{44}$$

$$\sigma_{\hat{\eta}}^2 = \sum_{i=1}^{\iota_{pcc}} a_i^2 \int_{\Omega} \Psi_i(\xi)^2 p df_{\xi} d\xi \qquad (45)$$

In addition, a PDF approximation of $\hat{\eta}$ can be derived in combination with Monte Carlo simulations and standard Kernel density estimation algorithm which are available in standard computation/statistic tools, e.g., routines available in MAT-LAB or in *R*!. Please bear in mind that $\hat{\eta}$ is an algebraic expression of ξ , Eq. (38). Therefore, MC simulations based on $\hat{\eta}$ can be performed at low computational costs. In summary, PCE benefits from its versatility and its good convergence behavior, see (Maitre & Knio, 2010) for additional details.

4. GLOBAL SENSITIVITY ANALYSIS

To assess the influence of the uncertain quantities (called inputs in what follows), ξ , on simulation results, $\eta(t)$, related sensitivities have to be analyzed. Whenever the considered inputs are almost certainly known, i.e. the variance of ξ is low, the sensitivities can be determined by a local approach evaluating the Sensitivity Matrix (SM)

$$SM(t_k) = \left. \frac{\partial \eta(t_k)}{\partial \xi} \right|_{\overline{\xi}} \tag{46}$$

Usually, this is not the case and global methods which take the scatter of inputs explicitly into account have to be applied. Variance-based approaches are tailored to cope with this situation well. Hence, treating inputs, ξ , and the output, $\eta(t)$, as random variables, the amount of variance that each element, $\xi[i]$, adds to the variance of the output, $\sigma^2(\eta(t))$, can be quantified.

The ranking of an input $\xi[i]$ is done by the amount of output variance that disappears, if this input $\xi[i]$ is assumed to be known, $\sigma^2(\xi[i]) = 0$. For any input $\xi[i]$, which is assumed

to be known, a conditional variance, $\sigma_{-i}^2(\eta|\xi[i])$, can be determined. Here, the subscript -i indicates that the variance is taken over all inputs other than $\xi[i]$. As $\xi[i]$ itself is a random variable in reality, the expected value of the conditional variance, $E_i \left[\sigma_{-i}^2(\eta|\xi[i]) \right]$, has to be determined. Here, the subscript E_i indicates that the expected value is only taken over the input $\xi[i]$. Finally, the output variance, $\sigma^2(\eta)$, can be separated (Saltelli, Ratto, Tarantola, & Campolongo, 2005) into the following two additive terms

$$\sigma^{2}(\eta) = \sigma^{2}_{i}(\underbrace{E}_{-i}[\eta|\xi[i]]) + \underbrace{E}_{i}[\sigma^{2}_{-i}(\eta|\xi[i])]$$
(47)

The variance of the conditional expectation, $\sigma_i^2(\underset{-i}{E}[\eta|\xi[i]])$, represents the contribution of input $\xi[i]$ to the variance $\sigma^2(\eta)$. The normalized expression in Eq. 48 is known as the first order sensitivity index (Sobol', 1993) and is used in the following for sensitivity analysis.

$$S_{i}^{\eta} = \frac{\sigma^{2}(E[\eta|\xi[i]])}{\sigma^{2}(\eta)}$$
(48)

The integrals associated to $\sigma^2(\eta)$, $E_{-i}[\eta|\xi[i]]$, and $\sigma^2(\eta|\xi[i])$ are commonly evaluated by Monte Carlo (MC) simulations (Sobol', 2001). MC simulations, however, come along with a prohibitively computational load. Thus, the PEM methodology is put in operation to reduce the computational demand significantly. In detail, the overall variance, $\sigma^2(\eta)$, is determined by the PEM5. A total number of $2n^2 + 1$ sample points have to be evaluated and analyzed. Subsequently, the evaluated samples can be reused to calculate the variance of the conditional expectation, $\sigma_i^2(E[\eta|\xi[i]])$, immediately. That means, the total number of function evaluations correlates to $2n^2 + 1$, i.e., PEM5 renders the Global Sensitivity Analysis into a feasible approach which can be applied with a manageable computational effort to real life scenarios. By implementing the proposed strategy, precision demands are fulfilled automatically, i.e., determined variances are related to monomials of precision 5, whereas the expectations are associated to monomials of precision 3.

5. CASE STUDY

The proposed concepts are demonstrated by a generic uncertainty propagation problem according to

$$\eta(t) = g(\xi', t) = \xi'[1]e^{-\xi'[2](e^{-\xi'[3]t})}$$
(49)

which may describe the progress in degradation of a technical device. The independent elements of the random vector, ξ' , are associated to a non-standard Gaussian, an Uniform, and

Log-Normal distribution, respectively. The detail specifications of the applied distributions (Fig. 2) are given by

$$\xi'[1] \sim \mathcal{N}(5, 0.1) \tag{50}$$

$$\xi'[2] \sim \mathcal{U}(1,3) \tag{51}$$

$$\xi'[3] \sim \ln \mathcal{N}(1, 0.12) \tag{52}$$

By applying feasible transfer functions, $q_i(\cdot)$, the problem of uncertainty propagation is based on standard Gaussian distribution, $\xi[i] \sim \mathcal{N}(0, 1)$; $\forall i = 1, 2, 3$, solely:

$$\eta(t) = g(q(\xi), t) = q_1(\xi[1])e^{-q_2(\xi[2])(e^{-q_3(\xi[3])t})}$$
(53)

Obviously, by applying PEM5 there is a need for evaluating $g(\cdot)$ 19 times ($\xi \in \mathbb{R}^3$, $2 \cdot 3^2 + 1 = 19$). In comparison to Monte Carlo simulations (10.000 simulation runs), the proposed PEM5 concept provides working results in approximating the mean and the variance of η by a minimum of computational load. The indirect approach, i.e. deriving PCE first and utilizing its coefficients to represent the first two moments of η , provides similar results with the same computational effort. The numerical outcome is illustrated in Fig. 3(a) and 3(b), respectively.



Figure 2. Assumed input uncertainties: $\xi[1]' \sim \mathcal{N}(5, 0.1)$, $\xi[2]' \sim \mathcal{U}(1, 3)$, and $\xi[3]' \sim \ln \mathcal{N}(1, 0.12)$.

In principle, with those approximated values confidence intervals, $CI(t) = E[\eta(t)] \pm q_p \cdot \sigma_{\eta}^2$, can be derived. Due to a potential non-Gaussian distribution associated to η symmetric confidence intervals might lead to misinterpretation in the prognostic framework as indicated by Fig. 4(a). Here, confidence intervals corrected by higher-order statistical moments, i.e. by applying PEM5 and the Cornish-Fisher expansion jointly, might be more credible as demonstrated in Fig. 4(b). Moreover, the indirect approach based on PCE mimics the real uncertainty propagation problem adequately (Fig. 4(c)), too. The entire PDF of $\eta(t)$ might be derived economically by Monte Carlo simulations which evaluate the PCE based surrogate expression, $\hat{g}(\cdot)$, but not a potential CPUintensive function, $g(\cdot)$. Corresponding snapshots at t = 0.2and t = 1.0 are illustrated in Fig. 5 and Fig. 6, respectively.



Figure 3. Here, the relative approximation error is illustrated in percentages. PEM5 as well as PCE have an excellent approximation power in relation to the mean, $E[\eta]$. In case of the variance, σ_{η}^2 , PEM5 shows an improved convergence in comparison to PCE.

Here, the non-Gaussian distribution is captured adequately by PCE.

Finally, global sensitivities are analyzed. Assuming the same configuration given in Eq. (50)-(52) the impact of each $\xi[i]$ to the overall variability/uncertainty of $\eta(t)$ is shown in Fig. 7. Here, too, the corresponding Sobol' indices are derived very efficiently. In detail, a total number of $2 \cdot 3^2 + 1 = 19$ function evaluations is sufficient - a remarkable low computational demand in the field of global sensitivity analysis.

6. CONCLUSION

The PEM is identified to be a credible as well as practical concept for the purpose of uncertainty propagation/management. It is demonstrated how PEM can e applied to non-Gaussian distributions by evaluating suitable transfer functions inherently. Moreover, the universal concept of PEM provides an efficient calculation of global sensitivities. Therefore, PEM is a versatile approach which may contribute to tackle an urgent issue in PHM - the reliable propagation of uncertainty in prognostics and health management.



(c) PCE based Monte Carlo simulations, i.e., instead of applying $g(\cdot)$ its efficiently to evaluate surrogate $\hat{g}(\cdot)$ is used

Figure 4. Benchmark Monte Carlo simulation vs. approximate concepts. The 99%- CI derived by PEM5 encloses the MC simulations, see (a). The performance can be improved by applying Cornish-Fisher, see (b). Here, the 99%- CI encapsulates the Monte Carlo simulations more reliably. The MC simulations based on PCE (c) fits to original MS simulations given in (a) and (b) quite well.

REFERENCES

- Anderson, T. V. (2011). Eficient, accurate, and non-gaussian statistical error propagation through nonlinear, closedform, analytical system models. Unpublished doctoral dissertation, Brigham Young University.
- Breipohl, A. M. (1970). *Probabilistic system analysis*. JOHN WILEY & SONS, INC.
- Daigle, M., & Goebel, K. (2010). Improving computational efficiency of prediction in model-based prognsotics using the unscented transformation. Proceedings of the Annual Conference of the Prognostics and



Figure 5. Histogram of a snapshot at t = 0.2. In (a), the histogram is related to the original evaluation of $g(\cdot)$. In (b), the PCE based surrogate, $\hat{g}(\cdot)$, is evaluated instead. The general characteristics of the distribution are preserved by PCE.

Health Management Society.

- Daigle, M., & Sankararaman, S. (2013). Advanced methods for determining prediction uncertainty in model-based prognostics with application to planetary rovers. *Annual Conference of the Prognostics and Health Management Society*.
- Daigle, M., Saxena, A., & Goebel, K. (2012). An efficient deterministic approach to model-based prediction uncertainty estimation. Annual Conference of the Prognostics and Health Management Society.
- Evans, D. H. (1967). An application of numerical integration techniques to statistical tolerancing. *Technometrics*, 9, 441-456.
- Evans, D. H. (1974). Statistical tolerancing: The state of the art. *Journal of Quality Technology*, *6*, 188-195.
- Hines, W. W., Montgomery, D. C., Goldsman, D. M., & Borror, C. M. (2003). *Probability and statistics in engineering*. JOHN WILEY & SONS, INC.
- Isukapalli, S. S. (1999). Uncertainty analysis of transporttransformation models. Unpublished doctoral dissertation, Rutgers, The State University of New Jersey.
- Julier, S. J., & Uhlmann, J. K. (1994). A general method for approximating nonlinear transformations of probability distributions (Tech. Rep.). Dept. of Engineering



(b) MC simulations based on PCE, $\hat{q}(\cdot)$

Figure 6. Histogram of a snapshot at t = 1. In (a), the histogram is related to the original evaluation of $g(\cdot)$. In (b), the PCE based surrogate, $\hat{g}(\cdot)$, is evaluated instead. Almost no differences can be detected between sub-figure (a) and (b).



Figure 7. Global parameter sensitivities of $\xi[1]', \xi[2]'$, and $\xi[3]'$ are shown. Obviously, $\xi[2]'$ contributes at most at the very beginning of the simulation. Whereas, $\xi[1]'$ remains the only source of uncertainty at the end of the simulation.

Science, University of Oxford.

- Julier, S. J., & Uhlmann, J. K. (2004). Unscented filtering and nonliner estimation. *Proceedings of the IEEE*, 92, 401-422.
- Kay, S. M. (1993). Fundamentals of statistical signal processing: Estimation theory. Prentice Hall PTR.
- Kulkarni, C. S., Biswas, G., Celaya, J. R., & Goebel, K. (2013). Physics based degradation models for elec-

tronic capacitor prognostics under thermal overstress conditions. *International Journal of Prognostics and Health Management*.

- Lapira, E., Brisset, D., Davari, H., Siegel, D., & Lee, J. (2012). Wind turbine performance assessment using multi-regime modeling approach. *Renewable Energy*, 45, 86-95.
- Lee, S. H., & Chen, W. (2007). A comparative study of uncertainty propagation methods for black-box type functions. In Asme 2007 international design engineering technical conferences & computers and information in engineering conference.
- Lerner, U. N. (2002). *Hybrid bayesian networks for reasoning about complex systems*. Unpublished doctoral dissertation, Stanford University.
- Maitre, O. P. L., & Knio, O. M. (2010). Spectral methods for uncertainty quantification. Springer.
- Mandur, J., & Budman, H. (2012). A polynomial-chaos based algorithm for robust optimization in the presence of bayesian uncertainty. In 8th ifac symposium on advanced control of chemical processes.
- Mattson, C. A., Anderson, T. V., Larson, B. J., & Fullwood, D. T. (2012). Efficient propagation of error through system models for functions common in engineering. *Journal of Mechanical Design*, 134.
- Mekid, S., & Vaja, D. (2008). Propagation of uncertainty: Expressions of second and third order uncertainty with third and fourth moments. *Measurement*, *41*, 600-609.
- Saha, B., Goeble, K., Poll, S., & Christophersen, J. (2009). Prognostics methods for battery health monitoring using a bayesian framework. *IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT*, 52(2).
- Saltelli, A., Ratto, M., Tarantola, S., & Campolongo, F. (2005). Sensititivity analysis for chemical models. *Chemical Reviews*, 105, 28112828.
- Sankararaman, S., Daigle, M., Saxena, A., & Goebel, K. (2013). Analytical algorithms to quantify the uncertainty in remaining useful life prediction. In *Aerospace conference*.
- Sankararaman, S., & Goebel, K. (2013). Uncertainty quantification in remaining useful life of aerospace components using state space models and inverse form (Tech. Rep.). NASA Ames Research Center; Moffett Field, CA, United States.
- Schenkendorf, R. (2014). *Optimal experimental design for parameter identification and model selection*. Unpublished doctoral dissertation, Otto-von-Guericke University, Magdeburg, Germany.
- Schöniger, A., Nowak, W., & Franssen, H.-J. H. (2012). Parameter estimation by ensemble kalman filters with transformed data: Approach and application to hydraulic tomography. *Water Resources Research*, 48.
- Sobol', I. M. (1993). Sensitivity analysis for nonlinear mathematical models. *Mathematical Modeling and Compu*-

tational Experiment, 1, 407-414.

- Sobol', I. M. (2001). Global sensitivity indices for nonlinear mathematical models and the monte carlo estimates. *Ma*, 55, 271–280.
- Stengel, R. F. (1994). *Optimal control and estimation*. Dover Publications.
- Templeton, B. A. (2009). *A polynomial chaos approach to control*. Unpublished master's thesis, Virginia Polytechnic Institute ans State University.
- Tyler, G. W. (1953). Numerical integration of functions of several variables. *Canadian Jn. Math.*, *5*, 393-412.
- Usaola, J. (2009). Probabilistic load flow with wind production uncertainty using cumulants and cornish-fisher expansion. *Electrical Power and Energy Systems*, *31*, 474-481.
- Williard, N., He, W., Osterman, M., & Pecht, M. (2013). Comperative analysis of features for determining state of health in lithium-ion batteries. *International Journal of Prognostics and Health Management*.
- Xue, J., & Ma, J. (2012). A comparative study of several taylor expansion methods on error propagation. In *Geoinformatics, 2012 20th international conference on geoinformatics.*
- Zhang, J. (2006). The calculating formulae, and experimental methods in error propagation analysis. *IEEE Transactions on Reliability*, 55, 169-181.
- Zhang, X., & Pisu, P. (2014). Prognostic-oriented fuel cell catalyst aging modeling and its application to healthmonitoring and prognostics of a pem fuel cell. *International Journal of Prognostics and Health Management*, 5.

BIOGRAPHIES

René Schenkendorf received his Dipl.-Ing. in Technical Cybernetics from the Otto-von-Guericke University, Magdeburg in Germany in 2007. From 2007 until 2012 he had been a Ph.D. student at the Max Planck Institute for Dynamics of Complex Technical Systems in Magdeburg, Germany. His dissertation titled "Optimal Experimental Design for Parameter Identification and Model Selection" has been submitted to the Otto-von-Guericke University, Magdeburg, Germany in 2013. The focus in this study was about uncertainty quantification and propagation. Since 2013 he is with the German Aerospace Center at the Institute of Transportation Systems. His current research interests include data analysis, statistical process control, uncertainty propagation, and modeling.
APPENDIX

Following Hermite polynomials have been applied:

$\Psi_0(\xi)$	=	1
$\Psi_1(\xi)$	=	$\xi[1]$
$\Psi_2(\xi)$	=	$\xi[1]^2 - 1$
$\Psi_3(\xi)$	=	$\xi[1]^3 - 3\xi[1]$
$\Psi_4(\xi)$	=	$\xi[2]$
$\Psi_5(\xi)$	=	$\xi[2]^2 - 1$
$\Psi_6(\xi)$	=	$\xi[2]^3 - 3\xi[2]$
$\Psi_7(\xi)$	=	$\xi[3]$
$\Psi_8(\xi)$	=	$\xi[3]^2 - 1$
$\Psi_9(\xi)$	=	$\xi[3]^2 - 3\xi[3]$
$\Psi_{10}(\xi)$	=	$\xi[1]\xi[2]$
$\Psi_{11}(\xi)$	=	$\xi[1]^2 \xi[2] - \xi[2]$
$\Psi_{12}(\xi)$	=	$\xi[2]^2 \xi[1] - \xi[1]$
$\Psi_{13}(\xi)$	=	$\xi[3]$
$\Psi_{14}(\xi)$	=	$\xi[1]^2\xi[3] - \xi[3]$
$\Psi_{15}(\xi)$	=	$\xi[3]^2\xi[1] - \xi[1]$
$\Psi_{16}(\xi)$	=	$\xi[2]\xi[3]$
$\Psi_{17}(\xi)$	=	$\xi[2]^2\xi[3] - \xi[3]$
$\Psi_{18}(\xi)$	=	$\xi[3]^2\xi[2] - \xi[2]$
$\Psi_{19}(\xi)$	=	$\xi[1]\xi[2]\xi[3]$

Following coefficients have been utilized:

$$\begin{split} &\int_{\Omega} \Psi_0(\xi)^2 \, pdf_\xi \, d\xi &= 1\\ &\int_{\Omega} \Psi_1(\xi)^2 \, pdf_\xi \, d\xi &= 1\\ &\int_{\Omega} \Psi_2(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_3(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_3(\xi)^2 \, pdf_\xi \, d\xi &= 1\\ &\int_{\Omega} \Psi_5(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_6(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_6(\xi)^2 \, pdf_\xi \, d\xi &= 1\\ &\int_{\Omega} \Psi_8(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{10}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{10}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{12}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{13}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{13}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{15}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{16}(\xi)^2 \, pdf_\xi \, d\xi &= 1\\ &\int_{\Omega} \Psi_{16}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{16}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{18}(\xi)^2 \, pdf_\xi \, d\xi &= 2\\ &\int_{\Omega} \Psi_{19}(\xi)^2 \, pdf_\xi \, d\xi &= 1\\ \end{split}$$

Integrated Diagnosis and Prognosis of Uncertain Systems: A Bond Graph Approach

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ABSTRACT

Bond Graph (BG) methodology is used to model the dynamic uncertain systems. Uncertainty is considered on the system parameters in form of intervals. The uncertain parameters are allowed to deviate within their prescribed interval limits. Single fault hypothesis is considered in this work such that the parameter undergoing degradation is known a priori. A new method for generation of interval valued thresholds is briefly described in the framework of BG models in Linear Fractional Transformation form. The diagnostic module is formed using such thresholds which detect the beginning of degradation of a parameter in the real system. The new concept of Interval Extension of Analytical Redundancy Relations (IE-ARRs) is introduced which consider the parametric uncertainties and the evolution of degrading parameter in real time. Then, the Centre and Range method for fitting linear regression models to interval symbolic data is adapted to fit piece wise linear models to the interval valued times series data of IE-ARRs. Further, the new concept of generation of failure thresholds from a nominal system model is introduced and developed. Finally, the fitted linear model is used to estimate the remaining useful life of the parameter under degradation. Simulations are carried out on an example DC motor model. Linear and non-linear parametric degradations are considered. Results are presented in form of simulations.

1. INTRODUCTION

Health monitoring of systems is essential and significantly necessary in ensuring the correct operation of complex engineering systems.

Mayank Shekhar Jha et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. The integral task of system health monitoring includes both the diagnostics and prognostics. Diagnostics involves detection of fault and its subsequent isolation whereas prognostics deal with the prediction of the remaining useful life of the different components or subsystems of the system.

1.1 Diagnosis of Uncertain Systems: Bond Graph and Interval Approaches

Bond Graph (BG) approach is a powerful tool for dynamical modeling and has established its efficiency for real applications. Further, because of its causal and structural properties, BG has been extensively used for Fault Detection and Isolation (FDI). A large body of research exists in the area of model based diagnosis in the framework of BG based approaches for modeling multi energetic dynamic systems. Various efficient algorithms have been implemented in dedicated software due to its graphical aspect which renders a clear insight into the physics of the system (Ould Bouamama, Staroswiecki, & Samantaray, 2006).

Recently, successful robust diagnostic methods have been developed using BG models in Linear Fractional Transformation (LFT) (Djeziri, Merzouki, & Ould Bouamama, 2007). The LFT representation of a global model can be derived from a BG model, by replacing each uncertain element by its LFT BG model. This form had been initially introduced in (Kam & Dauphin-Tanguy, 2005)for modelling and further for robust fault diagnosis (Djeziri, Merzouki, & Ould Bouamama, 2006). There in, procedures to generate robust Analytical Redundant Relations (ARRs) from a bond graph LFT model in derivative causality has been well developed .When used for FDI purpose, absolute values have been considered on the parameter uncertainties in the previous approaches. Adaptive thresholds that are robust to parameter uncertainties are generated, inside which the behavior of the system can be considered as healthy. For diagnosis of uncertain systems, bounding approaches have been developed where the parametric uncertainty is considered in the form of interval models. Early work on treatment of uncertain parameters as intervals and subsequent usage for diagnosis is found in works of Adrot (2000). The approach, called bounded approach, represented these uncertainties by a set of possible values for which only their bounds were known. Ragot, Alhaj Dibo and Maquin (2003), proposed an interval technique for the detection and the isolation of sensor faults in the case of a static linear model .The similar case is treated for dynamic systems by (Ragot & Maquin, 2003). They treated the problem of data validation in the case of certain systems with uncertain measurements through interval approach. In the works of (Fagarasan, Ploix, & Gentil, 2004) interval calculation laws are used to generate the exact estimated output, bounds of the estimates are computed using traditional numerical integration techniques from the uncertain parameter interval vertices, assuming that monotonic property holds. Thus, the envelopes generated, are primarily by the estimation of state or parameter.

1.2 Fault Prognosis using Time Series Data

In past one decade, there has been an exceeding surge in research for the development of fault prognostic methods. Prognosis methods can be developed in three categorized approaches namely: data-driven, physics based and hybrid approaches. Data-driven approaches mainly use information from previous collected data (training data) to identify the characteristic of currently measured damage state and to predict the future trend. Physics-based approaches assume that a physical model describing the behavior of damage is available, and combine the physical model with measured data to identify model parameters and to predict the future behavior (Yang, 2002), (James & Hyungdae, 2005) and (Ming, 2012). Hybrid approaches combine the abovementioned two methods to improve the prediction performance (Mohanty, Teale, Chattopadhyay, Peralta, & Willhauck, 2007). The data driven methods have been well developed from the point of view of time series prediction techniques. Method for predicting future conditions of machine operation, based on the time series prediction technique, associated with a classification tree and regression is proposed in (Trana, Yanga, Oha, & Tanb, 2008). (Wu, Hu, and Zhang(2007), proposed an extension of the basic Autoregressive Integrated Moving Average (ARIMA) approach, using bootstrap forecasting for machine life prognosis. Greitzer and Pawlowski (2002), propose a method of fault prognosis, based on a regression function, whose number of used points varies so that the prognosis remains consistent with the recent measures.

1.2.1 Prediction Using Interval valued data

Prediction techniques using interval data in symbolic form have been approached and developed by the communities of artificial intelligence, multivariate analysis and pattern recognition. They have been successful in dealing with prediction problem when the considered data is in interval form (Billard & Diday,2003). Such data arises in many situations such as recorded data for financial forecasting, daily interval temperatures at meteorological stations, daily interval stock prices etc. From the point of view of health monitoring of uncertain systems, such data are interesting and exploitable when the uncertain parameters are treated as intervals.

Linear regression models for predicting interval data was first approached in (Billard & Diday,2000), where the Centre method of fitting a linear regression model to symbolic interval data sets from the Symbolic Data Analysis(SDA) perspective is presented. It consists of fitting a linear regression model to the mid-points of the interval values assumed by the interval variables in the learning set and this model is applied to the lower and upper bounds of the interval values of the independent interval variables to predict the lower and upper bounds of the dependent variable, respectively. Minmax method (Billard & Diday, 2002), assumes independence between the values of lower and upper bounds of the dependent data intervals which are then estimated by different vectors of parameters. However, both of these methods consider information carried by midpoints only. As such, they fail to capture the influence of interval range on the estimation of parameters. This in turn, affects the prediction ability.

The *Centre and Range* approach to fitting a linear regression model to symbolic interval data was proposed in (Lima Neto & De Carvalho, 2008). There in, the problem was investigated as an optimization problem, which sought to minimize a predefined criterion. The approach considered the minimization of the sum of the mid-point square error plus the sum of the range square error, and the reconstruction of the interval bounds based upon the mid-point and range estimates. The lower and upper bounds of the interval values of an interval valued variable, linearly related to a set of independent interval-valued variables were predicted for independent data sets. It is shown that including information given by both center and the range of an interval data improves the model prediction performance very considerably.

1.3 Assumptions, Proposed Approach and Organization of the Work

In this work, BG methodology is used to model the dynamic uncertain systems. Uncertainty is considered only on the system parameters in form of intervals. The uncertain parameters are allowed to deviate within their prescribed interval limits. Single fault hypothesis is followed such that the parameter undergoing degradation is known *a priori*. In section 2, the new method of generation of interval valued thresholds proposed in (Jha, Dauphin-Tanguy, & Ould Bouamama, 2014) is briefly described in the framework of BG-LFT models. The diagnostic module is formed using such thresholds which detect the beginning of degradation of a parameter in the real system. In section 3, the new concept of Interval Extension of ARRs (IE-ARRs) is introduced which considers the parametric uncertainties and the evolution of degrading parameter in real time. Then, the Centre and Range method (Lima Neto et al, 2008) for fitting linear regression models to interval symbolic data is adapted to fit piece wise linear models to the interval valued times series data of IE-ARRs. The procedure is explained in the subsequent subsection 3.2. Further, the new concept of generation of failure thresholds from a nominal system model is introduced and explained in subsection 3.3. Finally, the fitted linear model is used to estimate the remaining useful life of the parameter under degradation. In section 4, the developed method is validated using a pedagogical DC motor example. Linear and non-linear parametric degradation of physical components are considered. Results are presented in form of simulations. Finally conclusions are drawn in section 5.

2. ROBUST DIAGNOSIS THROUGH BG-LFT MODELS

Diagnosis based on BG-LFT models is considered in this section. Recently the authors have proposed a novel way of generating thresholds over ARR where the uncertainties are modeled as intervals (Jha, Dauphin-Tanguy, & Ould Bouamama, 2014). The novelty there comes in the treatment of uncertain part in form of intervals and using the obtained *Interval Extension Functions* (IEF) for generation of robust optimized thresholds which are adaptive and non-symmetrical in general.

2.1 Generation of Interval valued robust thresholds

A system parameter θ_i with deviations as $\Delta \theta_{i,l}$ and $\Delta \theta_{i,u}$ in the negative and positive side respectively over its nominal value $\theta_{i,n}$ is represented in Eq.(1). For the parameter θ_i , the *Interval Uncertainty* denoted as $[\partial \theta_i]$ in Eq.(2) is obtained by bounding the uncertainties $\delta \theta_i$ over its nominal value $\theta_{i,n}$. For example, for an uncertain resistance parameter *R* with nominal value of 10 Ohm bounded in the interval as [8 Ohm, 13 Ohm], the nominal parameter is denoted as $R_n = 10$ Ohm, uncertainty interval is $[\partial R] = [-2,3], \Delta R_l = 2, \Delta R_u = 3$. Then, $[R] = [R_n - \Delta R_l, R_n + \Delta R_u] = [10 - 2, 10 + 3] = [8,13]$

$$[\theta_i] = \left[\theta_{i,n} - \Delta \theta_{i,l}, \theta_{i,n} + \Delta \theta_{i,u}\right] \tag{1}$$

$$[\partial \theta_i] = [-\Delta \theta_{i,l}, \Delta \theta_{i,u}]$$
⁽²⁾

$$0 \le \Delta \theta_{i,l}, 0 \le \Delta \theta_{i,u}$$

In general, in the framework of BG-LFT modeling, where $\theta_i \in \{R, C, I, GY, TF, RS\}$, a residual R is derived from LFT-BG with preferred derivative causality, so that the knowledge of initial conditions is not necessary for real time evaluation. Residual R is composed of two completely separated parts: a certain residual r and the uncertain part bas shown in (4),(5),(6) and (7) where TF_n and GY_n are respectively the nominal values of TF and GY moduli. R_n ; C_n ; I_n and RS_n are the nominal values of physical BG elements R, C, I and RS. SSe and SSt are the signal sources (measurement signals from real system) and δ_R , δ_L , δ_C , $\delta_{RS}, \delta_{TF}, \delta_{GY}$ are values of multiplicative uncertainty. Natural interval extension function IEF (Moore, 1996), B of the uncertain part b is formed by replacing each parameter multiplicative uncertainty with its prescribed interval uncertainty as in Eq.(8).The IEF. $B([\partial \theta_{1,n}], [\partial \theta_{2,n}], \dots, [\partial \theta_{q,n}], SSe, SSf)$ where q is the number of uncertain elements considered, agrees with the uncertain ARR function $b(\partial \theta_{1,n},...,\partial \theta_{a,n}SSe,SSf)$ such that Eq.(8) is satisfied for each of the degenerate intervals $[\partial \theta_{1,n}, \partial \theta_{1,n}], [\partial \theta_{2,n}, \partial \theta_{2,n}], \dots, [\partial \theta_{q,n}, \partial \theta_{q,n}].$ Through Extended Fundamental Theorem of Interval Analysis (Moore, 1996), Eq.(9) is satisfied for every interval set of Interval Uncertainty.

$$R = \Phi \begin{cases} \sum Se, \sum Sf, SSe, SSf, R_n, C_n, I_n, TF_n, \\ GY_n, RS_n, \sum w_i \end{cases}$$
(3)

$$R = r + b \tag{4}$$

$$r = \Phi \begin{cases} Se, Sf, SSe, SSf, R_n, C_n, I_n, TF_n, \\ GY_n, RS_n \end{cases}$$
(5)

$$b = \sum w_i = \Psi\{\partial \theta_{1,n}, \partial \theta_{2,n}, \dots, \partial \theta_{q,n}, SSe, SSf\}$$
(6)

$$w = \Theta \begin{cases} Se, Sf, SSe, SSf, R_n, C_n, I_n, TF_n, \\ GY_n, RS_n, \delta_R, \delta_I, \delta_C, \delta_{TF}, \delta_{GY}, \delta_{RS} \end{cases}$$
(7)

$$b(\partial \theta_{1,n}, \partial \theta_{2,n}, \partial \theta_{3,n}, \dots, \partial \theta_{q,n}, SSe, SSf)$$

$$\in B([\partial \theta_{1,n}], [\partial \theta_{2,n}], [\partial \theta_{3,n}], \dots, [\partial \theta_{q,n}], SSe, SSf)$$
(8)

When the system shows nominal behavior, an envelope around the residual R may be defined by the range of the function B. Under non-faulty conditions, the nominal residual r is around zero(theoretically). From Eqs.(5,6,7,8,9) the residual R can be written as in Eq.(10) and from Eq.(9), it is bounded by the interval valued thresholds B as shown in Eq.(11). Note that in this work, signals from dualised sensor effort sources and flow sources SSe, SSf respectively are not considered in the interval form following the hypothesis that sensor measurements are not considered faulty.

$$b(\partial \theta_{1,n}, \partial \theta_{2,n}, \dots, \partial \theta_{q,n}, SSe, SSf)$$

$$\subseteq B([\partial \theta_{1,n}], [\partial \theta_{2,n}], \dots, [\partial \theta_{q,n}], SSe, SSf)$$
(9)

$$R = r + b(\partial \theta_{1,n}, \partial \theta_{2,n}, \dots, \partial \theta_{q,n}, SSe, SSf) = 0$$
(10)

$$r = 0, R = b(\partial \theta_{1,n}, \partial \theta_{2,n}, \dots, \partial \theta_{a,n}, SSe, SSf)$$

$$R \subseteq B([\partial \theta_{1,n}], [\partial \theta_{2,n}], \dots, [\partial \theta_{q,n}], SSe, SSf)$$
(11)

Finding the most optimum thresholds narrows down to the problem of finding the exact range of IEFs (Armengol, 1999). The main limitation is that IEFs do not have some of the properties of real number arithmetic, for instance, the distributive property. This means that the exact range of a function is not always computable. However, the computed range is never an under-bounded one. The exact range is obtained if there are no multi-incident interval variables in $b(\partial \theta_{1,n}, \partial \theta_{2,n}, \dots, \partial \theta_{q,n}, SSe, SSf)$. The determination of the exact range of a function is a problem when there are multi-incident variables because each incidence is considered as an independent variable. In this case, this problem is similar to a global optimization one (Hansen, 1992).

3. FAULT PROGNOSIS THROUGH LINEAR REGRESSION OF INTERVAL EXTENSION ARRS (IE-ARRS)

Consider the scenario when a set of faulty parameters of the system undergo degradation and rest of the uncertain parameters deviate within their prescribed limits. In such cases, point data valued ARRs are not capable of capturing the sufficient information provided by such deviating uncertain parameters. To deal with such cases, *Interval Extension* ARRs (IE-ARRs) are proposed in this work which captures system information in form of interval data where the uncertain parameters are modelled in form of intervals.

3.1. Interval Extension ARRs (IE-ARRs)

Interval-valued functions are obtained by selecting a realvalued function f and computing the range of values f(x) takes as x varies through some interval X. By definition (Moore, 1996), the result is equal to the set image f(X).

Interval extensions of ARRs can be obtained by bounding each uncertain parameter involved in the ARR, within its prescribed interval limit. This is done by considering the uncertainties on the negative and positive sides $\Delta \theta_{i,l}$ and $\Delta \theta_{i,u}$ respectively, over the nominal value $\theta_{i,n}$ of the i^{th} uncertain parameter θ_i , to obtain the interval form $[\theta_i]$ as in Eq. (2). In Eq. (12) consider a_i as any ARR with mindependent parameters such that q ($q \le m$), of them are uncertain, $U = [u_1, u_2...]^T$ is the input vector, $\theta = [\theta_1, ..., \theta_q..., \theta_m]^T$ is the nominal parameter vector and $Y = [y_1, y_2, ...]^T$ is the output vector. The corresponding *Interval Extension (IE)*, *IEa_i* is obtained by bounding each uncertain parameter within their interval limits as shown in Eq.(12). In the BG framework, consider *r* in Eq.(5), which represents the point valued ARR with uncertain parameters with their nominal values R_n , C_n , I_n , TF_n , GY_n , RS_n .

$$a_{i} = f(U, \theta, Y) = f(U, \dot{U}, \dots, ((\theta_{1}, \theta_{2}, \dots, \theta_{q})))$$

$$\dots = \theta_{m-1}, \theta_{m})^{T}, Y, \dot{Y}, \dots) = 0$$

$$IEa_{i} = F(U, \theta, [\theta], Y) = F(U, \dot{U}, \dots, (([\theta_{1}], [\theta_{2}], \dots, [\theta_{q}])) \dots = \theta_{m-1}, \theta_{m})^{T}, Y, \dot{Y})$$

$$(12)$$

The *IE*, *R* is formed by considering each uncertain parameter as intervals Eq. (13). Note that the dualised signal sources (sensor measurements) are not considered faulty or uncertain. Also, it must be noted that *IE* of ARRs consider the parameter with uncertainties in the interval form $[\theta_i]$, whereas for the generation of interval valued thresholds in Eq. (9), only the parametric uncertainties are considered in the interval form $[\partial \theta_i]$.

$$R_{i}(t) = \Phi_{i} \begin{cases} Se, Sf, SSe, SSf, [R], [C], [I], [TF], \\ [GY], [RS] \end{cases}$$
(13)

3.2 Fitting a Linear Regression Model to Time Series Interval Valued Data

One way to represent this type of data is through the midpoint and range of interval (Lima Neto & De Carvalho, 2008).When such data are collected in chronological sequence, the time series of interval valued data is obtained. At each instant of time, t=1,2,3,...,n, where *n* is the number of intervals observed in the time series , $x_{l,t}$ and $x_{u,t}$

with $x_{l,t} \leq x_{u,t}$, are the upper and lower bounds of the interval respectively. The method employed here uses two time series: the interval mid-point series x^c ; and the half range interval series x^r . Considering the interval time series in Eq.(14), mid-point and half-range time series can be represented as in Eq.(15).

$$[x_{L,1}, x_{U,1}], [x_{L,2}, x_{U,2}], \dots, [x_{L,n}, x_{U,n}].$$
(14)

$$x_t^C = \frac{x_{L,1} + x_{U,1}}{2}, x_t^R = \frac{x_{L,1} - x_{U,1}}{2}$$

$$(t = 1, 2, ..., n)$$
(15)

In this work, the centre and range method (Lima et al., 2008) is adapted to fit a linear regression model to interval valued time series data.

Let $E = \{e_1, e_2, \dots, e_k\}$ be the set of time indexed data described by interval valued dependent variable *Y* and independent time variable *T* such that for each $e_i \in E(i = 1..k), Y_i = [y_{l,i}, y_{u,i}] \in \zeta = \{[a,b]: a, b \in R, a \le b\}$ and $T_i = [t_{l,i}, t_{u,i}] \in \zeta$. Parameter vector β , is estimated using the information contained in the mid-points and ranges of the intervals.

Let Y_i^c and T_i^c respectively, assume the value of the midpoint of the interval valued variables Y_i and T_i . Also let Y_i^c and T_i^r assume the value of the half range of interval valued variables Y_i and T_i .

Then, each e_i is represented as interval quantitative feature $w_i = (t_i^c, y_i^c)$ and $r_i = (t_i^r, y_i^r)$ where,

$$t_{i}^{c} = (t_{l,i} + t_{u,i})/2,$$

$$t_{i}^{r} = (t_{u,i} - t_{l,i})/2,$$

$$y_{i}^{c} = (y_{l,i} + y_{u,i})/2,$$

$$y_{i}^{r} = (y_{u,i} - y_{l,i})/2,$$

(16)

are the observed values of T^{c} , T^{r} , Y^{c} and Y^{r} respectively.

Consider the dependent variables Y^c and Y^r related to the independent time variable T^c and T^r according to the following linear regression relationship,

$$y_i^c = \beta_0^c + \beta_1^c t_i^c + \varepsilon_i^c \tag{17}$$

$$y_i^r = \beta_0^r + \beta_1^r t_i^r + \varepsilon_i^r \tag{18}$$

The sum of squares of deviations is given in Eq. (19). It represents the sum of the mid-point square error plus the sum of the range square error, considering independent vectors of parameters to predict the mid-point and the range of the intervals.

$$S = \sum_{i=1}^{k} ((\varepsilon_{i}^{c})^{2} + (\varepsilon_{i}^{r})^{2}) = \sum_{i=1}^{k} (y_{i}^{c} - \beta_{0}^{c} - \beta_{1}^{c} t_{i}^{c})^{2} + \sum_{i=1}^{k} (y_{i}^{r} - \beta_{0}^{r} - \beta_{1}^{r} t_{i}^{r})^{2}$$
(19)

Values of β_0^c , β_1^c , β_0^r and β_1^r that minimize *S* are found by differentiating Eq. (19) with respect to the parameters and setting the result equal to zero as in Eq. (20). It gives set of equations as shown in Eq. (21). The estimated parameter set $\hat{\beta}$ can be obtained by solving Eq.(21), as in Eq. (22). Note that imprecision on the independent time variable has been accommodated by modeling it in form of intervals. This way, imprecision arising due to sensor/measurement (acquisition) delay can be taken into account. In cases where the time variable is not treated as an imprecise quantity, the upper and lower bound remain the same resulting in the interval centre being equal to the time value at that instant as $t_i^c = t_i$ and the time interval range equal to zero. It is a special case when the *Centre-Range* method reduces to the *Centre* method (Lima et al).

3.3 Remaining Useful Life Estimation

Beginning of degradation is indicated by the diagnostic module when the point valued ARRs go outside the interval valued thresholds, developed in section 2. Once, degradation is indicated, IE-ARRs are taken into account. With single degrading parameter, the IE-ARR evolves into time as the degradation proceeds.

$$\frac{\partial S}{\partial \beta_0^c} = 0, \frac{\partial S}{\partial \beta_1^c} = 0, \frac{\partial S}{\partial \beta_0^r} = 0, \frac{\partial S}{\partial \beta_1^{\vee r}} = 0$$
(20)

$$\hat{\beta}_{0}^{c}k + \hat{\beta}_{1}^{c}\sum_{i=1}^{k}t_{i}^{c} = \sum_{i=1}^{k}y_{i}^{c}$$

$$\hat{\beta}_{0}^{c}\sum_{i=1}^{k}t_{i}^{c} + \hat{\beta}_{1}^{c}\sum_{i=1}^{k}(t_{i}^{c})^{2} = \sum_{i=1}^{k}y_{i}^{c}t_{i}^{c}$$

$$\hat{\beta}_{0}^{c}\sum_{i=1}^{k}\frac{k}{2}\sum_{i=1}^{k}(t_{i}^{c})^{2} = \sum_{i=1}^{k}y_{i}^{c}t_{i}^{c}$$
(21)

$$\beta_{0}^{r}k + \beta_{1}^{r}\sum_{i=1}^{k}t_{i}^{r} = \sum_{i=1}^{k}y_{i}^{r}$$
$$\hat{\beta}_{0}^{r}\sum_{i=1}^{k}t_{i}^{r} + \hat{\beta}_{1}^{r}\sum_{i=1}^{k}(t_{i}^{r})^{2} = \sum_{i=1}^{k}y_{i}^{r}t_{i}^{r}$$
$$\hat{\beta} = (\hat{\beta}_{0}^{c}, \hat{\beta}_{1}^{c}, \hat{\beta}_{0}^{r}, \hat{\beta}_{1}^{r})^{T} = (A)^{-1}d$$
(22)

3.3.1 Parametric Failure Threshold

For prediction of RUL of the degrading parameter, the value of the IE-ARR at the parametric failure state must be known. This is not known beforehand from the real system. It can however be provided by the system model. Let us denote the degrading parameter candidate as $\theta_{\rm deg}$. Its value at failure must be fixed. This can be fixed based upon system performance, stability or user defined conditions/thresholds. This value can be bounded in interval form as per the user/system dependant conditions. Let us denote such a value as $\theta_{\deg,fail}$. Then the deviation that the parameter must go in order to reach the failure state is $\Delta \theta_{\deg,fail} = \theta_{\deg,fail} - \theta_{\deg,n}$. Thus, it provides the value of parametric failure deviation $\Delta \theta_{\text{deg},fail}$.

Consider the interval thresholds in Eq. (9) generated in section 2, which form the envelop around the residual under nominal system condition. When the same expression is

considered with the value of failure deviation $\Delta \theta_{\text{deg},fail}$, parametric failure thresholds are obtained as Eq. (23), where the parametric uncertainty-interval form is considered for all the uncertain parameters sensitive to the corresponding residual. Also, unlike the diagnostic thresholds where sensor measurements from real system (*SSe*, *SSf*) are used, *B_{fail}* considers the corresponding outputs from nominal system model which has all the respective parameters in nominal state. Due to the considered parametric uncertainty of each uncertain parameters, upper and lower bounds of *B_{fail}* are generated as Eq.(24).

$$B_{fail} = \Psi(\Delta \theta_{deg,fail}, ([\partial \theta_{1,n}], [\partial \theta_{2,n}], ...$$
$$....[\partial \theta_{q,n}]).De_{model}, Df_{model})$$
(23)

$$B_{fail} \in [B_{fail,l}, B_{fail,u}]$$
(24)

3.3.2 RUL Estimation

The degradation information provided in form of interval valued data from the IE-ARRs is used to fit a linear regression model in a sliding window framework. Let the time window length be *k*. The interval time series data of degradation be obtained as $E = \{e_j, e_{j+1}, e_{j+2} \dots e_{j+k}\}$, where for each time indexed $e_i (j \le i \le j+k)$, $Y_i = [B_{faili,l}, B_{fail,i,u}]$ and $T_i = [t_{i,l}, t_{i,u}]$. T^c, T^r and Y^c, Y^r are to be obtained using Eq. (16). The parameter vector $\hat{\beta}$ is estimated using Eq. (22). Once $\hat{\beta}$ is obtained, the degradation can be approximated by the piece wise linear model of degradation for the *k* time instants in the present j^{th} time window. The regression model is fitted with parameter failure value to assess the RUL in j^{th} time window as,

$$t_{fail}^{c}(j) = (B_{fail}^{c} - \hat{\beta}_{0}^{c}) / \hat{\beta}_{1}^{c}$$

$$t_{fail}^{r}(j) = (B_{fail}^{r} - \hat{\beta}_{0}^{r}) / \hat{\beta}_{1}^{r}$$

$$B_{fail}^{c}(j) = (B_{fail,l} + B_{fail,u}) / 2,$$

$$B_{fail}^{r}(j) = (B_{fail,u} - B_{fail,l}) / 2$$

$$t_{fail} = [t_{fail}^{c} - t_{fail}^{r}, t_{fail}^{c} + t_{fail}^{r}]$$
(25)
(25)
(25)
(26)

The time window is shifted to t=j+1 for next k time instants and a similar routine is followed.

Thus, the value of the RUL can be obtained in the bounded form based on the piece wise linear approximation of degradation in sliding time window framework. The routine is repeated to obtain the RUL in the next time window. It should be noted that the RUL estimated, corresponds to the linear approximation of degradation. As such, in cases of gradual linear degradation an approximate constant value of RUL is obtained in interval form. However, in cases of non-linear or accelerated degradation, a distribution of RUL will be obtained. Analysis of such a distribution form has not been done here. The choice of window length is important in determining the correct linear approximation of degradation as in, a large window width is better in cases of gradual-linear degradation. This aspect has not been analyzed in this work and forms the future perspective.

4. SIMULATIONS AND RESULTS:

The proposed methodology is applied over a DC-motor model. Fig.1 shows the model schema and Fig.2 its associated BG in integral causality. The integral causal model is used for simulation purpose. The model parameters are taken as: $Ra = 2.4 \Omega$, the resistance of stator; La = 0.84 H, the inductance of the stator; ke= 0.14 N-m/A, the motor constant; $J_m = 0.08$ kg m², the moment of inertia of rotor; $f_m = 0.01$ Ns/ m, coefficient of friction of motor shaft, with the inputs Ua(t) being the input voltage of 220 V in magnitude and $\tau(t)$ being the load torque of 5 N m in magnitude. The observed outputs are: $i_m(t)$ current of inductor, and $\omega_m(t)$ being the angular velocity of the motor shaft (rad/s).

Considered model has uncertain parameters as *La*, *ke*, *f*, *Jm* and *Ra*. Single fault hypothesis is followed with the assumption that sensors/measurements are not faulty. Parametric degradation of the electrical resistance *Ra* is considered and simulated under various cases of degradation. Simulations have been carried out on SIMULINK[®] which is integrated with MATLAB[®]. Interval computations have been carried out through INTLAB, (Rump, 1998) a toolbox designed for MATLAB environment. It allows the more traditional infimum-supremum as well as the midpoint-radius representations of intervals.



Figure1. Schema of DC motor



Figure 2. Integral causal BG model of DC motor Consider the BG-LFT model in preferred derivative causality of DC-motor in Fig.3. The fictive inputs $w_i, i \in (R_a, L_a, k_e, J_m, f_m)$ are related to fictive outputs $z_i, i \in (R_a, ..., f_m)$ as follows.

$$w_{R_{a}} = -\partial_{R_{a}} \cdot z_{R_{a}}; z_{R_{a}} = R_{a} \cdot \{i_{m}\}$$

$$w_{L_{a}} = -\partial_{L_{a}} \cdot z_{L_{a}}; z_{L_{a}} = L_{a} \cdot (d\{i_{m}\}/dt)$$

$$w_{1,ke} = -\partial_{k_{e}} \cdot z_{k_{e}}; z_{k_{e}} = k_{e} \cdot \{w_{m}\}$$

$$w_{f_{m}} = -\partial_{fm} \cdot z_{fm}; z_{fm} = f_{m} \cdot \{w_{m}\}$$

$$w_{J_{m}} = -\partial_{Jm} \cdot z_{Jm}; z_{Jm} = J_{m} \cdot (d\{w_{m}\}/dt)$$

$$w_{2,k_{e}} = \partial_{k_{e}} \cdot z_{2,k_{e}}; z_{2,k_{e}} = k_{e} \cdot \{i_{m}\}$$
(27)

where ∂_{Ra_a} , ∂_{L_a} , ∂_{k_e} , ∂_{f_m} , ∂_{J_m} are the multiplicative uncertainties on the respective parameters.





$$R_{1} = \underbrace{U_{a} - L_{an} \cdot (d\{l_{m}\}/dt) - R_{an} \cdot \{l_{m}\} - k_{e,n}\{w_{m}\}}_{r_{1}} + \underbrace{W_{R_{a}} + W_{L_{a}} + W_{1,k_{e}}}_{b_{1}}$$
(28)

$$b_{1} = \Delta R_{a} \cdot \{i_{m}\} + \Delta L_{a} \cdot \{i_{m}\} | + \Delta k_{e} \cdot \{w_{m}\}$$

$$R_{2} = -\tau - f_{m,n} \cdot \{w_{m}\} - J_{m,n} \cdot (d\{w_{m}\}/dt) + k_{e,n}\{i_{m}\} + \frac{w_{fm} + w_{Jm} - w_{2,ke}}{b_{2}}$$

$$b_{2} = \Delta f_{m} \cdot \{w_{m}\} + \Delta J_{m} \cdot \{\dot{w}_{m}\} - \Delta k_{m}\{i_{m}\}$$
(29)

where b_1 and b_2 represent the uncertain part of each residual R_1 and R_2 with $\Delta \theta_i$ denoting the additive uncertainty on parameter θ_i . Then, each additive uncertainty is bounded in interval form to form the interval valued thresholds B_1 and B_2 respectively as Eq. (30) and Eq. (31).

Since R_a is sensitive to R_1 only, R_2 is not considered for subsequent analysis. L_a and k_e are considered to deviate within their interval limits but do not undergo any kind of degradation:

$$\begin{split} & L_a \in [L_{a_n} - (L_{a_n} * 0.1), L_{a_n} + (L_{a_n} * 0.5)] \\ & k_e \in [k_{e_n} - (k_{e_n} * 0.1), k_{e_n} + (k_{e_n} * 0.2)]. \\ & \text{Allowed deviation on } R_a \quad \text{is such that,} \\ & R_a \in [R_{a_n} - (R_{a_n} * 0.2), R_{a_n} + (R_{a_n} * 0.1)]. \end{split}$$

$$B_{1} = [-\Delta R_{al}, \Delta R_{au}] \cdot \{i_{m}\} + [-\Delta L_{al}, \Delta L_{au}] \cdot \{\frac{d}{dt}i_{m}\}$$
(30)

$$+[-\Delta k_{e_{l}}, \Delta k_{e_{u}}]\{w_{m}\}$$
(31)
$$B_{2} = [-\Delta f_{m_{l}}, \Delta f_{m_{u}}].\{w_{m}\} + [-\Delta J_{m_{l}}, \Delta J_{m_{u}}].\{\dot{w}_{m}\}$$

$$-[-\Delta k_e, \Delta k_{e_u}]\{l_m\}$$

4.1Case I: No Degradation.

All the three parameters R_a , L_a and k_e which are sensitive to R_1 deviate within their interval limits. Fig.5 shows the interval thresholds generated from Eq. (30) such that $B_1 = [B_{1,l}, B_{1,u}]$

where the considered allowed interval limits are: $\Delta R_{al} = R_{an} * 0.2, \Delta R_{au} = R_{an} * 0.1, \Delta L_{al} = L_{an} * 0.1,$ $\Delta L_{au} = L_{an} * 0.5, \Delta k_{el} = k_{en} * 0.1, \Delta k_{eu} = k_{en} * 0.2$

Fig. 5 shows the simulated residual R_1 which is generated from the real system with uncertain parameters deviating inside their prescribed interval limits. It is under the thresholds indicating no fault or degradation. The residual is different from zero indicating that parameters deviate within prescribed limits. Note that for the purpose of illustration, there is no noise considered in the simulations, assuming that sensor measurements are present with negligible noise.



Figure 5. Residual r_1 under nominal conditions

4.2 Case II: Gradual and Linear Degradation in Winding Resistance R_a

A degradation of the form $R_a(t) = R_{an}(1 + \alpha t)$ is considered in the real system model, where $\alpha = 2.5e^{-4}$. Fig. 6 shows the degradation profile. The diagnostic threshold should be crossed at t=400s when $R_a = R_{an} + \Delta R_{au}$. The failure value of R_a is set to be $R_{a,fail} = 3\Omega$ so that $\Delta R_{a\,fail} = 0.6\Omega$. Failure value is expected to be reached at t=1000s. Failure thresholds which consider model inputs can be formed following Eq. (23) as in Eq. (32), where the measurement inputs are from the nominal system model.

$$B_{Ra,fail} = \Delta Ra_{fail} \cdot \{i_{m,\text{mod}el}\} + [-\Delta La_l, \Delta La_u] \cdot \{\frac{d}{dt}i_{m,\text{mod}el}\} + [-\Delta ke_l, \Delta ke_u] \{w_{m,\text{mod}el}\}$$
(32)

Fault detection: Detection of the degradation on R_a is done by the diagnostic thresholds B_1 as shown in Fig.7. As expected, the thresholds are crossed by the residual at t=400s indicating the beginning of degradation. Failure thresholds $B_{Ra,fail}$ are formed from the inputs of a nominal system model.

Fault prognosis: As soon as the degradation is detected, the prognostic module is triggered on. The *Interval Extension* of r_{I_i} denoted by IEr_{I_i} is considered from there-on i.e. after t=400s as,

$$IEr_{1} = U_{a} - [L_{a_{n}} - \Delta L_{a_{l}}, L_{a_{n}} + \Delta L_{a_{u}}](d\{i_{m}\}/dt)$$

$$-R_{a_{n}} \cdot \{i_{m}\} - [ke_{n} - \Delta ke_{l}, ke_{n} + \Delta ke_{u}]\{w_{m}\}$$

$$(33)$$

Fig.7 shows the evolution of r_1 and IEr_1 as the degradation proceeds in time. Failure threshold $B_{Ra,fail} \in [B_{Ra,fail,l}, B_{Ra,fail,u}]$ considered for the estimation of RUL is also shown in the same figure. Fig. 8 shows the data of Fig. 7 between time 420s and 530s presenting the various intervals for better clarity. Linear regression model is then fitted to the interval data of IEr_1 in a sliding window of length k=5. Fig. 9 shows the obtained RUL in the interval form. As expected, the RUL is bounded around 1000s in interval form. Thus, for linear-gradual degradations, this approach is efficient in estimating the RUL.



Figure 6. Linear Degradation induced in R_a





4.3 Case III: Gradual and Non-Linear Degradation of Ra

gradual degradation Α non-linear, of the form $R_a = R_{a_n} e^{0.001.t}$ is considered on *Ra*. The diagnostic threshold should be t=95s crossed at when $R_a = R_{a_n} + R_{a_n} * 0.1$ (so that its maximum limit for allowed deviation is reached). The failure state value is prefixed as $R_{a, fail} = 3.0\Omega$, the expected RUL is 223s.

Fault detection and Prognosis: Fig. 10 shows the simulation of the residual which crosses the thresholds at t=95s, indicating the beginning of degradation. Once degradation is detected, IEr_1 is considered upon which the linear regression model is fit in sliding window of length k = 5*st where stis the sample time, taken as 0.01 s here. Fig.11 shows the estimated bounded RUL .It is noticed that the RUL evolves in time starting from 250s. It is estimated by approximation of the non-linear degradation through a linear fit model. At each instant, the obtained RUL depends upon the linear approximation of nature of degradation in that time window. The linear approximation is helpful in prediction with sufficient accuracy.



Figure 10. Detection of Degradation and IEr_1 profile



Figure 11. RUL estimation (Case: III)

5. CONCLUSION

The proposed interval valued thresholds are successful in detecting the beginning of parametric degradation in linear cases and gradual non-linear cases. The diagnostic module formed by interval valued thresholds; is derived from LFT model in derivative causality which detects the beginning of degradation. This in turn, enables the prognostic procedure where in, Interval Extensions of ARRs are used to carry the parametric degradation information in form of interval valued data time- series. Such IE-ARRs consider parametric uncertainty intervals of non-degrading uncertain parameters allowing them to deviate within their prescribed limits. For gradual, linear parametric degradation, the Centre and Range method can accurately predict the RUL as taking into account the imprecision brought in by the deviating uncertain parameters. For gradual, non-linear degradation, this method predicts the RUL by approximating the degradation as a linear model in sliding time window framework, with sufficient accuracy. This work does not consider noise brought in by sensor measurements or any external disturbances. Also, it lacks in being robust to outliers while approximating the linear model of degradation. Thus, further development is motivated . The proposed method needs to be developed to deal with nonlinear cases, accurately. It should be noted that this methodology is developed in the BG framework of modeling, as it enables a simplified and holistic approach towards multi energetic uncertain dynamic systems.

REFERENCES

- Adrot, O. (2000). Diagnosis based on uncertain models using interval analysis: the bounding approach. Doctoral Thesis, National Polytechnique Institute of Lorraine, Vandoeuvre-les Nancy, France.
- Armengol, J. (1999). Application of Modal Interval Analysis to the simulation of the behavior of dynamic systems with uncertain parameters, Phd thesis, University of Girona, Girona, Catalonia, Spain.

- Armengol, J., Vehi, J., Angel Sainz, M., & Herrero, P. (2003). 'Fault detection in a pilot plant using interval models and multiple sliding time windows. *Safeprocess*, (pp. 729-734). Washington, USA.
- Billard, L., & Diday, E. (2003). From the statistics of data to the statistics of knowledge: symbolic data analysis. *Journal of American Statistics Association*, 98 (462), 470-487.
- Billard, L., & Diday, E. (2000). Regression analysis for interval-valued data. Proceedings of the Seventh Conference of the International Federation of Classification Societies (IFCS'00).Data Analysis, Classification and Related Methods, pp. 369-374. Belgium: Springer.
- Billard, L., & Diday, E. (2002). Symbolic Regression Analysis. Proceedings of the Eighenth Conference of the International Federation of Classification Societies (IFCS'02), In: Classification, Clustering and Data Analysis,, pp. 281-288. Poland: Springer.
- Djeziri, M., Dauphin Tanguy, G., & Merzouki, R. (2007). Bond Graph Model Based For Robust Fault Diagnosis. *Proceeding of the 2007 American Control Conference*, (pp. 3017-3022). New York City.
- Djeziri, M., Merzouki, R., & Ould Bouamama, B. (2006). Fault Detection of Backlash Phenomenon in Mechatronic System with Parameter Uncertainties using Bond Graph Approach. Proceeding of the 2006 IEEE International Conference on Mechatronics and Automation, (pp. 600-605). Luoyang, China.
- Djeziri, M., Merzouki, R., & Ould Bouamama, B. (2007). Robust Fault Diagnosis Using Bond Graph Approach. *Journal of IEEE/ASME Transactions on Mechatronics*, 12 (6), pp. 599-611.
- Fagarasan, I., Ploix, S., & Gentil, S. (2004). Causal fault detection and isolation based on a set-membership approach. *Automatica*, *40*, 2099-2110.
- Greitzer, F., & Pawlowski, A. (2002). Embedded Prognostics Health Monitoring. 48th Annual Instrumentations, Systems, and Automation Society International Instrumentation Symposium. San Diego,USA.
- Hansen, E. (1992). *Global Optimization Using Interval Analysis*. New York: Marcel Dekker, Inc.
- Hargreaves, G. (2002). *Interval Analysis in MATLAB*. University of Manchester: Master's thesis, Department of Mathematics.
- James, C., & Hyungdae, L. (2005). Gear fatigue crack prognosis using embedded model, gear dynamic model and fracture mechanics. *Mechanical Systems and Signal processing*, 19 (4), 836-846.
- Jha, M., Dauphin-Tanguy, G., & Ould Bouamama, B. (2014). Robust FDI based on LFT BG and Relative Activity at Junction *European Control Conference:Accepted.* Starsbourg, France.

- Kam, C. S., & Dauphin-Tanguy, G. (2005). Bond Graph models for structured parameter uncertainities. *Journal of th Franklin Institute*.
- Lima Neto, E., & De Carvalho, F. (2008). Centre and range Method for fitting a linear regression model to symbolic interval data,Computational Statistics and Data Analysis. *Computational Statistics and Data Analysis*, 52, 1500-1515.
- Ming, Y. (2012). Fault diagnosis and prognosis of hybrid systems using Bond Graph model and Computational intelligence. Nanyang: PhD Thesis,School of Engineering and Electronic Engineering,Nanyang Techological Institute.
- Mohanty, S., Teale, R., Chattopadhyay, A., Peralta, P., & Willhauck, C. (2007). Mixed Gaussian process and state-space approach for fatigue crack growth prediction. *International Workshop on Stuctural Health Monitoring*, (pp. Vol 2,pp.1108-1115).
- Moore, R. (1996). *Interval Analysis*. Englewood Cliffs,NJ: Prentice Hall.
- Ould Bouamama, B., Staroswiecki, M., & Samantaray, A. (2006). Software for Supervision System Design In Process Engineering Industry. 6th IFAC, SAFEPROCESS, (pp. 691-695). Beijing, China
- Ragot, J., Alhaj Dibo, M., & Maquin, D. (2003). Validation of data by Bounding Approaches, *Journ ees Doctorales* d'Automatique, (pp. 347-352). Valencienne- France,.
- Ragot, J. & Maquin, D. (2003). Validation of data from systems of measurement uncertainty. *European Journal* of Automated Systems RS special issue JESA Applications tools set-calculations, 37 (9).
- Rump, S. (1998). INTLAB-INTerval LABoratory. *Developments in Reliable Computing*, 77-104.
- Trana, V., Yanga, B., Oha, M., & Tanb, A. (2008). Machine condition prognosis based on regression trees and onestep-ahead Prediction. *Mechanical Systems and Signal Processing*, 22, 1179-1193.
- Wu, W., Hu, J., & Zhang, J. (2007). Prognostics of machine health condition using an improved ARIMA-based prediction method. *IEEE*, (pp. 1062-1067). Harbin,China.
- Yang, S. (2002). "An experiment of state estimation for predictive maintenance using Kalman filter on a DC motor. *Realiablity Engineering & System Safety*, 75 (1), 103-111.

Wireless Modular System for Vessel Engines Monitoring, Condition Based Maintenance and Vessel's Performance Analysis

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ABSTRACT

Circumstances in shipping have rapidly changed within the past few years. The large increase of fuel cost, the decrease in the price of fares, the rapid progress in telecommunications, the crew reduction per vessel, the new environmental restrictions and the reinforcement of Green Shipping significance are facts that make remote monitoring and the evaluation of the vessel engines' performance an imperative need. The challenges occurring from changing the typical vessel engine monitoring and maintenance model are many, such as: equipment installation on moving vessels, lack of long-term vessel availability, experienced and trained crew being on land, many different types or ages of vessel and vessel manufacturers.

An extremely advantageous solution with proven positive results for this specific matter is the use of monitoring systems consisting of wireless smart sensors. These systems provide flexibility, adaptability, scalability and easy installation. The only system of this kind available in the global market, adjusted for Shipping and specifically for monitoring vessel engines, is the LAROS platform by NOMIA S.A. (member of Prisma Electronics SA).

In this paper we will present the current status of maintenance in maritime vessels and the abovementioned new innovative remote monitoring of a vessel's operational status electronic platform, which can greatly reduce the operational costs, enhance the operational vessel status and ensure the high quality of service a maritime company provides, as well as improve its environmental policy. Moreover, a case study of performance analysis regarding a vessel with the LAROS platform on board will be presented, showing the possibilities and the dynamics of vessel performance monitoring.

1. INTRODUCTION

For the last 30 years the model of Condition Based Maintenance (CBM) in Industrial Production Lines has been implemented with spectacular results in operating costs, environmental effects, productivity and safety. Predictive Maintenance (PdM) and its predecessor, Preventive Maintenance (PM), is a great factor of product quality assurance and cost reduction in all kinds of applications. PdM evaluates the condition of equipment by monitoring the condition of various critical parameters and plays an important role in production lines, quality control systems, health and food industry, goods transportation etc. Additionally, by employing Wireless Sensor Network (WSN) technology for Condition Monitoring (CM) and data transmission, PdM systems have been further developed and have become more efficient and smart, due to the inherent characteristics of WSNs, such as compactness, ease of installation, low power consumption, local data processing and storing. WSNs have found their way to the market and are becoming a core factor of PdM systems. As a consequence, the total revenues for wireless sensors and transmitters in industrial applications in 2009 reached \$526.7 million and are likely to reach \$1.8 billion in the next four years (Thusu, 2010).

Goods and raw transportation is a key factor of the global economy, especially today where the global market is continuously growing, so the need for effective, qualitative and low cost transportation is becoming greater. Maritime companies have adopted control systems on modern vessels, in order to keep the functionality of their vessels in a high

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state and reduce maintenance and repair costs, since they present a large portion of the operational costs. The need of operational cost reduction, of vessels' reliability increase and of vessel crew reduction leads to the implementation of more sophisticated control and maintenance systems. The maintenance of maritime vessels is a subject of major interest for everyone that is involved in Maritime. Every unscheduled day of vessel maintenance costs a maritime company an average cost of at least \$20.000, not including the repair costs. So it can be seen clearly that vessel maintenance is an important factor for the proper operation of a maritime company.

In our days, based on the new technologies it is possible to develop CBM systems in maritime industry. The cost in time and money to implement an on-line CBM system can be significantly reduced based on Wireless Sensor Networks for CM purposes. For the last 5 years, there are some pilot projects and a number of companies that offer condition analysis services to maritime companies. These off-line techniques can be used in a number of cases. With the new communication technologies it is possible to develop systems for on-line condition analysis which further maximize and enhance the benefits. A CBM system, based on wireless sensor nodes for monitoring various parameters which reflect the operational status of a vessel's engine or critical parts, will send a direct report to the maritime company headquarters when a fault or critical situation is inspected. In this way, the technical superintendents of the maritime company will have the ability to estimate the criticality of the situation and proceed rapidly to certain action steps to face the problem. This can lead to prevention of unpredictable machinery failures, repair time reduction, fewer spare parts usage. Regarding the vessels performance condition, wireless sensor nodes (Emmanouilidis Katsikas, Pistofidis and Giordamlis., 2009) can be easily installed to efficiently monitor various engine critical parameters, such as engine performance (produced torque and power), fuel and lubricant consumption, quality of fuel and exhaust emission, water temperature of the cooling system of the engine etc. By transmitting the available data to the company's headquarters' engineers, performance analysis can be easily made, so decisions and suitable actions can be taken in very short time and this can lead to significant vessel's working costs reduction due to fuel and lubricant consumption reduction and optimization of vessel's performance in general. Last but not least, the positive environmental impact of the reduction of fuel consumption can be a great factor for adopting this type of systems. As can be seen, adoption of a WSN system for condition monitoring on a vessel can have great benefits for a maritime company.

This paper is structured as follows. Section 2 presents the current status of vessels' maintenance and operation monitoring. Section 3 presents the idea of adopting WSNs for CBM purposes, how this can be implemented and which

can be the benefits. Section 4 describes the proposed solution named LAROS, a system for monitoring and diagnosing the operational status of a vessel and presents a use case. Section 5 presents the financial benefits of adopting LAROS for vessel maintenance and performance monitoring purposes. Finally in section 6 few conclusions are presented.

2. VESSELS MAINTENANCE CURRENT STATUS

In order to define the needs of the maritime companies that can be accommodated by a CBM model, we must analyze the operational procedures and the methods that are currently used.

2.1. Company Structure

Depending on the number of the ships, the fleet is organized into groups of 5 to 10 ships. For each group, there is a fleet manager with his technical and mechanical team. The fleet manager coordinates the execution of the scheduled tasks, observes the vessels' operational condition and is responsible to solve any technical or operational problem. The fleet managers report to the operational and to the technical manager of the company. The operational manager is responsible for the operational schedule of the ships and the technical manager is responsible for the operational condition of the ships. Finally the operational and technical managers' report to the general manager the maintenance schedules and the new buildings of ships. Figure 1 presents the typical structure of a maritime company, analyzed above.



Figure 1. Typical Structure of a Maritime Company

The vessel crew technicians either on a scheduled time basis or when an alarm from the control system appears, record some basic parameters from the control system's sensors. This report is given to the captain, who along with other data are sent to the fleet manager. The fleet manager along with its team revises a scheduled maintenance plan and provides solutions to technical problems. These decisions are sent to the captain for execution. So, the fleet manager has overview of the ships' conditions based on oral communication with the vessel captain and on periodical reports of various factors from the ships engineers, see figure 2.



Figure 2. The information flow diagram during a scheduled inspection or an alarm

2.2. Current Maintenance Model in Maritime

Regarding the maintenance operations, the model that is followed today and defined by the international regulations is the following: the various vessel parts, at least the critical ones, have a certain operation life cycle, based on asset's OEM specifications and after this period these parts must be changed, no matter their actual operational condition. No matter if a specific part is in good condition and can be further used without risking the vessel's operating status, it must be changed.

2.3. Disadvantages of the Current Maintenance Model

At the above mentioned model of information flow, the inspections of the engines and other critical parts are basically time scheduled. Additionally, there is a very considerable human factor in the reports, since various reports are based on the data that the vessel crew records. Also the communication between the fleet manager and the engineers is not direct.

So, this type of communication presents the following problems.

- The ship technicians carry out scheduled inspections and the results are not always accurate due to sensors fault or false measurements by the crew.
- The fleet manager has periodical indirect communication with the captain. The description of each situation is subjective and depended on the captain's approach.
- The decisions taken for the determination of repair actions and maintenance by the engineering team are not based on actual and real-time data, but on incomplete and unreliable data. Moreover, it is rather difficult to measure the effects of the execution of the various actions.

• The various part maintenance actions are workingtime scheduled, no matter the actual condition of the parts.

As a consequence of the maintenance model disadvantages reported above, the scheduled maintenance results in high cost of spare parts and maintenance procedures. The incomplete technical reports offer limited and unreliable data and cause difficulties in decision making and crew evaluation. Moreover, in most vessels there is no monitoring of the fuel and oil consumptions compared to the vessel instantaneous performance, or in most occasions depends on human observation, something that is in many occasions debatable, so a common policy to reduce fuel and oil consumption is difficult to be determined. Furthermore, the absence of a prognosis system makes it difficult to prevent breakdowns and provokes high cost and time-consuming repair procedures.

2.4. Environmental Impact

Maritime fuel oil type use is nowadays defined in several Sulphur Emission Control Areas (SECAs) by International Maritime Organization (IMO) in order to reduce specific vessel engine exhaust emissions such as CO, SO₂, NO_X. In the near future more SECAs are going to be defined and stricter rules are going to be adopted for maritime vessel gas emissions.

Moreover, monitoring the chemical composition of the vessel gas emissions can provide a detailed analysis of the burning process that can help a maritime company reduce the gas emissions, reduce the fuel consumption and optimize the engine's burning process. So, the operational costs of a vessel will be reduced due to lower consumption, but also the vessel gas emissions will be reduced, so there is a reduced environmental impact.

2.5. Vessel Maintenance Current Status Conclusions

As analyzed above, after recent research experience and operation analysis of maritime companies, the two main problematic issues they face is the absence of a complete remote monitoring system of the fleet as well as the environmental consequences of the vessels operation.

3. CONDITION BASED MAINTENANCE FOR VESSELS

3.1. Introduction

In all kind of industrial, manufacturing and transportation services, maintenance costs are among the most considerable factors of the operational costs. In plant production lines, transportation services, etc. maintenance requires significant time and amount of money. Efforts for reducing the maintenance costs through various technological solutions and asset management strategies have been presented (Holmberg, Jantunen, Adgar, Mascolo, Arnaiz and Mekid., 2010). The basic strategy of maintenance is Corrective Maintenance, where an asset is operated until it fails or breaks and then is replaced. A more advanced one is Preventive Maintenance or time-based maintenance or scheduled maintenance, where maintenance actions take place on regular, prescheduled time, based mostly on asset's OEM specifications. This kind of maintenance can be considered "over-maintenance", due to in many occasions assets are replaced before completing their actual life cycle. In recent times, where cost is a key factor for the sustainability of an enterprise, maintenance costs are driven to be as less as possible. So, a new type of maintenance has arisen, where all actions take place just before an asset reaches the end of its life cycle. This kind of maintenance is called Condition Based Maintenance and its most advanced representative is called Predictive Maintenance (Neelamkavil, 2010). In this kind of maintenance, critical parameters of a process, machine or asset are continuously monitored and analyzed in real-time and maintenance is performed just before breakdown. By adopting this type, maintenance takes place only when necessary, so asset availability costs, maintenance time and operational costs are reduced, efficiency is increased and generally the time and money spent for maintenance are reduced.

CBM refers to a maintenance strategy that recommends maintenance decisions based on the information collected through CM. The main steps that CBM consists of are: data acquisition, data processing and maintenance decisionmaking (Jardine, Lin and Banjevic, 2005). Technologies, human skills and various layers of communication are involved in the CBM process in order to make timely decisions about the maintenance requirements of critical equipment and to organize the available condition data, such as diagnostic and performance data, maintenance histories, operator logs and design data (Cheng, 2007).

According to recent advances, new regulations by international maritime organizations and insurance companies are going to be adopted in the recent future that will allow the use of assets further to OEM specifications, if these assets are monitored regarding their operating condition and good operational condition is concluded.

3.2. Benefits of Vessel's Operational Status by Using CBM

In our days, maritime companies have to face the limited crew number, the low technical quality of the crew and the big competition in rates along with the increase of the fuel and assets costs. Additionally, they need to increase the reliability and reduce the environmental impact that a vessel creates due to its inherent operation. These are the basic reasons for adopting a CBM model in Maritime.

A very important issue is the reduction of fuel and lubricant costs. This can be achieved by monitoring the fuel quality

and the fuel and lubricant consumption, as well as the exhaust emissions; various sensors can monitor the fuel loading process, the fuel and lubricant consumption and the exhaust gases for identifying the chemical composition and quality of fuel oil and lubricants. This can lead to detailed reports for the fuel consumption process, in order to identify possible actions for reducing these costs.

Another issue is the frequency and context of the reports that are sent from the vessel to the maritime headquarters. The reports are sent in a steady daily basis, so the engineers at the headquarters are not informed in real-time when a maintenance task must take place. Also, the reported values have been instantly taken and no long asset operation monitoring time is adopted. So, as can be easily understood, they are not able to safely estimate a critical situation when needed. An on-line remote health monitoring system can be a trustful source of information crucial to take decisions, reschedule the maintenance plan and provide specific repair instructions to the crew.

By adopting an additional CBM system that works independently from the vessel's control system, provides a safe diagnosis method in an alarm situation. The engineers have extra information for the problem that has arisen in order to take the right decision. This can lead to reduction of the costs and time required for the repair actions.

In Maritime, Preventive Maintenance is the main maintenance model, where various parts are being replaced or repaired on steady time basis, based on the technical specifications of the parts. This leads, as abovementioned, to unneeded replacements and maintenance actions that cost more time and money. A PdM system that collects sensor data and processes them with advanced algorithms, can provide maintenance alarms only when is truly needed. So, the parts are repaired or replaced when they reach the end of their life cycle and the maintenance costs and time are greatly reduced. This can also lead to increase of the time interval between drydockings, where drydocking is called the process of removing the vessel from the water in order to enable work to be performed on the exterior part of the ship below the waterline. Moreover, unscheduled vessel immobilization due to engine failure that costs a great amount of money is greatly reduced. Another advantage is the independence of the maintenance tasks from the human factor, since sensor data are directly sent to the vessel's Bridge and Headquarters, without human interference.

A critical issue for a maritime company is when wants to buy a used vessel. The old vessel maintenance technical reports are probably destroyed and a great amount of money and time is spent for the appropriate inspection before the transaction. A system that can help in extracting critical data before the transaction, as well as during the early operation phase is really helpful in order to effectively monitor the general operational vessel status. The communication expenses are another main issue of a vessel's expenses, because the costs depend on the volume of data that are sent. So, sending technical reports and communicating, when a breakdown occurs, burdens the communication expenses. Adopting a system that sends updates only when the operational status is changed or data only when required reduces this kind of expenses.

Moreover, the safety of the vessel's crew during operation, as well as during maintenance can be increased with a monitoring system. For example by monitoring the presence of explosive and toxic gases during maintenance may prevent life threatening cases for the maintenance crew. At last by monitoring the environmental impact of a vessel operation via continuous monitoring of the fuel consumption and exhaust gases a maritime company can manage more effectively and reduce fuel consumption and improve its environmental policy.

Also a common monitoring system (independent from the type and age of a maritime enterprise vessels), may strongly simplify all the internal processes of the enterprise and manage more effectively the human resources.

As can be easily understood an operational status monitoring system can provide great benefits at a maritime company, ensure the high quality of maintenance and operation of ships, reduce operational, repair and maintenance costs, increase crew safety, promote the environmental policy of the company, as well as ensure the high quality of service that the company provides

3.3. Wireless Sensor Networks for Vessel Maintenance Purposes

Advances in wireless communications, digital electronics, MEMS technology, miniaturization, low power circuit design and computing enhanced the effort of developing sensor nodes that are small size, lightweight, compact, autonomous, rather cheap, have low power needs, communicate wirelessly and can process and store the sensor data locally (Karl and Willig, 2003; Akyildiz, Su, Sankarasubramaniam and Cavirci., 2002). Their inherent compactness, autonomy, low power consumption, data and and storing capability processing wireless communication have given a great leap forward for implementing an effective monitoring tool for maintenance purposes.

But why using a WSN for monitoring a vessel's engine status? One main reason is the low cost and ease of installation of a WSN. For deploying a WSN no wires are needed for communication purposes between the sensor and the coordinator (gateway). The deployment of extra wires for the sensor network purposes are an additional concern, with significant cost in money and time, difficulties in expansion or changes of the network and drawback for the sensor deployment. This leads to a considerable amount of new wires, which add complexity on the sensor network installation process, as well as on the overall complexity of the sensor network. Furthermore, a wireless sensor node is much easier to be recollected when for various reasons, such as the placement of a new one with different specifications, this is needed.

When installing a sensor network for developing an effective maintenance model many factors are going to change on the way to finally achieve this, because the process of developing a maintenance model is a continuous one. You don't just install the sensors and you are done. The amount of sensors needed, as well as where to be installed, what specifications they should have etc. are more or less assumed at the beginning of the development of a maintenance model. On the way to finally have an effective maintenance model, the sensor network must be easily adoptable and expandable. The above mentioned are the two main factors for adopting a WSN compared to a wired one.

4. LAROS PLATFORM STRUCTURE DESCRIPTION

LAROS is a hardware and software platform that monitors various critical parameters at a vessel in order to identify the vessel operational status. It is not a control system; most of the ships, especially the new ones, have very advanced control systems with more than 300 sensors. LAROS is a monitoring system based on collection of data and signals from sensors, instruments and systems that are present in a vessel. The platform is specifically developed in order to be able to collect most of the signal and data types that are available in the various systems that are present in a vessel, either these are just simple analog/digital signals from sensors (i.e. voltage, current, pulses etc.) or complicated data types from various control interfaces (data extracted from various serial protocols). It can be installed on all kind of vessels, whatever the vessel's age and type is. Monitoring is direct with the maritime headquarters via satellite link.



Figure 3. LAROS system vessel basic components along with the main control system.

LAROS is completely independent from the main control system. It consists of several smart collector nodes most of them wireless and each one with the ability of preliminary local processing of the selected data. Furthermore, it is fully adaptable, expandable and configurable in order to be able to add new services and procedures and has an inherent distributed nature. All these collector nodes take real-time measurements, estimate the status based on pattern recognition algorithms and send the results wirelessly to a server located somewhere inside the vessel via a gateway, see figure 3. Each node can have either single or multiple inputs, depending on the type of the input, either from sensors of the same type and/or system or from different ones. Moreover can be powered either with AC or with DC voltage supply. The nodes can be easily placed at any metallic surface, thus eliminating the need for any mechanical modifications.

After data processing a variety of conclusions can be derived concerning the vessel's operational status. In case any change is observed, a notification in the form of either a report or an alarm will be sent to the headquarters of the maritime company. Along with the notification, the Fleet Manager and the technical team will acquire detailed measurements from the sensor network in order to plan the appropriate actions. A more detailed description of the LAROS system is shown in figure 4.



Figure 4. LAROS system vessel basic components along with the main control system

The collector nodes monitor various parameters, such as engine performance parameters (RPM, torque, power, fuel oil and lubricant oil consumption, various pressures and temperatures), engine's cooling water and sea temperature since sea water is used as water for the cooling system, the opening rate of the fuel's supply valves, the propeller's shaft vibration, as well as the electric generators' produced power and operating pressures, the exhaust gas temperature and chemical composition, the turbochargers' rpm and incoming and outgoing air temperatures, bearings' temperatures etc. Moreover a variety of navigation and weather parameters are recorded, such as vessel's speed, drafts, inclination, geographical position, wheel position, water longitudinal and transverse speed, wind angle and speed, environmental temperature and humidity.

With all this variety of parameters monitored, the operating and performance status of the vessel can be greatly analyzed and various actions can be followed in order to enhance performance, monitor and reduce fuel consumption, reduce gas emissions, extend assets lifetime.

The sensors that are used employ various technologies like MEMS, photonic, organic electronics and mechanical. The sensor nodes or collectors are based on either a microcontroller with embedded software or a digital signal processor (DSP) for more demanding signal analysis applications like vibration and acoustic analysis. The operating system is developed with main characteristics: the low power consumption, the increased communication reliability, the improved system adaptation and the reduced time and complexity for the development of new applications.

The wireless network is an implementation of the ZigBee protocol based on the IEEE 802.15.4 standard. There is a gateway that sets and coordinates the wireless network and all the collector nodes are connected to this gateway, either directly, or in case there cannot be a direct connection with the help of other collectors or routers. As has been pointed in other research projects (Kdouh, Brousseau, Zaharia, Grunfeleder and El Zein, 2012) the connectivity between wireless collectors inside a vessel, where metallic surfaces are the common, is not a problem even when the collectors are placed in different rooms, where theoretically it is very difficult to have an unproblematic connection. The collectors transmit the processed data via the gateway in order to be stored to a MIMOSA-type database at a server located inside the vessel. The data can be accessed by the captain and the vessel's engineers. Reports, alarms and all the monitored parameters are sent via satellite link to the main server at the company headquarters, in order to be available to the Fleet Manager and its team of engineers for further evaluation.

To the abovementioned stands the advantage and uniqueness of LAROS platform compared to similar solutions by other vendors. LAROS is adaptable in order to collect signals and data from most of the various different sensors, instruments, systems and controls inside a vessel, not just offer a solution for collecting and monitoring a short range of data, such as for example Fuel Oil consumption monitoring or just Main Engine (M/E) Torque and Power monitoring. Independent of the various systems, LAROS has the ability to collect data from them and give to the engineers all these data to a single unified platform, where doing data analysis provides much more information and knowledge for the vessel performance and maintenance.

5. A USE CASE OF THE LAROS PLATFORM IMPLEMENTATION

We will present here some experimental measurements and results of the LAROS platform installed on a container vessel. At figure 5 you may see the architecture of the WSN installed at a vessel regarding the vessel's performance. The installed platform can of course be customized to the Maritime Company's specific needs. The platform monitors various engine performance parameters such as Main Engine RPM, torque, power and fuel oil consumption, turbochargers' rpm. Moreover, in order to have specific navigation data, vessel's drafts and two-axis inclination are continuously monitored, as well as wheel position, vessel's speed, water longitudinal and transverse speed, wind angle and speed from the bridge various instruments.

A data analysis and monitoring software tool is also provided presenting all these data, in all kind of waveforms, analyses them, produces alarms if needed and gives specific guidelines. Moreover, certain customized rules can be inserted in this software. By these means a comprehensive and analytical monitoring overview for performance analysis and maintenance is available.



Figure 5. LAROS system network architecture

5.1. Specific Fuel Oil Consumption (SFOC) Analysis

On the next figures you may see an analysis that is performed for a certain period of time with the help of the LAROS data analysis and monitoring software by the maritime company headquarters engineers. The goal is to measure the SFOC (Specific Fuel Oil Consumption) for this vessel. For this reason, we present the M/E power over time at a diagram, see figure 6.



Figure 6. Main Engine produced power vs time

In order to find the vessel's SFOC, we have to find a certain time period where the power produced by the vessel's engine has the minimum deviations, so is rather stable. We find this time period and we focus at it, see figure 7.



Figure 7. Main Engine produced power vs time for the specific time period

For this time period, we check that specific rules are true, that are:

- Minimum vessel's inclination distribution.
- Minimum vessel's speed distribution.
- Minimum M/E RPM distribution.

We can see that the abovementioned rules are true for this time period, see the figures 8 to 11.



Figure 8. Vessel's inclination at x-axis for this time period



Figure 9. Vessel's inclination at y-axis for this time period



Figure 10. Vessel's speed distribution for this time period



Figure 11. M/E RPM distribution for this time period

So, for this specific period, safe results can be obtained regarding the vessel's SFOC, see figure 12.



Figure 12. M/E Heavy Fuel Oil (HFO) consumption for this time period

Moreover, various statistics concerning the parameters monitored can be extracted, see figure 13.



Figure 13. M/E Power, RPM & Speed statistics for this time period

By studying the vessel's performance at this period of time, the SFOC can be extracted and can be compared with the SFOC that the vessel's manufacturer has provided by the sea trials. If the SFOC extracted by this kind of analysis has great difference to the sea trials, further reasons can be investigated, like wind speed and direction, vessel's drafts, vessel's rudder angle.

In the below figures you may see another time period where the M/E power had low deviation, so it was chosen for a SFOC analysis as well.



Figure 14. Main Engine produced power vs time for the specific time period



Figure 15. Vessel's speed distribution for this time period

But, as it can be clearly seen, due to high fluctuations of vessel's speed during the period under consideration, safe results cannot be obtained in this case.

6. FINANCIAL BENEFITS FROM ADOPTING LAROS PLATFORM

As it is rather obvious, when a maritime company uses LAROS system, its engineers are provided with a very powerful tool for various parameters overview that can help them for vessel performance analysis. Moreover, it is better to predict and prevent a situation of lowered operational capability, than to deal with the consequences after an incident has occurred. This statement implies a simple logic that can be supported by actual numbers, showing the benefits for a maritime company that will choose to change its philosophy towards the predictive maintenance. The operational expenses are defined at a ratio of 37% by the crew payment expenses, 40% by the communication, maintenance, repair and fuel expenses, while the rest represent insurance expenses, tolls, docking, loading and unloading procedures. LAROS targets the percentage that represents the communication, maintenance, repair and fuel expenses.

A great amount of maritime companies are based at three geographical areas; Greece, Japan and North Europe. These three areas represent 47% of the global fleet. This market spends about 11 billion dollars every year for maintenance, repair and fuel costs. We estimate that the use of a fully deployed LAROS system will lead to an up to 40% reduction of maintenance and repair costs, along with reduction of vessels' operational cost by 15%, reduced possibility of engine breakdown and increased crew and cargo safety. Along with the direct economic benefits the maritime enterprise that will choose to embody the LAROS architecture will also have a solid and reliable control on all environmental issues that emerge from an operational vessel. In terms of efficiency, along with an optimized maintenance schedule, the key economical features are listed below:

- Fuel consumption cost reduction by 8%
- Repair costs by 40%
- Maintenance costs by 40%

The statistical analysis we have conducted is based on the most recent market data and provides interesting conclusions about the actual profits of a potential adoption of LAROS system. The figure that follows shows a linear prediction regarding the reduction of operational costs per year. Additionally, one must take into account the long term development of this solution. LAROS is not a monolithic solution but an expanding and continuously adaptive system to meet all the new needs that will emerge during the operation of a fleet. It works as "multiplication factor" in the whole effort to minimize operational costs and organize systematically a maintenance schedule.



Figure 16. Cost reduction when using LAROS platform

7. CONCLUSIONS

The development of Wireless Sensor Networks with intelligent characteristics, like data processing capabilities, along with the development of new communication protocols has enabled the use of WSNs on a new market like Maritime. WSNs as part of a Condition Monitoring system can be employed in order to monitor the condition of various engine parameters and extract conclusions about the vessel operational and performance status. These data can be also available to the headquarters engineering team in real-time, in order to have a more complete and comprehensive solution for every problem that occurs. This can lead to a significant reduction of a vessel's operational expenses, as well as the environmental impact.

LAROS platform has all the abovementioned characteristics that can provide to a maritime company a complete monitoring system for Condition Based Maintenance and performance analysis.

NOMENCLATURE

- *CBM* Condition Based Maintenance
- *PdM* Predective Maintenace
- *PM* Preventive Miantenace
- WSN Wireless Sensor Networks
- *CM* Condition Monitoring
- SECAs Sulphur Emission Control Areas
- *IMO* International Maritime Organization
- *M/E* Main Engine
- SFOC Specific Fuel Oil Consumption
- *RPM* Revolutions Per Minute

HFO Heavy Fuel Oil

REFERENCES

- Akyildiz I. F, Su W., Sankarasubramaniam Y. & Cayirci E. (2002). Wireless sensor networks: a survey. Computer Networks: The International Journal of Computer and Telecommunications Networking, volume 38 (Issue 4), pages 393-422. doi: 10.1016/S1389-1286(01)00302-4
- Cheng H., (2007). Implementation Strategies and Tools for Condition Based Maintenance at Nuclear Power Plants, (pages 1011–4289). International Atomic Energy Agency, IAEA-TECDOC-1551 (ISBN:92-0-103907-7)
- Emmanouilidis C., Katsikas S., Pistofidis P. & Giordamlis C. (2009). A Wireless Sensing Development Platform for Ubiquitous Condition Monitoring. 22rd International Congress on Condition Monitoring and Diagnostic Engineering Management (pages 657-664), June 9- 11, San Sebastian, Spain. Fundacion TEKNIKER, Eibar, ISBN:978-84-932064-6-8
- Holmberg K., Jantunen E., Adgar A., Mascolo J., Arnaiz A.& Mekid S. (2010). *E-maintenance*. Springer. ISBN 978-1-84996-204-9
- Jardine A.K.S., LinD. & Banjevic D. (2005). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, volume 20 (Issue 7), pages 1483-1510. doi : 10.1016/j.ymssp.2005.09.012
- Karl H. & Willig, A. (2003). A short survey of wireless sensor networks. TKN Technical Report TKN-03-018. Technical University Berlin, Telecommunication Networks Group.
- Kdouh H., Brousseau C., Zaharia G., Grunfeleder G. & El Zein G. (2012). A Realistic Experiment of a Wireless Sensor Network on Board a Vessel. *9th International Conference on Communication COMM 2012* (pages 189-192, June 21-23, Bucarest . doi: 10.1109/ICComm.2012. 6262594
- Neelamkavil J., (2010). Condition-based Maintenance Management in Critical Facilities. Institute for Research in Construction, National Research Council Canada. Available from http://www.managementparadise.com/arunvani/docume nts/531/condition-based-maintenance-management-incritical-facilities/ [Accessed 2014/03/05].
- Thusu R., (2010). Wireless Sensor Use Is Expanding in Industrial Applications. Sensors Magazine. Available from http://www.sensorsmag.com/networkingcommunications/ wireless-sensor/wireless-sensor-useis-expanding-industrial-applications-7212 [Accessed 2014/03/05]

Smart Sensors for Condition Based Maintenance: a Test Case in the Manufacturing Industry

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ABSTRACT

Condition Based Maintenance (CBM) is a well-known concept and it has been demonstrated that it is the way ahead to prognostic maintenance for failure avoidance and for the reduction of maintenance cost.

This paper presents an application for Condition Based Maintenance, with a specific focus on State Detection, according to MIMOSA OSA-CBM reference architecture. The papers aims at presenting peculiarity of development of such a kind of solution when considering the use of Smart Sensors instead of traditional devices.

Indeed, breakthrough in CBM is expected from the development of ICT and embedded systems. This technology supply integrated chips implementing all the necessary circuitry to manage field data capture, data processing, local diagnosis, local feedback (where possible) and information transfer to the upper control levels. These so-called smart sensors exploit new technologies of micro sensors (MEMS, micro electro mechanical systems) and wireless communication together with the computing power of a microprocessor.

In particular, applications related to maintenance and human safety appear to be very promising due to the unstructured nature of these domains, where self-configuring networks of intelligent devices can better comply with an ever changing and partially unpredictable environment.

A test case is deployed on a typical manufacturing equipment: a robot. The objective of the test case presented by the paper is not to develop new diagnostic algorithms, but to implement some statistical analysis within a monitoring infrastructure built with Smart Sensors. The case of analysis that the paper will present grounds on the use of wireless sensor devices for temperature measures gathered on the electric motors of the robot. Then, data are transmitted through a wireless network to a receiver unit that accomplishes also elaboration by using statistical methods and then, thanks to a web-service communication, results are made available to external requests and users.

An advisory is generated when something is out of the normal behaviour of the equipment. Finally, the user can check this information through the Human Machine Interface available via web-service.

1. INTRODUCTION

In order to reduce the expenses for maintenance, new technologies can provide proper capability to support the decision making process through proper monitoring of the factory to manage maintenance, production and logistic issues. Service oriented architecture (SOA) is a solution that is nowadays analysed by many researchers and that promises an interesting solution for the issues related to controlling of the plant. To this end, some European funded projects related with SOA and the issues related to monitoring of plant condition are mentioned herein. SOCRADES (Cannata et al. 2008, www.socrades.eu) and SODA (www.soda-itea.org) mainly focused on SOA and wireless based communication infrastructures for intelligent embedded systems. AESOP (http://www.imc-aesop.eu/) proposed a SCADA/DCS infrastructure based on a service oriented architecture. This enables a cross-layer serviceoriented collaboration between services on the same level and among different levels of the enterprise. Other objectives of AESOP are to investigate the limits of SOA in enterprise architecture and to propose a transition path from legacy systems to SOA based ones. EMMON (www.artemis-emmon.eu) targets the realization of large

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scale monitoring of huge geographical areas in real time, using wireless sensor devices in specific scenarios (water pipelines, urban quality of life, forest and marine environments, civil protection). While the above-mentioned projects are focused on monitoring through SOA system and embedded devices, the project **DYNAMITE** (http://dynamite.vtt.fi) targeted maintenance related issues, and in particular it emphasized on predictive maintenance, supporting the concept of e-maintenance with ICT tools such as PDA, CMMS and web services (Muller et al., 2008); the project adopted also the MIMOSA OSA-CBM reference architecture, that is an implementation of ISO-13374 functional specification.

Indeed, the present paper presents a part of a research developed in the scope of a European funded project on this topic, namely eSONIA, that aimed at further developing the results obtained in the above mentioned research projects, while targeting practical implementation issues.

The specific objective of the eSONIA project was to overcome the traditional monitoring activity. Within the project view, traditional monitoring and data gathering techniques have been extended with the ability to elaborate raw data and offer high value information as web services at various levels. This allowed to avoid the use of large centralized systems to collect data where processing is concentrated, while the use of embedded devices improved the data collection possibility. The project demonstrated that Web Services and embedded devices can serve to improve the re-configurability and the interoperation of the monitoring devices while supporting the smooth transition between the legacy device and the new technology ones.

The paper shows how smart sensors may be adopted for monitoring activities and provides feedback to the scientific community about how they can be used for supporting Condition Based Maintenance (CBM), in particular the State Detection activity. As explained by MIMOSA a CBM program consists, in fact, of the following modules (MIMOSA OSA-CBM, Bengtsson, 2003):

- 1. Data Acquisition (DA) has the purpose to collect data and properly format them to store/transmit information to upper levels;
- 2. Data Manipulation (DM) serves to clean and preprocess data, typical operations are: normalization, smoothing, outlier removal, missing data imputation, etc.;
- 3. State Detection (SD) works to monitor the machine state by checking if the machine parameters are compliant with target ranges; it can generates alarms and warnings when compliancy is not reached;
- 4. Health Assessment (HA) receives data from the SD module or other HA modules and it detects through an analysis if the health state of the system or sub-system

has degraded; moreover, it can suggest possible fault causes.

- 5. Prognostic Assessment (PA): this module works on the results of the previous modules; it is used to calculate the future health of an asset and the calculation of the Remaining Useful Life (RUL) is possible by taking into account also the future usage profile.
- 6. Advisory Generation (AG): this module receives data from HA and PA modules, and it generates suggestions on recommended action(s) related to the maintenance how to run the asset under actual conditions;
- 7. Presentation, this module presents the outputs from the SD, HA, PA and AG modules to the user through a Human Machine Interface (HMI).

At a glance, the importance of Smart Sensors for the maintenance is due to the possibility to build or configure custom devices dedicated to the monitoring and diagnostics of equipment. Furthermore, Smart Sensors are enhanced by the use of MEMS technology that allows including many different types of micro sensors into the device or into a single chip. In this way, the broad spectrum of applications and the power of a comprehensive data acquisition system is made available in the small and self-contained package of the smart sensor (Garetti et al., 2007). This allows concentrating within the sensors the activity of Data Acquisition and first Data Manipulation, leaving to other levels of the architecture the duty of carrying on State Detection.

The paper aims, thus, at demonstrating how this can be achieved practically within a manufacturing environment, considering a test case. To this end, it is structured as follows: paragraph 2 details the benefits for the overall approach proposed by eSONIA project and presents the proposal for an heterogeneous implementation of the mentioned technologies, allowing the integration of new solutions with existing ones. Paragraph 3 explains how the condition-based maintenance management module, which is included in the proposed architecture, is built. Paragraph 4 explains how a demonstrator has been deployed for implementation of the research outcomes, showing the role of the maintenance management functions. Eventually, paragraph 5 concludes the paper envisioning future challenges in this research field.

2. BENEFITS OF THE SOA ARCHITECTURE FOR CONDITION BASED MAINTENANCE

The use of Service-oriented Architecture (SOA) and Web Services (WS) is introducing interesting opportunities in factory automation; in fact, they allow to make incremental adoptions of new application and technologies, while avoiding a green field approach or to make big investments in order to update automation system. Therefore, new automation solutions based on SOA and WS approach could run in parallel to already existing ones.

eSONIA solution grounded on a conceptual description of the architecture. SOA is a flat architecture where all the services can interact together. This consequently makes the control architecture almost flat from an hardware and software point of view, but cannot overcome, of course, a certain hierarchy among the functionalities that the service carries on. Figure 1 shows how embedded solutions communicate with Application tools.



Figure 1. eSONIA conceptual implementation scheme.

Following this architectural approach, already existing "Applications" and "Traditional devices" can still be used on a brand new technology-based architecture simply integrating them by ad-hoc gateway services (see number 4 in the circle), thus enabling the co-existence of Web Service devices and traditional devices (e.g. PLC). This approach allows a smooth and incremental transition to an entire Service Oriented Architecture. On such a kind of architecture "Application Tools" (see number 2 in Figure 1) and "User & Business Applications" (see number 3 in Figure 1) are services hosted on computer servers. On "Embedded Device Level", many "Embedded Solutions" (see number 1 in Figure 1) can run web services hosted on embedded devices to provide various functions. SOA, differently from traditional one, allows each Embedded Solution (so the physical device) to interact with other Embedded Solutions on other devices, implementing a low level/distributed monitoring and control capability.

Thus, transformation from raw data to information is accomplished at embedded systems level, then information is transmitted to the higher level of the architecture represented by "application solutions" or "user & business applications" (see Figure 1). The interaction between embedded solutions and, for example, application tools are based on the capability of the service oriented architecture.

3. THE ESONIA CONDITION-BASED MAINTENANCE MANAGEMENT MODULE

Maintenance Management tools in the scope of the proposed architecture are mainly related to condition based maintenance. The main idea of CBM is to use the information on asset health retrieved from on-line sensing techniques (i.e. embedded sensors) to minimize the system downtime and the risk of failure.

The MIMOSA functions, presented in Section 1, can be seen as independent modules that can be built in a Service Oriented Architecture. In this way, each module can be "encapsulated" in a web service.

Scientific contribution provided by this paper on this aspect is related to the proof of concept that eSONIA project guaranteed. Indeed, what is presented herein represents a validation of the use of smart sensors for CBM within an industrial environment. To sustain the use of such technology within an industrial environment, specific attention has been paid to identification of industrial needs and building of a solution compliant with standard (i.e. ISO-13374) and sufficiently easy to be adopted by practitioners. Interoperability issues, communication problems, software development for the smart sensor boards adopted have been tackled in order to achieve a functioning solution that could act as demonstrator, neglecting a specific improvement of the state of the art ICT solutions. Nevertheless effort spent on this should not be neglected by readers interested in replicating the solution proposed herein.

In order to achieve the proof of use of smart sensors for CBM, the MIMOSA modules have been deployed in the eSONIA project in order to build the following functions.

Malfunction advisory generator represents a first function and it is realized on the basis of the State Detection (SD) module. It is deployed to trigger alarms when the value of a parameter overcomes a predefined threshold, then the function provides a list of the related warnings or alarms. Each advisory is completed with certain information and KPIs. The main scope of this function is to show advisories about maintenance problems (i.e. machine malfunctions) and provide related information and KPIs. To this end, proper advisories are generated, providing the operator with the necessary and updated information to understand the problem that is occurring. Operationally, the user can utilize the function as follows:

- He/she configures the malfunction advisories; namely he/she should choose the thresholds of the KPIs on a machine/equipment or section of the plant;
- He/she can read advisories: if a fault happens, the system generates malfunction advisories according to the set thresholds;

• He/she can select a machine/equipment or a plant section and list all the recent and past advisories.

A second function of the eSONIA maintenance management modules is represented by health state reporting. The purpose of the application related to this function is to properly present the health state report of a selected machine or a section of the plant. This tool presents to the user updated health state reports, which are helpful to take a decision on maintenance actions. This function strongly grounds on Health Assessment function derived by MIMOSA framework.

The use of the web service introduces a flexible approach in the realization of an application based on the two presented functions. In particular, it is important to underline that the services are interoperable, in this way it is possible to combine different services to obtain a new and more complete one. Moreover, the access can be granted to all network devices (e.g. other services of computers). Web services can be accessed from machine and from user through a common browser. In the first case the information are transmitted by means of XML data format, in the latter case the information can be included in a html page to obtain an user friendly data presentation (Lastra et al., 2006; Lobov et al. 2009).

The test case presented in the next section 4 focuses on a part of the eSONIA maintenance management module, in particular on the realization of the data acquisition, data manipulation, state detection and health assessment by means of embedded devices.

4. APPLICATION DOMAIN: AUTOMOTIVE MANUFACTURING DOMAIN

Different use cases have been addressed by eSONIA project and different applications have been analyzed (see Macchi et al. 2011 for further information). Herein, the test case related with the manufacturing application domain is described.

The objective of the test case is to implement proper existing diagnostic algorithms as web services, neglecting to develop new ones.

The application has been implemented on a welding robot with the purpose to support the operator in detecting malfunction state; the robot has been equipped with MB851 wireless sensing boards connected to sensing probes. This solution allowed placing the sensing probes very close to the electric motor windings and the welding actuator. Figure 2 shows the board the probe.



Figure 2. Wireless sensing board MB851 (on the left) and the sensing probe (on the right), please note that images are not scaled.

An overview of the functional architecture is provided by Figure 3. Data are collected from the field through the sensing probes (label number 1), then Data Acquisition function (DA) is performed (label number 2) by wireless sensing boards.



Figure 3. Functional architecture of the test case.

Data are gathered by a receiver node (label number 3) that provides data manipulation (DM) and State Detection (SD), then data are published on the network through web services. Bi-directional flow of information indicated by the arrows in Figure 3 refers to the type of communication between the different nodes, i.e. the requests made by the web-services.

Label number 4 indicates the Health Assessment (HA) function. The operator can access the SD and HA outputs through the HMI device browser (label number 6), which is connected to the Ethernet network through the robot control cabinet (label number 5).

An hardware oriented view of the architecture is shown in Figure 4.



Figure 4. Hardware architecture of the test case.

The wireless sensing probes collect several kind of data, such as accelerations, angular speed, magnetic field and temperatures; in the presented test case the temperatures were sampled. Wireless sensing board, namely MB851, provides Data Acquisition (DA) functions. The boards are battery powered. In order to avoid a fast discharge due to computation energy demand, it was decided to use them mainly for data acquisition and transmission, so neglecting data manipulation, because data manipulation would request a too high energy demand to such boards. A longer battery operating time has been preferred for this application.

Data Manipulation (DM) is provided down way the data stream by another device. In fact, all data are transmitted through ZigBee wireless network (IEEE 802.15.4) to a receiver node, which is wired to a computing board. This last board is based on the Tsunami Interface Baseboard for TAO-3530 and it is intended to provide a complete data manipulation (DM), a State Detection (SD) function and to provide also web service access to other devices on the network. In particular, the Tsunami board is connected on the Ethernet network and acts as a sort of gateway for the sensors. Hence, Tsunami board can be considered part of the architecture of smart sensors. In this way, the Tsunami board allows to have a sensing network uncoupled from the output requests. Moreover, it has enough computational capacity to provide web service access to each data stream of the nodes. Otherwise, the web services had to be published on each node of the sensing network and this will increase battery consumption, changing the technical requirements of the sensing boards.

Through the web service it is possible to access the collected data simply by means of a browser equipped device. In fact, in the test case, it was possible to connect the operator's HMI to the so-realized sensing network. However, the information provided after Data Manipulation function is not user friendly. In order to overcome this limitation a State Detection (SD) function is used to produce easy-to-read KPIs, so the operators can quickly be informed on the asset warnings and alarms. In other words, the SD function quickly detects abnormal deviation of working

parameters (e.g.: an over-temperature status) and/or an abnormal dynamic behavior (e.g.: an heating trend on the equipment), then it produces and indicator to measure "how much" the parameters are in the expected range and, in faulty cases, it generates a warning/alarm message to the operator. As in the DM function, the computing results of SD are published on the network in form of web services. Health Assessment (HA) module is, instead, implemented and run on a high computational device, namely a desktop computer, that is connected on the Ethernet network, in order to get data from SD and DM web services. The desktop computer host HA because computational constraints of the TAO-3530. HA, as SD and DM modules, elaborates data and provides an output through the web service technology. Overall, the operator can easily retrieve information from HA and SD functions from the browser of the already-in-use device, and so have a quick and complete feedback on the robot health state.

Figure 5 shows an example of the web page generated for the HMI, focusing on the information coming from one single sensing probe. State Detection function runs as a web service on the TAO-3550, the graph shows the actual level of the monitored variable while some KPIs are indicated on the page.





The information available on the network are formatted into an html page (see HTML 4.01 Specification) to be displayed in a user-friendly way on a common browser (see Figure 5 and Figure 6).

Figure 6 shows another example of the web page available to the operator. The whole represented area covers all the possible working condition of the robot; an indicator will point out a sub-area so indicating, in a quick and userfriendly way, the fault. In fact, each sub-area is associated to a robot working condition and a fault cause. The HA function is designed based on Principal Component Analysis (PCA) theory and tailored using history sample data on the machine behavior, according to the research presented in Fumagalli et al. (2014).

Figure 7 provides the legenda on how to read the HA information provided on the robot controller.



Figure 6. Example of the web page as shown on the robot remote controller (HMI). Information is related with Health Assessment.



Figure 7. Explanation on how to read the result showed by HA functionality.

Within the presented test case, the setting of the parameters of the Smart Sensors was done by the researchers involved in the eSONIA project. This represents one key issue to be considered when the proposed solution is transposed from a test case within an industrial environment to an operating environment, when real production is performed. In the latter case, in fact, maintenance operators would be the ones called to deploy such architecture within the specific application context. In this case, the key aspect for setting up of the system is the identification of the right physical or statistical model to be used for state detection and health assessment, considering the specific machines where smart sensors are installed.

5. CONCLUSIONS

The paper presented the condition-based maintenance management module within the context of the eSONIA project, in particular it focused on the developed tools, based on smart sensors and web services. The tools have been adopted in the eSONIA Service Oriented Architecture and it was demonstrated how it is possible to smoothly introduce the presented technologies in a real industrial environment. In fact, the tools have been designed considering that they can be used in an already-working environment, so new functionalities can be introduced in the system with a minimum effort to configure the legacy system. Moreover, the tools consider the possibility to interact with IT systems that are external sources to the proposed architecture. To this end, it was shown how it is possible to easily share information on the network from machine to machine and that it is also possible to properly format the information to obtain a machine to human communication.

Overall, the monitoring architecture presented within eSONIA project and, in particular, the condition-based maintenance management module discussed in this paper, demonstrate a smooth migration from an existing monitoring architecture towards a new one, based on new technologies (i.e. smart sensors), while avoiding deep and high cost upgrades of the existing infrastructure. The test case provides feedback to the scientific community about how smart sensors and Web Services can be used for supporting CBM.

Further research can be envisioned on the improvement of configurability of the upper layers of MIMOSA (i.e. SD and HA), enabled by the use of smart sensors that cover lower layers (i.e. DA and DM). Configurability of the upper layers may depend on an analysis of diagnostic and prognostic techniques. Such analysis should consider the definition of diagnostic and prognostic techniques, their functional features and how these features can be exploited in the MIMOSA architecture. MIMOSA, in fact, is a good guideline that can be further enhanced with such analysis, in order to get an easier adoption by industry.

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REFERENCES

- Al Najjar, A., (2006). Enhancing a company's profitability and competitiveness using integrated vibration-based maintenance: A case study. European Journal of Operational Research 157 (2004), pp.643–657.
- Bengtsson, M., (2003). Standardization issues in condition based maintenance. Condition Monitoring and Diagnostic Engineering Management - Proceedings of the 16th International Congress, August 27-29, 2003.
- Fumagalli, L., Ierace, S., Macchi, M., & Cavalieri, S. (2010). Assessment of industrial applicability of Electric Signature Analysis as diagnostic and prognostic tool. Proceedings of ESREL 2010 annual conference, Rhodes, Greece.
- Fumagalli, L., Tavola, G., Macchi, M., Garetti, M., Holgado Granados, M., Checcozzo, R., Rusinà, F., Lionetto, A., Abbate N. (2011). Maintenance Management tools within a Service Oriented Architecture: Proposal for practical implementation. Proceedings of XVI Summer School "F. Turco", Abano Terme (Padova), 14-16 September 2011, Italy.
- Fumagalli, L., Pala, S., Macchi, M. (2014). A web servicebased toolbox for machine diagnostics based on statistical analysis. Proceedings of The 3rd International Workshop and Congress on eMaintenance, 17-18 June 2014, Lulea, Sweden.
- Garetti, M., Macchi, M., Terzi, S., & Fumagalli, L. (2007, October). Investigating the organizational business models of maintenance when adopting self diagnosing and self healing ICT systems in multi site contexts. Proceedings of the IFAC Conference on Cost Effective Automation in Networked Product Development and Manufacturing IFAC-CEA (Vol. 7).
- HTML 4.01 Specification. W3C Recommendation 24 December 1999. http://www.w3.org/TR/html4/
- IEEE standard 802.15.4d-2009
- ISO 13374:2007 Condition monitoring and diagnostics of machines Data processing, communication and presentation.
- Jardine, A., Lin, D., & D. Banjevic (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20 (7), pp. 1483-1510.

- Lee J., Abujamra R., Jardine A.K.S., Lin D., & Banjevic D. (2004). An integrated platform for diagnostics, prognostics and maintenance optimization. Proceedings of the IMS '2004 International Conference on Advances in Maintenance and in Modeling, Simulation and Intelligent Monitoring of Degradations. Arles, France.
- Lastra J. L. M., Delamer M. (2006). Semantic web services in factory automation: fundamental insights and research roadmap IEEE Transactions on Industrial Informatics. IEEE Transactions, 1 (2), 1-11.
- Lobov A., Ubis Lopez F., Villasenor Herrera V., Puttonen J., Lastra J. L. M. (2009). Semantic Web Services Framework for Manufacturing Industries. International Conference on Robostics and Biomimetics. Bangkok, IEEE, 2104-2108.
- Macchi, M., Fumagalli, L., Garetti, M., Tavola, G. Checcozzo, R., Rusinà, F., Vidales Ramos, A., Jokinen, J., Popescu, C., Martinez Lastra, J. L., Karhumäki, O., & Vainio, M. (2011) A Use case analysis method for the implementation of service-oriented solutions for monitoring and diagnostics. COMADEM.
- MESA 'SOA in Manufacturing Guidebook', While Paper 27, MESA International, IBM Corporation and Capgemini, 21May 2008.
- Keith Mobley, R., (2002). An introduction to predictive maintenance. Butterworth-Heinemann, 2 edition, ISBN 0750675314
- MB851 user manual. UM0894. http://www.st.com/stwebui/static/active/en/resource/technical/document/user _manual/CD00262415.pdf
- MIMOSA. OSA-CBM specification, version 3.3.1. http://www.mimosa.org/?q=resources/specs/osa-bm v331
- Muller, A., Crespo Marquez, A. & Iung, B. (2008) On the concept of e-maintenance: Review and current research. Reliability Engineering and System Safety, pp. 1165– 1187.
- Tsunami development board for TAO-3530 user manual. http://www.technexion.com/images/datasheets/tsunami. pdf

Linear Polarization Resistance Sensor Using the Structure as a Working Electrode

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ABSTRACT

A direct method of measuring corrosion on a structure using a micro-linear polarization resistance (μ LPR) sensor is presented. The sensor includes three electrodes, where each electrode is fabricated on a flexible substrate to create a circuit consisting of gold-plated copper. The first two electrodes, or the counter and reference electrodes, are configured in an interdigitated fashion with a separation distance of 8 mil. The flex cable contains a porous membrane between the pair of electrodes and the structure. A third electrode, or the working electrode makes electrical contact to the structure through a 1 mil thick electrically conductive transfer tape placed between the electrode and structure. The reference and counter electrodes are electrically isolated from the working electrode and physically separated from the surface of the structure by 1 mil. The flex cable can be attached to the structure through the use of adhesives or in the case of placement in a butt joint or lap joint configuration, by the joint itself. Corrosion is computed from known physical constants, by measuring the polarization resistance between the electrolytic solution and the structure. A controlled experiment using the ASTM G85 Annex 5 standard verifies the precision and accuracy of sensor measurements by comparing the estimated mass loss with witness coupons.

1. INTRODUCTION

Recent studies have exposed the generally poor state of our nation's critical infrastructure that has resulted from wear and tear under excessive operational loads and environmental conditions. SHM (Structural Health Monitoring) Systems aim at reducing the cost of maintaining high value structures by moving from SBM (Scheduled Based Maintenance) to CBM (Condition Based Maintenance) schemes (Huston,



Figure 1. AN110 installed on a C-130H

2010). These systems must be low-cost, simple to install with a user interface designed to be easy to operate. To reduce the cost and complexity of such a system a generic interface node using low-powered wireless communications has been developed. This node can communicate with a myriad of common sensors used in SHM. In this manner a structure such as a bridge, aircraft, or ship can be fitted with sensors in any desired or designated location and format without the need for communications and power lines that are inherently expensive and complex to route. Data from these nodes is transmitted to a central communications Personal Computer (PC) for data analysis. An example of this is provided in Figure 1 showing an embedded AN110 SHM system installed on a C-130H aircraft.

The μ LPR presented in this paper improves on existing LPR

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technology by using the structure as part of the sensor system. Further improvements are realized by narrowing the separation distance between electrodes, which minimizes the effects due to solution resistance. This enables the μ LPR to operate more effectively outside a controlled aqueous environment, such as an electrochemical cell, in a broad range of applications (eg. civil engineering, aerospace, petrochemical).

The remainder of the paper is organized as follows. Section 2 provides the background into different corrosion sensing technologies, LPR theory, and the new 3-electrode μ LPR sensor design. Section 3 describes the experimental procedure used to evaluate the new sensor design through a controlled ASTM G85-A5 test. Section 4 presents the results of experimental testing. Finally, the paper is concluded in Section 5 with a summary of the findings and future work.

2. BACKGROUND

Corrosion sensors can be distinguished by the following categories, *direct* or *indirect* and *intrusive* or *non-intrusive*. Direct corrosion monitoring measures a response signal, such as a current or potential, resulting from corrosion. Examples of common direct corrosion monitoring techniques are: corrosion coupons, electrical resistance (ER), electrochemical impedance spectroscopy (EIS), and linear polarization resistance (LPR) techniques. Whereas, indirect corrosion monitoring techniques measure an outcome of the corrosion process. Two of the most common indirect techniques are ultrasonic testing and radiography. An intrusive measurement requires access to the structure. Corrosion coupons, ER, EIS, and LPR probes are intrusive since they have to access the structure. Non-intrusive techniques include ultrasonic testing and radiography.

Each of these methods have advantages and disadvantages. Corrosion coupons provide the most reliable physical evidence possible. Unfortunately, coupons usually require significant time in terms of labor and provide time averaged data that can not be utilized for real-time or on-line corrosion monitoring (Harris, Mishon, & Hebbron, 2006). ER probes provide a basic measurement of metal loss, but unlike coupons, the value of metal loss can be measured at any time, as frequently as required, while the probe is *in situ* and permanently exposed to the structure. The disadvantage is ER probes require calibration with material properties of the structure to be monitored. The advantage of the LPR technique is that the measurement of corrosion rate is made instantaneously. This is a more powerful tool than either coupons or ER where the fundamental measurement is metal loss and some period of exposure is required to determine corrosion rate. The disadvantage to the LPR technique is that it can only be successfully performed in relatively clean aqueous electrolytic environments (Introduction to Corrosion Monitoring, 2012). EIS is a very powerful technique that can provide a corrosion rate and classification of the corrosion mechanism. Disadvantage with EIS is sophisticated instrumentation in a controlled setting is required to obtain an accurate spectrum. In fielded environments, EIS is susceptible to noise. Additionally, interpretation of the data can be difficult (Buchheit, Hinkebein, Maestas, & Montes, 1998). Finally, ultrasonic testing and radiography can be used to detect and measure (depth) corrosion through non-destructive and non-intrusive means (Twomey, 1997). The disadvantage with the ultrasonic testing and radiography equipment is the same with corrosion coupons, both require significant time in terms of labor and can not be utilized for real-time or on-line corrosion monitoring.

2.1. LPR Theory

Corrosion occurs as a result of oxidation and reduction reactions occurring at the interface of a metal and an electrolyte solution. This process occurs by electrochemical halfreactions; (1) anodic (oxidation) reactions involving dissolution of metals in the electrolyte and release of electrons, and (2) cathodic (reduction) reactions involving gain of electrons by the electrolyte species like atmospheric oxygen, O₂, H₂O, or H+ ions in an acid (Harris et al., 2006). The flow of electrons from the anodic reaction sites to the cathodic reaction sites creates a corrosion current. The electrochemically generated corrosion current can be very small (on the order of nanoamperes) and difficult to measure directly. Application of an external potential exponentially increases the anodic and cathodic currents, which allows instantaneous corrosion rates to be extracted from the polarization curve. Extrapolation of these polarization curves to their linear region provides an indirect measure of the corrosion current, which is then used to calculate the rate of corrosion (Burstein, 2005).

The electrochemical technique of LPR is used to study corrosion processes since the corrosion reactions are electrochemical reactions occurring on the metal surface. Modern corrosion studies are based on the concept of mixed potential theory postulated by Wagner and Traud, which states that the net corrosion reaction is the sum of independently occurring oxidation and reduction (Wagner & Traud, 1938). For the case of metallic corrosion in presence of an aqueous medium, the corrosion process can be written as,

$$\mathbf{M} + z\mathbf{H}_{2}\mathbf{O} \stackrel{f}{\underset{b}{\leftrightarrow}} \mathbf{M}^{z+} + \frac{z}{2}\mathbf{H}_{2} + z\mathbf{O}\mathbf{H}^{-}, \tag{1}$$

where z is the number of electrons lost per atom of the metal. This reaction is the result of an anodic (oxidation) reaction,

$$\mathbf{M} \stackrel{f}{\underset{b}{\leftrightarrow}} \mathbf{M}^{z+} + ze^{-}, \tag{2}$$

and a cathodic (reduction) reaction,

$$zH_2O + ze^- \stackrel{f}{\leftrightarrow} \frac{z}{2}H_2 + zOH^-$$
 (3)

It is assumed that the anodic and cathodic reactions occur at a number of sites on a metal surface and that these sites change in a dynamic statistical distribution with respect to location and time. Thus, during corrosion of a metal surface, metal ions are formed at anodic sites with the loss of electrons and these electrons are then consumed by water molecules to form hydrogen molecules. The interaction between the anodic and cathodic sites as described on the basis of mixed potential theory is represented by well-known relationships using current (reaction rate) and potential (driving force). For the above pair of electrochemical reactions (2) and (3), the relationship between the applied current I_a and applied potential, E_a , follows the Butler-Volmer equation,

$$I_a = I_{corr} \left[e^{2.303(E_a - E_{corr})/\beta_a} - e^{-2.303(E_a - E_{corr})/\beta_c} \right], \quad (4)$$

where β_a and β_c are the anodic and cathodic Tafel parameters given by the slopes of the polarization curves $\partial E_a/\partial \log_{10} I_a$ in the anodic and cathodic Tafel regimes, respectively and E_{corr} is the corrosion, or open circuit potential (Bockris, Reddy, & Gambola-Aldeco, 2000). The corrosion current, I_{corr} , cannot be measured directly. However, *a priori* knowledge of β_a and β_c along with a small signal analysis technique, known as polarization resistance, can be used to indirectly compute I_{corr} . The polarization resistance technique, also referred to as linear polarization, is an experimental electrochemical technique that estimates the small signal changes in I_a when E_a is perturbed by $E_{corr} \pm 10$ mV (G102, 1994). The slope of the resulting curve over this range is the polarization resistance,

$$R_p \triangleq \left. \frac{\partial E_a}{\partial I_a} \right|_{|E_a - E_{corr}| \le 10 \mathrm{mV}}.$$
(5)

ASTM standard G59 outlines procedures for measuring polarization resistance. Potentiodynamic, potential step, and current-step methods can be used to compute R_p (G59, 1994). The potentiodynamic sweep method is the most common method for measuring R_p . A potentiodynamic sweep is conducted by applying E_a between $E_{corr} \pm 10$ mV at a slow scan rate, typically 0.125 mV/s. A linear fit of the resulting E_a vs. I_a curve is used to compute R_p . Note, the applied current, I_a , is the total applied current and is not multiplied by the electrode area so R_p as defined in (5) has units of Ω . Provided that $|E_a - E_{corr}|/\beta_a \ll 1$ and $|E_a - E_{corr}|/\beta_c \ll 1$, the first order Taylor series expansion $e^x \approx 1 + x$ can be applied to (4) and (5) to arrive at the Stern-Geary equation,

$$I_{corr} = \frac{B^{\star}}{R_p},\tag{6}$$

where,

$$B^{\star} = \frac{\beta_a \beta_c}{2.303 \left(\beta_a + \beta_c\right)} \tag{7}$$

Knowledge of R_p , β_a , and β_c enables direct determination of

 I_{corr} at any instant in time. The corrosion rate, R_{loss} , can be found by applying Faraday's law,

$$R_{loss}(t) = \frac{B_{corr}}{R_p(t)},\tag{8}$$

where,

$$B_{loss} = \frac{B^{\star}}{FA_{sen}} \left(\frac{AW}{z}\right),\tag{9}$$

such that *F* is Faraday's constant, *z* is the number of electrons lost per atom of the metal during an oxidation reaction, A_{sen} is the effective area of the sensor, and *AW* is atomic weight. The total mass loss, M_{loss} , due to corrosion can be found by integrating (8),

$$M_{loss}(t) = \int_{t_0}^t R_{loss}(\tau) d\tau.$$
(10)

Finally, since R_p is not measured continuously (10) needs to be discretized for the sample period T_s ,

$$M_{loss}(t)\bigg|_{t=NT_s} = T_s \sum_{k=1}^{N} R_{loss}(kT_s)$$
(11)

2.2. Sensor Design

Each electrode is fabricated on a flexible substrate to create a circuit consisting of a noble metal, typically gold-plated copper. The first two electrodes, counter and reference electrodes, are fabricated with a thickness of 2 mil configured in a interdigitated geometric layout with a separation distance of 8 mil. The flex cable contains an insulated / porous scrim material between the pair of electrodes and the structure. A third electrode, or working electrode, is placed in close proximity to the counter and reference electrodes and makes electrical contact to the structure by placing a 1 mil thick electrically conductive transfer tape between the electrode and structure. The flex cable, shown in Figure 2, can be attached to the structure through the use of adhesives or in the case of placement in a butt joint or lap joint configuration, the holding force is provided by the joint itself. Corrosion is computed by measuring the polarization resistance between the electrolytic solution and the structure using the three electrodes and applying (11).

3. EXPERIMENTAL PROCEDURES

3.1. Tafel Measurements

ASTM standard G59 outlines the procedure for measuring the Tafel slopes, β_a and β_c . First, E_{corr} is measured from the open circuit potential. Next, E_a is initialized to E_corr-250mV. Then, a potentiodynamic sweep is conducted by increasing E_a from $E_{corr} - 250$ mV to $E_{corr} + 250$ mV at a slow scan rate, typically 0.125 mV/s. Finally, a Tafel curve is plotted for E_a vs. $\log_{10} I_a$. Values for β_a and β_c are estimated



Figure 2. The μ LPR sensor (a) as fabricated on a flexible circuit, (b) illustration identifying each electrode, and (c) using the structure as the third electrode.

from the slopes of the linear extrapolated anodic and cathodic currents.

3.2. Sample Preparation

New samples were cut to length and uniquely stamped with stencils close to the edge of both faces of the sample. The samples were then cleaned using an alkaline cleaner, TURCO 4215 NC-LT – 50 s/L for 35 min at 65°C. Afterward, the samples were rinsed with Type IV reagent grade deionized water and immersed in a solution of 70% (v/v) nitric acid for 5 min. The samples were then rinsed again in the deionized water and air dried. The weights were recorded to the nearest fifth significant figure and the samples were assembled in a lap-joint configuration and coated with 2 mil of epoxy-based primer and 2 mil of polyurethane.

3.3. Accelerated Testing

Corrosion tests were performed in a cyclic corrosion chamber running the ASTM G85-A5 test. This test consisted of two one-hour steps. The first step involved exposing the samples to a salt fog for a period of one-hour at 25°C. The electrolyte solution composing the fog was 0.05% sodium chloride and 0.35% ammonium sulfate in deionized water. This step was followed by a dry-off step, where the fog was purged from the chamber while the internal environment was heated to 35°C. Electrical connections for the flex sensors were made to an AN110 positioned outside the sealed chamber by passing extension cables through the bulkhead in the chamber. Temperature, relative humidity, and μ LPR data was acquired at 1 min intervals.

3.4. Sample Cleaning

3.4.1. Lap-Joint Panels

Lap joints were removed from the environmental chamber and disassembled. Following disassembly, the polyurethane and epoxy coatings on the aluminum panels were removed by placing them in a solution of methyl ethyl ketone. After immersion for 30 min the panels were removed and rinsed with deionized water. These panels were again alkaline cleaned with a 35 min immersion into a constantly stirred solution of 50g/L Turco 4215 NC-LT at 65°C. This was followed by a deionized water rinse and immersion into a 90°C solution of 4.25% phosphoric acid containing 20g/L chromium trioxide for 10min. Following phosphoric acid treatment the panels were rinsed with deionized water and placed into a 70% nitric acid solution for 5 min at 20°C. Plates were then rinsed with deionized water, dipped in ethanol, and dried with a heat gun. This cleaning process was repeated until mass values for the panels stabilized. These values were then compared with mass loss values calculated from the μ LPR data.

3.4.2. Control Coupons

Control samples, free of any corrosion, were weighed before and after being subjected to the same cleaning process as the corroded samples to determine the extent of metal loss resulting from the cleaning procedure. Corroded samples were lightly brushed with nylon bristles. The corroded samples were then placed in a solution of TURCO 4215 NC-LT – 50g/L for 1 hour at 65°C. Afterward, in accordance with ASTM G1, the standard practice for preparing, cleaning, and evaluating corrosion test specimens, the samples were placed in a 90°C solution of 4.25% phosphoric acid containing 20g/Lchromium trioxide for 10min. Next, the samples were placed in 70% (v/v) nitric acid for 5 min at 20°C. Following this step the samples were rinsed with deionized water. Finally, the samples were dipped in ethanol, dried, and stored in a desiccator cabinet.

4. RESULTS

This experiment ran over a period of 230 hours, where the environment inside the chamber was varied in temperature and humidity to promote corrosion. Once the experiment began, the Tafel constants were acquired while the panels were undergoing a wetting cycle. The Tafel constants were acquired and plotted as applied voltage vs. the logarithm of the applied current magnitude, shown in Figure 3. From this plot the Tafel constants were computed as, $\beta_a \approx 0.40 \text{ V/dec}$ and $\beta_c \approx 0.15 \text{ V/dec}$. The corrosion constant, B_{loss} , was computed using (9) with the material properties for AA2024-T3 and sensor properties defined in the nomenclature. Panels 1-4 were removed 33, 130, 170, and 230 hours into the experiment, respectively. Plots of the measured temperature and humidity vs. time are provided in Figure 4. The corrosion rate,







Figure 4. Plots of (a) temperature and (b) relative humidity vs. time.

shown in Figure 5, was computed from R_p measurements using (8).

The total corrosion, shown in Figure 6, was computed for each panel by applying (10) to integrate the corrosion rate with respect to time. The error bars correspond to the standard deviation observed at the time when the mass loss was computed. Finally, the measured and computed corrosion from the μ LPR measurements were compared in a scatter plot, shown in Figure 7. The error bars in the y-direction correspond to observation error. These results indicate the measured corrosion to within 95% confidence (two standard deviations of the observation error).



Figure 5. Computed corrosion rate vs. time.



Figure 6. Computed corrosion vs. time.



Figure 7. Measured vs. computed corrosion.

5. CONCLUSION

A new μ LPR sensor design was presented for direct corrosion monitoring in Structural Health Management (SHM) applications. The new design improves on existing technologies by (1) using the structure as part of the sensor measurement, (2) improving sensor lifetime by making the electrodes from a non-corrosive material, and (3) improving on sensor performance by reducing the separation distance between the working, reference, and counter electrodes. Corrosion tests were performed in a cyclic corrosion chamber running ASTM G85-A5 salt-fog test. The results indicate the μ LPR sensor data correlated with the measured mass loss to within 95% confidence (two standard deviations of the observation error). This demonstrates the μ LPR sensor can accurately measure the change in the corrosion rate as a function of time for a given electrolyte condition. Future work includes:

- Demonstrate µLPR sensor accurately measures the corrosion rate as a function of solution conductivity. This is important as the environment (in terms of bare metal surfaces) will experience wet-dry cycles.
- Establish the µLPR sensor can accurately measure corrosion in atmospheric conditions where corrosion rates are lower than in an "accelerated corrosion chamber" (i.e. what is the lowest rate of corrosion that the sensors can measure when a monolayer of electrolyte is present).
- Investigate the surface morphology of the coupons using a scanning electron microscope (SEM) and correlate their measured corrosion rate as a function of their corrosion behavior (e.g. pitting vs. uniform corrosion) as determined by the *µ*LPR sensor data over time.

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NOMENCLATURE

$eta_a \ eta_c$	V/ _{dec} V/ _{dec}	0.40 0.15	anodic Tafel constant cathodic Tafel constant
τ	s	-	time variable
d au	S	-	time step
k	-	-	sample index
			-

t	S	-	time
t_0	S	-	initial time
z	-	3	electron loss
Asen	cm ²	4.233×10^{-2}	sensor area
AW	g/mol	$2.899 imes 10^1$	atomic weight
B^{\star}	V/dec	$4.95 imes 10^{-2}$	constant
B _{loss}	$\Omega{\cdot}g\!/cm^2/s$	$1.170 imes 10^{-4}$	constant
E_a	V	-	applied potential
E_{corr}	V	-	corrosion potential
I_a	A/cm^2	-	applied current
Icorr	A/cm^2	-	corrosion current
F	C/mol	9.649×10^4	Faraday's constant
M _{loss}	g/cm ²	-	mass loss
Ν	-	-	total samples
R _{loss}	$g/cm^2/s$	-	corrosion rate
R_p	Ω	-	polarization resistance
T_s	S	60	sample period

REFERENCES

- Bockris, J. O., Reddy, A. K. N., & Gambola-Aldeco, M. (2000). Modern electrochemistry 2a. fundamentals of electrodics (2nd ed.). New York: Kluwer Academic/Plenum Publishers.
- Buchheit, R. G., Hinkebein, T., Maestas, L., & Montes, L. (1998, March 22-27). Corrosion monitoring of concrete-lined brine service pipelines using ac and dc electrochemical methods. In *Corrosion 98*. San Diego, Ca.
- Burstein, G. T. (2005, December). A century of tafel's equation: 1905-2005. *Corrosion Science*, 47(12), 2858-2870.
- G102, A. S. (1994). Standard practice for calculation of corrosion rates and related information from electrochemical measurements. *Annual Book of ASTM Standards*, 03.02.
- G59, A. S. (1994). Standard practice for conducting potentiodynamic polarization resistance measurements. *Annual Book of ASTM Standards*, 03.02.
- Harris, S. J., Mishon, M., & Hebbron, M. (2006, October). Corrosion sensors to reduce aircraft maintenance. In Rto avt-144 workshop on enhanced aircraft platform availability through advanced maintenance concepts and technologies. Vilnius, Lithuania.
- Huston, D. (2010). Structural sensing, health monitoring, and performance evaluation (B. Jones & W. B. S. J. Jnr., Eds.). Taylor and Francis.
- Introduction to corrosion monitoring. (2012, August 20). Online. Available from http://www.alspi.com/introduction.htm

Twomey, M. (1997). Inspection techniques for detecting corrosion under insulation. *Material Evaluation*, 55(2), 129-133. Wagner, C., & Traud, W. (1938). *Elektrochem*, 44, 391.

BIOGRAPHIES

Douglas W. Brown is the Senior Systems Engineer for Analatom, Inc. He received the bachelor of science degree in electrical engineering from the Rochester Institute of Technology and his master of science and doctor of philosophy degrees in electrical engineering from the Georgia Institute of Technology. Dr. Brown has eight years of experience developing and maturing Prognostics & Health Management (PHM) and fault-tolerant control systems in avionics application. He is a recipient of the National Defense Science and Engineering Graduate (NDSEG) Fellowship and has received several best-paper awards in his work in PHM and fault-tolerant control.

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Diagnostics of Mechanical Faults in Power Transformers - Vibration Sensor Network Design under Vibration Uncertainty

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ABSTRACT

Power transformer is a critical component in energy transmission, and its failure can cause catastrophic social loss. Among many techniques to prevent the transformer failures. ones using vibration signals show good capability of detecting the mechanical faults. For on-site power transformers, numerous vibration sensors are installed to take into account vibration uncertainty which comes from sizable and complex transformers and random operating condition. It, however, brings about the high maintenance cost of sensing system as well as superfluous data obstructing precise diagnostics. This study proposes sensor positioning to detect mechanical faults of power transformers. Thirty six onsite power transformers in nuclear power plants were employed. Their vibration signals are processed based upon the principles of transformer vibration. Vibration characteristics are analyzed in terms of spectrum analysis, vibration contour plot and high vibration locations. Then the sensor network design framework is proposed which adjusts the number of sensors and their locations to measure high vibration signals robustly under vibration uncertainty. It is demonstrated that the designed sensing system evaluates the health status of the power transformers successfully with the significantly reduced number of sensors.

1. INTRODUCTION

Power transformer, used in a transmission network to step-up or-down a voltage with above 200MVA rating, is the one of key components in power plants. It is also one of the most frequently failed components due to the harsh operating condition such as high temperature, high electric loads, nonstop operation, and outdoor installation. Moreover, deterioration and being high capacity increase the failure rate Joung Taek Yoon et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. even more. As the unexpected failure of power transformers can cause the plant shut down with tremendous capital loss, the power transformer should be monitored and maintained properly.

For this purpose, enormous researches have been investigated and these were reviewed by Wang, Vandermaar, and Srivastava (2002), Duval (2002) and Saha (2003). The commonly used techniques are (1) dissolved gas analysis (DGA), (2) power factor analysis, (3) internal temperature measurement, (4) thermography, (5) partial discharge testing (PD), (6) degree of polymerization, and (7) frequency response analysis test (FRA). Among them, the diagnostics using vibration signals is one of the most effective methods to detect mechanical faults such as joint loosening, winding/core movement, wear crack and high vibration. According to Lee, Jung, and Yang (2003), the mechanical failures are important because of their high portion of total failures (about 40% in Korean nuclear power plants) with little researches against them compared with the other chemical and electrical failures. In order to diagnose the transformers, Ji, Cheng, and Li (2005), Ji, Luo, and Li (2006) and Ji, Zhu, and Li (2011), used core vibration signals by analyzing the correlation between electrical signals and core vibration. Bartoletti, Desiderio, Di Carlo, Fazio, Muzi, Sacerdoti, and Salvatori (2004) classified the transformers health condition with health-related parameters from the spectrum of a transformer tank vibration. Garcia, Burgos, and Alonso (2006) proposed the tank vibration model which is a function of current, voltage and temperature. Hu, Wang, Youn, Lee, and Yoon (2012) proposed two health indices and a copula-based health grade system from tank vibration spectrum signals. Li, Zhao, Zhang, and Lou (2012) employed hidden Markov model to diagnose the mechanical faults of on-load tap changer (OLTC) and Borucki (2012) measured
the vibration of transient state and analyze in time-frequency domain to distinguish the 4 health states.

Above researches have proven that the vibration signals are effective to detect the mechanical faults in transformers. In order to apply these researches to on-site power transformers, the one of things required is a sensor network (SN) design that is to design the type, number and locations of the sensors. In general, field experts install numerous vibration sensors on the transformer tank to cope with the vibration uncertainty coming from its large size, complexity and variant operating conditions. The sensing system with numerous sensors has high failure rate with low reliability and high install/maintenance cost. Also it may acquire healthirrelevant superfluous data obstructing precise transformer health assessment. Above researches suggested to install few sensors based upon a transformer structure and vibration mechanics without the quantitative analysis on transformer vibration characteristics. Only Garcia et al. (2006) install the sensor of which the vibration is most similar to that of inner winding. This method has limitations that 1) it is hard to be applied in the operating transformers of which the inner part is not accessible and 2) can be prone to measure a core vibration which is correlated with mechanical faults in core. Therefore this paper aims at developing the framework of SN design capable of detecting the mechanical faults of power transformers using the minimized number of sensors. The rest of this paper is organized as follows: Section 2 explains transformer vibration principle, employed target power transformers and data acquisition method; Section 3 analyzes the characteristics of power transformer vibration with acquired vibration data; Section 4 proposes the framework of SN design; Section 5 shows the diagnostics of mechanical faults in power transformers followed by the conclusions in Section 6.

2. OVERVIEW OF TRANSFORMER VIBRATION AND DATA ACQUISITION

2.1. Principles of transformer vibration

Transformer vibration originates from an inner core and winding shown in Fig. 1. Their vibrations are induced by magnetostriction and electromagnetic force respectively. Magnetostriction, shape changing of a ferromagnetic material due to alternating magnetic field, yields the core vibration. And electromagnetic force, interaction force between winding current and leakage flux, results in the winding vibration. Two forces are respectively proportional to the squared voltage and current of electrical signal. Therefore, the excitation frequency of the core and winding is twice frequency of alternating current. Additionally it is known that the core has higher harmonic frequencies due to the nonlinearity of core magnetostriction.



Figure 1. Core, winding and electromagnetic signals

2.2. Description on target power transformers

In this study, the thirty six power transformers in two nuclear power plants are employed. They are almost homogeneous in terms of a same manufacturer, same type (single phase, oilfilled, shell type), and similar power capacity. They are divided into six groups according to their tank surface structure and install year ranging from the oldest 1988 to the newest 2003. Table 1 summarizes the informations above with repair history and the number of installed sensors explained in next subsection. The power transformers operate at 100% full power and their electrical signals are overall steady with 60Hz frequency.

Table 1. Information about target power transformers

Group	1	2	3	4	5	6
Plant	α plant			β plant		
Unit #	1, 2	3,4	5,6	1, 2 3, 4 5, 6		
Chan		single-pl	hase, san	ne manu	facturer,	
Char.		0	il-filled,	shell typ	pe	
Capa. (MVA)	362*3	353*3	396*3	360*3	353*3	396*3
Install year	88	96	03	86	93	01
Replaced	0	Х	Х	0	0	Х
# of sensors	44	48	48	44	36~40	38~40

2.3. Data acquisition

In order to measure the transformer vibrations, it is desirable to install sensors inside where the vibration originates from. However highly intense electromagnetic field, inner-filled oil and high temperature make it impossible. Instead, the sensors were installed on the tank surfaces of the power transformers. As the vibration of core and winding is transmitted to the surfaces through the inside oil, it is possible to measure the inner parts vibrations indirectly. The tank surface was reinforced with rib structures to reduce the vibration, thus the sensors were installed in the grids of the four side surfaces as shown in Fig. 2. According to the accessibility of the power transformers, the numbers of installed sensors are slightly different as shown in Table 1. In this study, B&K 4381 and PCB 357B33 charge type accelerometers and charge amplifiers (RION UV-06A) were used.



Figure 2. Sensor install on the a) left and b) front side tank surfaces of power transformer

Based upon the transformer vibration principle in Section 2.1, we know that the power transformer vibrates at low to medium frequency range and its spectrum data is informative to assess the condition of the core and winding where most mechanical failures occur. Thus, vibration velocities at every 1.25Hz up to 2000Hz were measured. Depending on the test availability of each transformers, the vibrations were measured for three times with the interval of 10 and 6 months. As a result, 108 measurements (=36 transformers*3 measurements) were conducted and each measurement include the spectrum data from multiple sensors.

3. POWER TRANSFORMER VIBRATION CHARACTERISTICS

This section analyzes the vibration characteristics of the power transformers in terms of spectrum signals, vibration signal trend, vibration contour plots and operation years. This helps the understanding of overall transformer behavior and the development of the SN design framework which the goal of this research.

3.1. Spectrum signal characteristic

Fig. 3 shows the spectrum signals from the sensors #1 and 2 of unit #1 phase A transformer in plant α . This transformer is one of the oldest ones, and should be mainly concerned. The



operation year in figure 3 is the duration from the transformer install to the measurement. The observations are listed below.

- Peak signals occur at every 120Hz which is twice frequency of electrical signal (60Hz), highly according with Section 2.1.
- In general, 120Hz fundamental signals has the largest value and subsequent harmonic signals become smaller as shown in Fig.3 b). There are exceptions as well like Fig. 3 a).
- In Fig. 3, sensor 1 installed 30cm apart from sensor 2 has under half 120Hz amplitude of sensor 2. For 120Hz signals from whole sensors of the same transformer, the maximum and minumum values are 34.3 and 0.19 mm/sec. Therefore, it is concluded that the transformer vibration signals strongly depend on their sensor locations.

3.2. Vibration signal trend

Fig. 4 shows the 120 and 240Hz signals, representative of fundamental and harmonic signals, from the right-side sensors of the same transformer. The numbers in legend indicate the operation years.

- The signals do not increase as the operation year increases. This is because the measurement interval, maximum 1.3 years, is too short to observe transformer health degradation comparing to its design lifetime 30-50 years.
- Regardless of the operation years, signal are mixed up overall. It means that the vibration signals have randomness and high amplitude signals are robust to the randomness. The vibration randomness comes from uncertainty factors such as manufacturing defect,



Figure 4. Sensor-wise 120 & 240Hz signals of unit #1 phase A transformer in α plant (group 1)

maintenance, measurement time (temperature & humidity), measurement error, electrical signal input.

• For the other uncertainty factors, it is known that sensor install position error is allowable within 5cm (Ji et al., 2011), the transformer temperature does not affect the vibration severely (Canadian electricity association, 1997), and the electrical signal input is highly steady.

3.3. Vibration contour plots

In order to analyze vibration aspect specifically, the normalized contour plots of 120 and 240Hz signals from the right-side sensors of unit #1 transformers in α plant is depicted in Fig. 5.

- Although three transformers have the exactly same tank surface structure, their vibration aspect are different. The difference comes from the uncertainty factors discussed in Section 3.2.
- For 120Hz, the high vibrations are concentrated on an upper region consistently.
- For 240Hz, whereas, the high vibrations are scattered in whole region and do not maintained through time flow. The reason why 240Hz signals have high randomness is

3.4. Aging effect on vibration

As the measurement interval is too short to observe the health degradation, whole 36 transformers are compared together. The Fig. 6 plots the root mean square (RMS) and maximum value of whole measurements along their operation time. It is found that the scale of maximum values are about three times that of RMS values meaning that each vibration measurement consists of small amplitudes values for the most part. That is, the transformer vibration can be characterized by the high amplitude values. This inference can be verified by the more

obvious signal increase of 120Hz maximum value along the operation time compared with that of 120Hz RMS value. The reason why 240Hz signals do not increase as 120Hz ones is that it is only affected by the core health degradation whereas 120Hz by core, winding, joint loosening, and other mechanical faults.

4. SENSOR NETWORK DESIGN FRAMEWORK

This section propose the SN design framework in order to diagnose the mechanical faults in power transformers with the minimized number of sensors. The analyzed transformer vibration characteristics in Section 3 can be summarized as follows.

- The transformer vibration has the fundamental frequency of 120Hz and harmonic frequencies at every 120Hz.
- Many uncertainties prevail in the transformer vibration making vibration aspects in an identical transformer different and signals mixed up.
- Only few sensor points give high amplitude signals which are resistant to uncertainty factors and characterizing the vibration condition of transformers.
- High amplitude points are concentrated on upper surface region consistently for 120Hz and scattered for 240Hz.

Thus, the designed SN needs to (i) be robust to the vibration uncertainty such as moving high amplitude location and (ii) detect the high amplitude signals of 120Hz and 240Hz signals which are relevant to the mechanical health condition of power transformers. To make it realized, multiple sensors should be utilized, meanwhile their quantity can be minimized using the consistency of high vibration locations, especially for 120Hz. The procedures to design the SN are listed below.





Figure 6. RMS and maximum values of whole vibration measurements

- (1) Determine target relative signal levels δ_f for fundamental and 2nd harmonic frequencies respectively. In this study, f = 120,240Hz.
- (2) For all measurements and two frequencies, extract sensor locations sets {*i*}^f_j measuring the signal above the target relative signal level δ_f.

Find
$$\{i\}_{j}^{f}$$
 such that $\frac{s_{i,j}^{f} - \min_{i} s_{i,j}^{f}}{\max_{i,j} s_{i,j}^{f} - \min_{i} s_{i,j}^{f}} \ge \delta_{f}$ (1)

where $S_{i,j}^{f}$ indicates the signals at f frequency from *i*th sensor of *j*th measurement.

(3) Find an intersection sensor location set {k} having at least one sensor location in common with the extracted sensor location sets {i}^f_i in step (2).

Find {k} such that $N(\{k\} \cap \{i\}_{i}^{f}) \ge 1$ for all j & f (2)

(4) In case of multiple intersection sensor location sets {k}_l, choose one set having the highest mean detectability which is the overall measure of detecting relatively high amplitude signals.

$$\underset{l}{\operatorname{argmax}} \underset{f,j}{\operatorname{mean}} \frac{\underset{i}{\underset{l}{\max}} S_{i=\{k\}_{l},j}^{f} - \underset{i}{\underset{min}{\underset{k}{\max}}} S_{i,j}^{f}}{\underset{min}{\underset{k}{\max}} S_{i,j}^{f} - \underset{i}{\underset{k}{\min}}}$$
(3)

The designed SN is capable of measuring the relatively high signals above δ_f for all measurements, and has high probability of detecting the high amplitude signals in following new measurements, that is robust to the transformer vibration uncertainty. As the result of SN design, the number of used sensors for different target relative signal levels is plotted in Fig. 7. As the target relative signal level rises, the required number of sensors increase. The increment in the number of sensors is larger for 240Hz signals having more uncertainty compared with 120Hz signals. Fig. 8 show the designed sensor positioning for group 1 transformers at different target relative signal levels. For the low target level, the important sensor locations are selected first and then



Figure 7. The number of sensors used in SN design for allocated target relative signal levels (group 1)



additional sensors are installed in other locations for the higher target level.

In order to demonstrate the performance of the designed SN, the maximum values from the whole sensors and the designed SN with δ_{120} , $\delta_{240} = 0.7$ from 6 groups are plotted in Fig. 9. The designed SN can detect the 70% above signals for all measurements. With respect to the maximum amplitudes, it can detect 87.7% of 120Hz and 64.9% of 240Hz maximum values while reducing the number of sensors about 75%.

5. DIAGNOSTICS OF MECHANICAL FAULTS

This section shows the diagnostics of mechanical faults in power transformers based upon the designed SN. From Section 2 and 3, the high vibration signals at fundamental and 2nd harmonic frequencies are related to the mechanical health states. If the fundamental frequency signals increase only, the mechanical faults of the winding can be predicted. If the 2nd harmonic signals increase, that of the core can be predicted. And when both arise, both faults can be predicted as well.

In this study, the two health indices are proposed; fundamental health index (*FHI*) and harmonic health index (*HHI*) which are the maximum values of acquired signals at fundamental and 2nd harmonic frequencies respectively.

$$CHI = \max_{i \in \{k\}} S_i^{120} \tag{4}$$

$$HHI = \max_{i \in \{k\}} S_i^{240} \tag{5}$$

where $S_{i,j}^{f}$ is the signals at f frequency from *i*th sensor of *j*th measurement and {k} is the sensor sets of designed SN. According to the vibration principles in Section 2,1, *FHI* is related to the health condition of the winding and core and *HHI* is related to that of the core. Fig. 10 plots two health indices of power transformers using the designed SN ($\delta_{120}, \delta_{240} = 0.7$). The diagnostics results are listed below.

- The newest transformers in two power plants (group 3 and 6) have low health indices.
- Group 4 in has high *FHI* without changing *HHI*, meaning that winding health condition has degraded. The transformers in group 4 were replaced by field experts due to its health degradation.



sensors and designed SN (δ_{120} , $\delta_{240} = 0.7$)

- Group 1 and 5 have high *HHI* and low *FHI* similar to that of the newest transformers group 3 and 6 are estimated to have the core in bad health condition. Those transformers were replaced by field experts due to its health degradation.
- The middle aged group 2 locates between the oldest group 1 and the newest group 3.

The diagnostic results coincide with the repair history and operating times, demonstrating the performance of the proposed SN design framework and two health indices.

6. CONCLUSIONS

This paper proposed the SN design framework for mechanical fault detection of power transformers. Using the acquired vibration that from the on-site power transformers in nuclear power plant, the characteristics of the power transformers are analyzed in various respects. The proposed SN design framework adjusts the number of sensors and their locations to be robust to the vibration uncertainty and detect high amplitude signals of fundamental and 2nd harmonic frequency relevant to the mechanical health condition of power transformers. The fault diagnostic of power transformers is conducted based upon the designed SN with the proposed two health indices, FHI and HHI. From the accordance of diagnostic results with the repair history and operating times, the proposed method are proved to be suitable for mechanical fault diagnostic for power transformers. Moreover, the designed SN consists of significantly reduced number of sensors, and this saves the data size by measuring health-relevant data and the cost of sensor install/maintenance.

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b) Health indices of transformers in β plant Figure 10. Health indices of power transformers using the design SN ($\delta_{120}, \delta_{240} = 0.7$)

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REFERENCES

- Bartoletti, C., Desiderio, M., Di Carlo, D., Fazio, G., Muzi, F., Sacerdoti, G., & Salvatori, F. (2004). Vibro-acoustic techniques to diagnose power transformers. *Ieee Transactions on Power Delivery*, 19(1), 221-229. doi: 10.1109/tpwrd.2003.820177
- Borucki, S. (2012). Diagnosis of technical condition of power transformers based on the analysis of vibroacoustic signals measured in transient operating conditions. *Ieee Transactions on Power Delivery*, 27(2), 670-676. doi: Doi 10.1109/Tpwrd.2012.2185955
- Duval, M. (2002). A review of faults detectable by gas-in-oil analysis in transformers. *Ieee Electrical Insulation Magazine*, 18(3), 8-17. doi: Doi 10.1109/Mei.2002.1014963

- Garcia, B., Burgos, J.C., & Alonso, A.M. (2006a). Transformer tank vibration modeling as a method of detecting winding deformations - part i: Theoretical foundation. *Ieee Transactions on Power Delivery*, 21(1), 157-163. doi: Doi 10.1109/Tpwrd.2005.852280
- Garcia, B., Burgos, J.C., & Alonso, A.M. (2006b). Transformer tank vibration modeling as a method of detecting winding deformations - part ii: Experimental verification. *Ieee Transactions on Power Delivery*, 21(1), 164-169. doi: Doi 10.1109/Tpwrd.2005.852275
- Hu, C., Wang, P.F., Youn, B.D., Lee, W.R., & Yoon, J.T. (2012). Copula-based statistical health grade system against mechanical faults of power transformers. *Ieee Transactions on Power Delivery*, 27(4), 1809-1819. doi: Doi 10.1109/Tpwrd.2012.2202406
- Ji, S.C., Cheng, J., & Li, Y. (2005). Research on vibration characteristics of windings and core of oil-filled transformer. *Journal of Xi'an Jiaotong University*, 39(6), 616-619.
- Ji, S.C., Luo, Y.F., & Li, Y.M. (2006). Research on extraction technique of transformer core fundamental frequency vibration based on olcm. *Ieee Transactions on Power Delivery*, 21(4), 1981-1988. doi: Doi 10.1109/Tpwrd.2006.876665
- Ji, S.C., Zhu, L.Y., & Li, Y.M. (2011). Study on transformer tank vibration characteristics in the field and its application. *Przegląd Elektrotechniczny*, 87(2), 205-211.
- Lee, W.-R., Jung, S.W., Yang, K.H., & Lee, J.S. (2005, 11-14 July 2005). A study on the determination of subjective vibration velocity ratings of main transformers under operation in nuclear power plants. *Paper presented at the In Proceedings of the 12th International Congress on Sound and Vibration (12th ICSV)*, Lisbon, Portugal.
- Li, Q.M., Zhao, T., Zhang, L., & Lou, J. (2012). Mechanical fault diagnostics of onload tap changer within power transformers based on hidden markov model. *Ieee Transactions on Power Delivery*, 27(2), 596-601. doi: Doi 10.1109/Tpwrd.2011.2175454
- Saha, T.K. (2003). Review of modern diagnostic techniques for assessing insulation condition in aged transformers. *Ieee Transactions on Dielectrics and Electrical Insulation*, 10(5), 903-917. doi: Doi 10.1109/Tdei.2003.1237337
- Wang, M., Vandermaar, A.J., & Srivastava, K.D. (2002). Review of condition assessment of power transformers in service. *Ieee Electrical Insulation Magazine*, 18(6), 12-25.
- Yi, T.H., & Li, H.N. (2012). Methodology developments in sensor placement for health monitoring of civil infrastructures. *International Journal of Distributed Sensor Networks*. doi: Artn 612726, Doi 10.1155/2012/612726
- Canadian electricity association (1997). On-line vibration monitoring of power transformers and reactors, Volume

1: Vibration monitoring of tap changers and windings. 474 T 955.

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Motor current signature analysis for gearbox health monitoring: Experiment, signal analysis and classification

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ABSTRACT

Preventing downtimes in machinery operation is becoming fundamental in industrial standards. The most common strategy to avoid costly production stoppages is the preventive maintenance, combining it with reactive maintenance in detected malfunctions. Condition-based maintenance can reduce costs, and help maintaining the quality of the produced goods. Gearboxes, as crucial elements in industrial machinery, are conventionally monitored using accelerometers, which are expensive and can be hard to install in place to provide useful information.

Motor current signature analysis overcomes these inconveniences. This analysis technique provides a nonintrusive method, and it is based on readily available signals. Changes in the input voltages are related with variations of the speed and/or load of the electric motor. The health state of the gearbox can be examined through an exhaustive analysis of the input currents.

A gear prognosis simulator (GPS) test bench has been used to perform an extensive experimentation campaign. This test bench is particularly convenient due to the flexibility it provides. Different sets of sensors can be placed in different positions, and multiple combinations of speeds and loads can be established. Three damage categories in the gears have been analyzed, high damage, moderate damage and little damage. The test parameters have been selected to simulate the working conditions of electromechanical actuators and machine tools. Constant speed and transient tests have been performed. In the transient tests, fast speed changes are performed to produce acceleration, to investigate the concomitant changes produced in the signal. The analysis has been performed in both the time and the frequency domain, and complementarily, using the wavelet decomposition. The results obtained allow discerning the different type of defects on the gears, thus allowing detecting the different fault conditions and enabling the assessment of the health state of the gearbox.

1. INTRODUCTION

Regarding machinery maintenance, different strategies are usually followed. The most ordinary trend is the preventive maintenance, combined with reactive or corrective equipment management; a cradle-to-grave strategy to preserve equipment functions, avoid the consequences of failure, ensure the productive capacity and maintain the quality of produced goods (Dhillon, 2002). The use of socalled condition-based maintenance tries to help achieve these objectives. The main obstacle for the implementation of condition-based maintenance is the cost and the knowledge required to properly install sensors. Sensors and other monitoring techniques are not so standard and require costly and, sometimes, hard implementations.

Machinery internal signals, in some cases, are readily available, and can give information of the health state. Avoiding the expenditure and implementation problems of adding sensors. Internal signals give an economical approach to condition monitoring; although they may require complex signal processing. Internal signals are typically controlled in most of the machines and could be available in an easy way.

Gear boxes are crucial elements in industrial machinery. A defect can cause costly downtimes. Gearboxes have been monitored in the past, using the vibration signal (Randall, 2002). But using the vibration signal involves installing accelerometers, with which are often costly and hard to install. This research has been carried out to monitor the

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health state of gearboxes using electrical motor current (Kar & Mohanty, 2006). If a fault condition does exist, the effective load torque varies with the rotor position. Subsequently, these variations produce spectral components in the current consumed by the driving motor (Hachemi 2000). As a first approach to the use of internal signals, in this paper the current signal is obtained by means of external sensors.

In this paper we present the investigation carried on a gearbox test rig. Three health states are included in this investigation (Severe damage, Medium damage and little damage. The current is analyzed extracting features form the signal, and by previously using a wavelet decomposition, showing the suitability of the preprocessing technique.

The investigation carried out in this paper constitutes a step forward in our quest for using internal signals for condition based maintenance in gear boxes. The information obtained in this research will permit the identification of fault conditions, hopefully allowing in a close future to implement prognosis. The possibilities of using the timefrequency domain analysis are being explored.

2. EXPERIMENTAL

For the procurement of experimental results a Gear Prognostics Simulator (GPS) test rig was used, from Spectra Quest. The data obtained from the test rig are of capital importance as it is in effect, real machinery. So it is perfect for the validation of our algorithms. The most suitable working conditions were selected. In this way the translation from the test rig to actual machinery may be less costly. It is remarkable that it permits the testing of defects that can be hard or impossible to be tested in real machinery.

The GPS consists mainly of two confronted motors, a reduction gear box for the load motor and the monitored gearbox. One of the motors acts as a drive and the other motors acts as the load. The drive motor provides the speed that is commanded by the control. And the load control supplies de torsion load applied to the gearbox. Both motors are three-phase, two pair of poles asynchronous motors.



Figure 1 Description of the Gear Prognostics Simulator Test rig.

The monitored gear box is composed by three shafts with different gears. The gear that is being tested in this work is right the first one after the motor.

The test rig allows a fast gear change, so different gears with different defects have been studied. Another property is the adaptability of the gear box that permits the installation of diverse sensors. Hence accelerometers, current sensors, torque sensors, load cells and encoders have been installed.

There are several factors that affect the tests. Operating conditions don't only affect the test, but also the current signals measured. Speed and load are two of those operating parameters, to avoid their effects they are set to 1500 rpm and no load condition. To reduce the effect of other unwanted contributions the tests are carefully performed using the same conditions. For reassurance in avoiding the effect of parameters that could not have been identified and, to get statistical robustness, several repetitions of each gear test are performed.

2.1. Gears tested

A collection of gears have been tested. All of them are spur gears. Different gears with different faults are present in this collection.

Several sensors are installed in the test rig, accelerometers, current sensors, torque sensors and encoders. In order to classify the faulty gears, the signal obtained from the acelerometers has been analyzed. Unsupervised learning techniques combined with tribological expertise have been applied to the tests, after a vibration signal pre-processing, in order to find hidden similarities and to group them. As a result, three different categories have been identified: severe damage, moderate damage and little damage.

Gear number	Health assessment		
0003G	Severe damage		
0005G	Severe damage		
0007G	Severe damage		
0010G	Severe damage		
0011G	Little damage		
0012G	Moderate damage		
0013G	Moderate damage and little damage		
0014G	Little damage		

Table 1. Classification of the gears using the informationfrom the accelerometers.

2.2. Test procedure

Each test was done with a length of 15 seconds to allow the slowest gear in the gear box to be able to perform at least 10 revolutions.

Each test condition was repeated 15 times to enable statistical robustness. And each repetition was independent to the rest as between two repetitions the speed is taken to zero, and the test is re-launched. But all of the tests were performed in the same speed and load conditions, thus eliminating the influence of these two parameters.

3. DATA PROCESSING TECHNIQUES

At naked eye differences between little damage and severe damage gear's current is indistinguible, hence making data processing mandatory.



Figure 2 Current raw signal from the 0003G, U channel.

The data that have been processed are the data from the channel U of the drive motor.

Two types of analysis were performed. One for the case of the raw signal, in the time domain, and another one for the time-frequency domain of the wavelet decomposition signal.

In the case of the raw signal analysis, 14 features from the signal were obtained. The features are: rms, average, peak value, crest factor, skewness, kurtosis, median, minimum, maximum, deviation, variance, clearance factor, impulse factor, shape factor (Chandran, Lokesha, Majumder, Raheemv, 2012). They have been obtained from the each repetition, and a median of all of the results is calculated.

On the other hand, time-frequency domain analysis is performed, in comparison with frequency analysis, it overcomes problems such as frequency resolution and magnitude accuracy (Cusidó, Romeral, Ortega, Rosero, García Espinosa, 2008), (Peng & Chu, 2004). In the work carried out, constant speed signals have been analyzed. Several wavelet decomposition levels have been studied. And in each level the 14 features that were achieved for the time domain case, are also achieved. Also another feature is calculated, this feature represents the difference between one level and the next (Subasi, 2007). Before the average of the features of the different levels a one-way analysis of the variance was performed. The objective is to reduce the number of levels and the number of features.

In this way the variables with the biggest F number, have more difference between the group variability than among within the same group, thus revealing the feature that exposes the most difference between the different gears.

4. RESULTS

Both time domain analysis and time-frequency domain analysis are compared.

4.1. Time domain analysis

After analyzing the several features, we arrive to the conclusion that not all of them provide useful information. Out of the 14 features just half of them give results, good enough to differentiate the good condition gears, and the gears with faults. The useful features are: Average, deviation, maximum, median, peak value, root mean square and variance.





Figure 3 Variance of the raw signal.

In this case the difference between the good condition gears (0011G and 0014G), and the rest (high damage, and moderate damage) is most obvious. It is of about 2 or 3 units. In the case of comparing it in percentage points, the difference is not that pronounced.

It is to be highlighted that the moderate damage gears are not discriminated.

The root mean square value also gives a remarkable difference. However the difference in percentage points is more remarkable, but the absolute variation is not that evident.



Figure 4. Root mean square of the raw signal.

4.2. Time-frequency domain analysis

The mother wavelet used was a daubechies 44 (Rafiee, Rafiee, Tse, 2010).

As stated before a one-way analysis was performed. All of the gears were introduced in the one-way analysis, instead of the gears representing the failure groups. In the next table the results of this one way analysis are shown.

Level 1		Level 2		
Variables	F-test	Variables	F-test	
Shape factor	328.5494	Skewness	159.9297	
Variance	287.8911	Average	73.0568	
Crest factor	241.6040	Ratio	60.8824	
Peak Value	54.8416	Peak Value	10.8254	
Impulse factor	12.5476	Crest factor	10.4561	
Clearance factor	10.97	Deviation	7.3155	
Rms	4.1327	Clearance factor	4.4491	
Skewness	2.8228	Impulse factor	3.4263	
Deviation	2.264	Median	2.9218	
Minimum	1.3558	Shape factor	1.5086	
Average	1.159	Maximum	1.4948	
Median	0.9807	Minimum	1.0227	
Maximum	0.9549	Variance	0.8998	
Kurtosis	0.6377	Rms	0.7296	
		Kurtosis	0.507	

Table 2. Table with the F tests.

The results of the one-way analysis test unveiled that the best levels for the decomposition are the levels 1, 4 and 15.

The most interesting variables for level 1 are crest factor, peak value, shape value and variance. In the case of level 4 are average, skewness and ratio. And last but not least important for the case of the level 15 decomposition the best variables are the clearance factor, the median, the ratio and the variance.

Going through a thoughtful analysis to find among those variables that pointed out the one-way analysis, the ones that provided the most information were selected.

In the next image the difference between the gears is noticeable.



Figure 5. Variance of the signal obtained in the level 15 wavelet decomposition.

It is also remarkable that the results are more in concordance with the classification of the accelerometer data than the analysis of the raw signal. The gear 13 was classified as having some results as moderate damage and others as little damage, and as we can see in the image above the dispersion of this results are in between the high damage area and the little damage area. It is also visible that the gear number 12, classified as moderate damage, has got slightly different values than the gears categorized as high damage. This can also be seen in other variables. And the difference is bigger in value than in the case of the time domain analysis, providing an easier differentiation.



Figure 6. Ratio of level 4 wavelet decomposition.

Though in this case, due to the dispersion of the signal the difference may not be that easily noticeable.

As a result the time-frequency domain produces a differentiation between the gears with a greater match with the results obtained from the vibration analysis.

5. CONCLUSION

It has been shown that the analysis of the signals obtained in the wavelet analysis produces better results than the analysis of the raw signal for the differentiation of the different states of the gears, analyzing the motor current signal. This paper is a step forward for the use of internal signals of machinery in condition based maintenance for gear boxes. Providing a non intrusive an easy to implement method. The final goal is that the manufacturers implement this method and provide more accurate information on the state of the machinery, provide recommendations on the problems that the client may have and to provide information on the use, so that future designs can be improved. There is still space for more improvement, as the technique will be further perfected. The mother wavelet will be optimized; data from the frequency components of each decomposition level will be analyzed.

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REFERENCES

- Chandran P., Lokesha M., Majumder M.C., Raheemv K.F. A. (2012) Application of Laplace Wavelet Kurtosis and Wavelet Statistical Parameters for Gear Fault Diagnosis, *International journal of multidisciplinary sciences and engineering*, vol. 3 (issue 9), pp. 1-8
- Cusidó J., Romeral L., Ortega J.A., Rosero J.A., García Espinosa A. (2008). Fault Detection in Induction Machines Using Power Spectral Density in Wavelet Decomposition, *IEEE Transactions on Industrial Electronics*, vol. 55 (issue 2), pp. 633-643. doi:10.1109/TIE.2007.911960
- Dhillon B.S. (2002). ENGINEERING MAINTENANCE A modern approach. USA: CRC Press
- El Hachemi Benbouzid M. A. (2000). Review of Induction Motors Signature Analysis as a Medium for Faults Detection, *IEEE Transactions on Industrial Electronics*, vol. 47, (issue 5), pp. 984 - 993. doi: 10.1109/41.873206
- Kar C., & Mohanty A.R. (2006). Monitoring gear vibrations through motor current signature analysis and wavelet transform. *Mechanical Systems and Signal Processing*, vol. 20 (issue 1), pp. 158-187
- Peng Z.K., Chu F.L. (2004) Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography, *Mechanical Systems and Signal Processing*, vol. 18, pp. 199-221, doi: 10.1016/S0888-3270(03)00075-X
- Rafiee J., Rafiee M.A., Tse P.W. (2010). Application of mother wavelet functions for automatic gear and bearing fault diagnosis, *Expert Systems with Applications*, vol. 37 (issue 6), pp. 4568-4579, doi: 10.1016/j.eswa.2009.12.051
- Randall Robert B. (2002). State of the Art in Monitoring Rotating Machinery – Part 1, *ISMA 2002 conference*, September, Leuven, Belgium. www.sndv.com/downloads/0403rand.pdf

Subasi A. (2007). EEG signal classification using wavelet feature extraction and a mixture of expert model, *Expert model with applications*, vol. 32, pp. 1084-1093, doi: 10.1016/j.eswa.200602.005

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Effect of parameters setting on performance of discrete component removal (DCR) methods for bearing faults detection

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ABSTRACT

Separation between non-deterministic and deterministic components of gearbox vibration signals has been considered as important signal processing step for rolling-element bearing fault diagnostics. In this paper, the performance of bearing fault detection after applying various discrete components removal (DCR) methods is quantitatively compared. Three methods that have become widely used, namely (i) time synchronous average, (ii) self adaptive noise cancellation (SANC) and (iii) cepstrum editing, were considered. The three DCR methods with different parameter settings have been applied to vibration signals measured on two different gearboxes. In general, the experimental results show that cepstrum editing method outperforms the other two methods.

1. INTRODUCTION

Detecting bearing faults on rotating machinery based on vibration signals is often a challenge due to the high energy (dominating) signals; originating from various machine elements including gears, screws, and shafts; that can mask weak signals (i.e. non-deterministic) generated by bearing faults. These dominant signals are deterministic, meaning that they will appear as discrete components in the frequency domain. When bearing faults detection is of interest, it is therefore important to remove these discrete components prior to applying further signal processing. Several methods have been proposed in literature for separating discrete components and non-deterministic components (i.e. residual signals) useful for bearing fault detection. Recently R. Randall and Sawalhi (2011) have presented a new method for separating discrete components from a signal based on cepstrum editing. The

choice of setting parameters when applying these methods can have a significant effect on the residual signals. A qualitative comparison of different methods has also been recently performed by R. Randall et al. (2011). However, to the authors' knowledge, the effects of different parameters setting on the performance of bearing fault detection have not been discussed yet elsewhere. To fill this gap, this paper aims at discussing the effects of parameters setting and eventually providing a quantitative comparison. The performance of bearing fault detection after applying different DCR methods is analyzed. Here, two other methods are evaluated and compared to the cepstrum editing method, namely synchronous average and synchronous adaptive noise cancellation (SANC).

The paper first presents the 3 discrete component removal (DCR) methods and discusses adjustable parameters for each one, and second, applies the methods to vibration signals measured on two gearboxes: (i) an industrial gearbox which is a part of a transmission driveline on the actuation mechanism of secondary control surface in civil aircraft and (ii) a laboratory gearbox used in the PHM09 data competition. The residual signals obtained from these three methods are processed following the optimized envelope analysis by using spectral kurtosis for determining the optimal frequency band for demodulation. Bearing detection performance is assessed on the envelope spectrum.

2. DISCRETE COMPONENT REMOVAL METHODS (DCR)

There exist a number of methods for separating signal components with different pros and cons, such as time synchronous averaging (TSA), linear prediction, adaptive and self-adaptive noise cancellation (SANC), discrete/random separation (DRS), and the recently developed method, i.e. cepstral editing. The three methods considered in this work are briefly discussed in the following subsections.

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2.1. Synchronous adaptive noise cancellation (SANC)

SANC is an adaptive filtering method where the filter coefficients w are adaptively updated according to the scheme shown in Figure 1. The filter coefficients are updated such that the prediction error e(n) obtained by subtracting the filtered signal y(n) from the original signal x(n) is minimized. The input of the filter d(n) is a delayed version of the original signal. SANC allows separation between deterministic and non-deterministic signals. The reason is that a nondeterministic signal is not correlated to previous sample unlike deterministic signal. However, one needs to ensure that the delay should be greater than the time of decorrelation of the non-deterministic signal but it should exceed the decorrelation time of the deterministic part. The filter output y(n) is the deterministic signal containing gears and shaft signals and the output error represents the non-deterministic part containing bearing signals

The most used adaptation algorithm is the celebrated least mean-square (LMS) developed by Widrow and Hoff (Widrow, Hoff, et al., 1960). It is characterized by its robustness and a low computational complexity. Its recursive procedure computes the output of the filter and compares it to the original signal. The error is used to adjust the filter coefficient as shown in Eq. (1)

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu . e(n) . \mathbf{d}(n) \tag{1}$$

where

 $y(n) = \mathbf{w}^{\mathbf{T}} \mathbf{d}$ is the filter output, e(n) = x(n) - y(n) is the output error,

d(n) is the delayed signal,

 $\mathbf{w}(n) = [w_0(n), w_1(n), \dots, w_{M-1}]^T$ are the filter coefficients at the time index n,

 $\mathbf{x}(n) = [x(n), x(n-1), \dots x(n-M+1)]^T$ is the input signal,

 μ is the step size parameter that must be selected properly to control stability and convergence.

The use of SANC implies the choice of 3 parameters and its performance relies on them:

- the prediction depth or time delay L
- the step size μ
- the filter length M

Antoni and Randall (2004) have discussed optimal settings of these parameters giving general guidelines, also presented in (R. Randall et al., 2011). The delay L should be chosen large enough to exceed the memory of the noise but not so long to destroy the correlation, which can be a bit disturbed in case of slight speed fluctuation. The length of the filter M should not exceed the signal length to have enough time for adaptation. The step size μ represents the convergence rate and will be a trade off between the desired accuracy and the computational cost. A low step size value results in high accuracy.



Figure 1. SANC filter process.

2.2. Time synchronous average (TSA)

Time Synchronous average (TSA) is a signal processing method aiming at extracting components from a signal that are phaselocked to the shaft revolution by means of averaging several signal segments. The segments can represent one or several shaft revolutions. TSA cancels or significantly reduces the presence of non-synchronous phenomena, which can comprise bearing signals and background (white) noise. In order to perform TSA, the shaft position information is needed for re-sampling the signal in the angular domain. This information can be retrieved from a tachometer or encoder signal. If the tachometer is not located on the shaft of interest, transformation is needed to convert angular positions of the shaft with the tachometer to angular position of the shaft of interest.

In the absence of tachometer signal, Bonnardot et al. (2005) have reported a technique allowing TSA using a virtual tachometer signal generated from accelerometer signal. However, this tachometer-less technique presents some limitations since it requires a very low variation of the speed. TSA can also be used for discrete component removal by subtracting the synchronous signal from the original signal. The remaining or the residual signal contains non-deterministic components comprising bearing signals. The adjustable parameter is the number of average which is related to the number of revolutions in averaged segments.

2.3. Cepstrum editing

The cepstrum editing method gives some advantages compared with all the techniques noted previously. One notable advantage of the editing cepstral method is that it can be used to remove the selected frequency components in one operation, without order tracking as long as the speed variation is limited, but it can leave some periodic components if desired. In some applications where the sidebands are not harmonics of the shaft speed, families of uniformly spaced sidebands can be removed with the editing cepstral method. The detailed explanation and the performance of the latter method can be found in (R. Randall & Sawalhi, 2011). The following paragraphs will briefly revisit the method. Let y be the measured vibration signal and Y(f) be the corresponding frequency domain signal. By definition, the cepstrum of this signal $C(\tau)$ is calculated by taking the inverse Fourier transform of the logarithm of Y(f), i.e.

$$C(\tau) = \mathcal{F}^{-1}\left[\log\left(Y(f)\right)\right],\tag{2}$$

with \mathcal{F}^{-1} denoting the inverse Fourier operation.

In the same way that the word "cepstrum" was coined from "spectrum" by reversing the first syllable, the term "quefrency" is used for the x-axis of the cepstrum (even though it is time), "rahmonic" means a series of equally spaced peaks in the cepstrum domain (resulting from a series of harmonics or sidebands in the log spectrum) and "lifter" represents a filter applied to the cepstrum (Bogert, Healy, & Tukey, 1963).

Based on the cepstrum definition, it is quite simple to deduce the rationale behind the editing cepstral based DCR method. Given the fact that in the frequency domain, the response signal Y(f) is a multiplication of the excitation signal X(f) and the frequency response function H(f), i.e.

$$Y(f) = X(f) \times H(f), \tag{3}$$

by taking the logarithm of the response signal Y(f), Eq. (3) can thus be written as:

$$\log\left(Y(f)\right) = \log\left(X(f)\right) + \log\left(H(f)\right). \tag{4}$$

Furthermore, by taking the inverse Fourier transform of Eq. (4):

$$\mathcal{F}^{-1}\left[\log\left(Y(f)\right)\right] = \mathcal{F}^{-1}\left[\log\left(X(f)\right)\right] + \mathcal{F}^{-1}\left[\log\left(H(f)\right)\right].$$
(5)

It is clear now from Eq. (5) that in the cepstrum domain, the excitation signal and the transfer path are additive. This implies that the unwanted excitation signal (e.g. gear and shaft related signals) can be removed (i.e. edited) in the cepstrum domain. The cepstral editing based DCR method developed by (R. Randall & Sawalhi, 2011; Sawalhi & Randall, 2011) is schematically shown in Figure 2.

Figure 3 further illustrates the editing process in the cepstrum domain. To remove unwanted rahmonics corresponding to periodic components (i.e. gear signals), the lifter width Δ should be chosen appropriately. Up to now, there is no an automatic way for determining the lifter width Δ . The (constant) width is typically selected visually based on inspection of the resulting signal.

3. EXPERIMENTAL STUDY

3.1. Description of test rigs

To compare the cepstrum editing DCR method to TSA and SANC and assess the effect of parameters setting on performance for bearing faults detection, two sets of experimental



Figure 2. Schematic diagram of the editing cepstral method for removing selected families of harmonics and/or sidebands from time domain signals, reproduced from (R. Randall & Sawalhi, 2011).



Figure 3. Liftering to remove unwanted rahmonics, reproduced from (Gao & Randall, 1996).

data from gearboxes are used (hereafter called dataset#1 and dataset#2).

3.1.1. Test rig#1

Dataset#1 is measured on an industrial gearbox which is a part of a transmission driveline of the actuation mechanism of secondary control surface in civil aircraft shown in Figure 4. The test rig was designed to simulate the actual operation conditions during the life cycle of the aircraft control system which implies the gearbox would experience a range of speed and torque conditions. It is driven by an electrical motor. A second motor acted as a generator is used to apply load to the system. The nominal speed of the motor is 710 rpm. The gearbox consists of two spur bevel gears, each with 17 teeth producing a gear ratio of 1:1. Two angular contact bearings are used to support the gears.

The characteristic bearing fault frequencies for the operating speed of 60 rpm (1 Hz) and for the operating speed of 710 rpm (11.83 Hz) including, (i) ball pass frequency of inner race (BPFI), (ii) ball pass frequency of outer race (BPFO), ball



Figure 4. (a) The transmission gearbox test rig of a civil aircraft, (b) The gearbox layout and sensors location.

damage frequency (BDF) and fundamental train frequency (FTF), are listed in Table 1. All vibration data are acquired using accelerometers fixed on the outer case of the gearbox. The sampling frequency is of 5 kHz.

Table 1. Theoretical bearing fault frequencies for dataset#1.

	Fault frequencies [Hz]		
Rotation speed	60 rpm	710 rpm	
BPFI	7.03	83.2	
BPFO	4.96	58.8	
BDF	4.37	51.2	
FTF	0.41	4.9	

3.1.2. Test rig#2

Dataset#2 has the particularity of being measured on a multipleshaft gearbox. These data were used for tghe PHM09 data competition on gearbox fault diagnosis. The gearbox test setup used for generating these data is depicted in Figure 5. On this gearbox setup, two different gear geometries can be used including spur and helical gears. The dataset analyzed in this paper is collected for which the gearbox is assembled with spur gears. The gearbox configuration is as follows:

- Input shaft: input pinion of 32 teeth,
- Idler shaft: 1st idler gear of 96 teeth,
- Idler shaft: 2nd (output) idler gear of 48 teeth,
- Output shaft: output pinion of 80 teeth.

Vibration data are acquired by means of two Endevco 10 mV/g accelerometers (Sensor resonance frequency > 45 kHz). One of the two accelerometers is mounted on the input shaft side and the other one is mounted on the output shaft side. The external load is applied thanks to a magnetic brake. Data are sampled synchronously from the two accelerometers. The sampling frequency is of $\frac{200}{3}$ kHz. A tachometer generating 10 pulses per revolution is attached on a properly selected location. The vibration signal analyzed here was collected at 50 Hz shaft speed, under high loading. The characteristic fault frequencies of the bearing of interest are given in Table 2 for two speeds.

Table 2. Theoretical bearing fault frequencies for dataset#1.

	Fault frequencies [Hz]		
Rotation speed	60 rpm	3000 rpm	
BPFI	4.947	247.4	
BPFO	3.052	152.6	
BDF	3.984	199.2	
FTF	0.382	22.89	

3.2. Results and discussion

Data from the two test rigs have been processed to remove discrete components using the different methods presented



Figure 5. Gearbox diagnosis setup used in the PHM09 data competition.

above. The residual signals containing non deterministic components are further processed using the envelope analysis proposed in R. B. Randall (2011). Note that the demodulation frequency band used in the envelope analysis is determined by means of spectral kurtosis analysis using the fast kurtogram algorithm (Antoni, 2007).

3.2.1. Fault indicator

To assess the performance of bearing fault detection, a fault indicator is define as the amplitude of peak at the fault frequency normalized with respect to the DC value in the envelope spectrum. In dataset#1, the concerned fault is a bearing outer race fault while the fault present in dataset#2 is located on the inner race.

3.2.2. Analysis of dataset#1

The SANC is performed with different values of delay and filter length. The step size is kept equal to 0.01. The delay L is chosen among the following values: 100, 200, 500, 1000, 1500, 2000, 5000 and 10000, while the filter length M = 12. The results show the best performance with L = 100 as shown in Figure 6 (i.e. highest fault indicator value). Then this best delay value is used with various filter lengths to calculate the corresponding fault indicator values as shown in Figure 7.

The cepstrum editing method is also applied to dataset#1 with different normalized liftering widths chosen among the following values: 0.02, 0.04, 0.08, 0.16 and 0.32. It is important to notice here that the *normalized liftering width* is de-



Figure 6. Effect of SANC delay on bearing fault indicator.



Figure 7. Effect of SANC filter length on bearing fault indicator.

fined as the ratio of the lifter width with respect to the period of discrete component of interest. The fault indicator values corresponding to the selected liftering widths are shown in Figure 8.



Figure 8. Effect of cepstrum editing lifter width on bearing fault indicator.

The results obtained with TSA using different number or shaft revolutions per segment are shown in Figure 9. By analyzing the best fault indicator values resulting from the above different DCR methods, it comes that the cepstrum editing method gives the best fault indicator. Figure 10 shows the envelope spectra of residuals signals obtained for the 3 DCR methods. One can notice the low background noise achieved with the cepstrum editing method. This can be also concluded by observing the kurtosis values of the corresponding residual signals listed in Table 3. As shown in Figure 11, the cepstrum editing method leads to the most impulsive residual signal.



Figure 9. Effect of TSA number of revolutions on bearing fault indicator.



Figure 10. Comparison of envelope spectrum for dataset#1.

Table 3. Kurtosis of the residual signals of dataset#1.

	Kurtosis
TSA residual	4.0158
SANC residual	4.3990
Cepstrum residual	5.0627

3.2.3. Analysis of dataset#2

Similar to the analysis on dataset#1, the SANC is performed with different values of delay and filter length. The step size is kept equal to 0.01. The delay L is first chosen among the following values: 100, 200, 500, 1000, 1500, 2000, 5000 and 10000 while the filter length M = 12. The results show the best performance with L = 2000 as shown in Figure 12. Then this best delay value is used with varying filter length to calculate the fault indicator as shown in Figure 13.

The cepstrum editing method is applied to dataset#2 with different liftering widths chosen among the following values:



Figure 11. Normalized residual signals for dataset#1 obtained after applying 3 DCR methods.



Figure 12. Effect of SANC delay on bearing fault indicator for dataset#2.



Figure 13. Effect of SANC filter length on bearing fault indicator for dataset#2.

0.02, 0.04, 0.08, 0.16 and 0.32. Subsequently, the fault indicator values for the corresponding liftering widths are calculated as shown in Figure 14.



Figure 14. Effect of cepstrum editing lifter width on bearing fault indicator.

The result obtained with TSA using different number or shaft revolution per segment is shown in Figure 15. In line with the results obtained from dataset#1, the cepstrum editing method also provides the best performance for dataset#2. Figure 16 shows the envelope spectra of residuals signals obtained for the 3 DCR methods. It is seen in the figure that the cepstrum editing method highlights the fault frequency better than the other methods. The kurtosis values of the corresponding residual signal are given in Table 4. This indicates that the cepstrum editing leads to the most impulsive signal as it can also be seen in Figure 17.

Table 4. Kurtosis of the residual signals of dataset#2.

	Kurtosis
TSA residual	3.9653
SANC residual	4.0478
Cepstrum residual	6.7035



Figure 15. Effect of TSA number of revolutions on bearing fault indicator.



Figure 16. Comparison of envelope spectrum for dataset#2.



Figure 17. Normalized residual signals for dataset#2 obtained after applying 3 DCR methods.

4. CONCLUSION

The performance of three different discrete component removal (DCR) methods, namely (i) time synchronous averaging (TSA), (ii) self adaptive noise cancellation (SANC) and (iii) cepstrum editing, has been quantitatively compared in this paper. For the comparison purposes, two metrics, i.e. the peak values at the fault frequencies of the envelope spectrum and the kurtosis of the time domain signal, were considered. These metrics have been extracted from the vibration signals measured on industrial and laboratory gearboxes by applying the three DCR methods with different parameter settings. The optimal parameter setting of each DCR method was deduced by visual inspection on the values of the two metrics. The higher the metric value is, the better the performance of a DCR method will be. The experimental results show that the values of the two metrics based on the cepstrum editing method are higher than those of the other two DCR methods. This suggests that the cepstrum editing method outperforms the other considered methods.

REFERENCES

- Antoni, J. (2007). Fast computation of the kurtogram for the detection of transient faults. *Mechanical Systems and Signal Processing*, 21(1), 108 - 124.
- Antoni, J., & Randall, R. (2004). Unsupervised noise cancellation for vibration signals: part ievaluation of adaptive algorithms. *Mechanical Systems and Signal Processing*, 18(1), 89–101.
- Bogert, B. P., Healy, M. J., & Tukey, J. W. (1963). The quefrency alanysis of time series for echoes: Cepstrum, pseudo-autocovariance, cross-cepstrum and saphe cracking. In *Proceedings of the symposium on time series analysis* (pp. 209–243).
- Bonnardot, F., El Badaoui, M., Randall, R., Daniere, J., & Guillet, F. (2005). Use of the acceleration signal of a gearbox in order to perform angular resampling (with limited speed fluctuation). *Mechanical Systems and Signal Processing*, 19(4), 766–785.
- Gao, Y., & Randall, R. (1996). Determination of frequency response functions from response measurementsii. regeneration of frequency response from poles and zeros. *Mechanical systems and signal processing*, 10(3), 319– 340.
- Randall, R., & Sawalhi, N. (2011). A new method for separating discrete components from a signal. *Sound and Vibration*, 45(5), 6.
- Randall, R., Sawalhi, N., & Coats, M. (2011). A comparison of methods for separation of deterministic and random signals. *International Journal of Condition Monitoring*, 1(1), 11–19.
- Randall, R. B. (2011). Vibration-based condition monitoring: industrial, aerospace and automotive applications. John Wiley & Sons.
- Sawalhi, N., & Randall, R. (2011). Signal pre-whitening using cepstrum editing (liftering) to enhance fault detection in rolling element bearings. In Proceedings of the 24 international congress on condition monitoring and diagnostic engineering management (comadem2011), may (pp. 330–336).
- Widrow, B., Hoff, M. E., et al. (1960). Adaptive switching circuits.

A Model-based Approach to Detect an Under-Lubricated Condition in a Ball Bearing

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ABSTRACT

Bearings with an insufficient amount of lubricant can lead to early field failures, especially in applications which fail due to lubricant degradation, such as cooling fans used for thermal management of electronics. A reduced amount of lubricant can accelerate the wear process in the bearing, since there is not enough lubricant film thickness to support the operating load on the bearing. Qualification of bearings in cooling fans is carried out by time-truncated tests, where cooling fans have to operate without failure for a predetermined period of time. Under-lubricated bearings can survive without failure in these tests leading to the usage of these bearings in the field resulting in field returns and warranty claims.

A non-linear dynamic model of a ball bearing is developed to simulate the transfer of load from the inner race to the outer race of the bearing as well as the acceleration signal as a function of time. An under-lubricated bearing condition is simulated in this model by changing the load transmitted to the outer race due to the reduced amount of lubricant. The simulated acceleration signal of the under-lubricated bearing condition is compared with that from the normal bearing to develop a fault-characteristic feature. The changes observed in the fault-characteristic feature from the simulation is validated by comparing with that obtained from experiments conducted on bearings with varying amounts of grease, ranging from none to the nominal amount specified by the manufacturer. The vibration level of these bearings was monitored at various operating speeds during the experiment. The changes observed in the fault-characteristic feature from the experiment due to a reduction of the lubricant in the bearing were similar to that observed in the simulations. This study resulted in the development of an experimental methodology and a fault-characteristic feature which can be used as a method for rapid acceptance testing of bearings. The dynamic model developed in this study can be used to determine the fault-characteristic feature for any bearing design.

1. INTRODUCTION

Bearings are used in machinery where the components in relative motion have to be supported on a stationary structure. For example, ball bearings are used to support a rotating shaft on a fixed structure. Bearing failures are the foremost cause for breakdown in rotating machinery: 40-50% of all industrial motor failures have been reported to be caused by bearings (Nandi, Toliyat, & Li, 2005), 43% of all cooling fan failures in electronic devices have been attributed to bearing failures (Kim, Vallarino, & Claassen, 1996), and longer down time during maintenance in wind turbines has been attributed to bearing failures (Ribrant & Bertling, 2007). Bearing fault diagnostics has been carried out to detect faults on the bearing components: the inner race, outer race, cage and the rolling elements. This is carried out by analyzing vibration signals obtained from a faulty bearing and comparison of the results with a bearing having no faults (Tandon & Choudhury, 1999). An insufficient lubrication condition in a bearing is also a fault condition which has not been studied extensively. Lubricants are used in the bearing to reduce the friction between bearing surfaces in relative motion. An improper lubrication condition in the bearing can be an overlubricated condition, an under-lubricated condition or one with no lubricant in the bearing. The first case can increase the power required to maintain the motion of the rotating surfaces, since the excess lubricant increases the viscous drag forces in the bearing. The last two cases can accelerate the degradation process in the bearing since the lubricant film thickness is not sufficient to support the load acting on the bearing elements.

The relevant literature which pertains to bearing fault detection of an improper lubrication condition consists of the following two studies. Detection of bearings without any

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lubricant has been accomplished using envelope analysis of their vibration signals (Boškoski, Petrovčič, Musizza, & Juričić, 2010). The frequency band selection for the envelope analysis was carried out based on spectral coherence and spectral kurtosis analysis. The amplitudes at the fundamental train frequency (FTF) and the ball spin frequency (BSF) were higher for the bearing without any lubricant compared to that with lubricant. Detection of an over-lubricated condition in the bearing has also been carried out in the literature (Morinigo-Sotelo, Duque-Perez, & Perez-Alonso, 2010). Tests were conducted on bearings with excess lubrication which were allowed to operate for 30 days, during which the excess lubricant was expelled from the bearing. The frequency spectrum of the stator electrical current of the motor driving the bearing was analyzed to detect the excess lubrication condition. Differences were observed in the amplitudes of the FTF and BSF in the electrical current spectrum between the excess lubricated and normal lubricated case of the bearing. Neither of these studies addressed the issue of detecting a bearing condition containing lubricant between the nominal amount and none at all. A reduction in the lubricant from the nominal amount can reduce the life of the bearing, resulting in earlier failures than that specified by the manufacturer. Qualification tests carried out on bearings can fail to detect this fault condition, especially if the test is a time-truncated test, where the bearing has to operate without failure for a specified period of time. An example of such a qualification test is the IPC-9591 standard used to qualify bearings used in cooling fans for electronics applications. Hence, the detection of an improper lubrication condition is of value in acceptance testing of bearings, and these tests would have to be carried out in a limited time in such a scenario. A modelbased approach is adopted in this study for detection of an improper lubrication condition in a bearing. A dynamic model of the ball bearing components is created to simulate the rotational motion between the different components of a ball bearing. A fault condition is simulated using this model and the acceleration signal is compared with that of the normal lubrication condition. The simulation results are compared with results obtained from experiments using inadequately lubricated bearings.

2. BEARING MODEL

A dynamic model of the components of a ball bearing is developed assuming that the outer race is fixed. The transmission of forces between the individual components is modeled using a spring and damper system. In order to model the forces and deformation in the rolling contact between the components, Hertzian contact theory is used. The contact force for a point contact is given by the following relation:

$$f_b = k_b \delta^{1.5} \tag{1}$$

where k_b is the nonlinear bearing stiffness corresponding to the bearing deformation δ . The nonlinear bearing stiffness is a function of the bearing material and the bearing geometry. For point contact between two bodies made of the same material, the relation between contact deformation and contact force is given by the following relation:

$$\delta = 1.5 \left(\frac{2K}{\pi\mu}\right)_{3} \sqrt{\frac{1}{E} \left(1 - v^{2}\right) \left(\frac{\sum \rho}{3}\right) f_{b}^{2}}$$
(2)

In this relation, bearing material properties are the Young's modulus (*E*) and the Poisson's ratio (v). The Hertzian coefficients $\Sigma\rho$ and $2K/\pi\mu$ can be obtained from standard bearing tables based on the bearing contact geometry (Eschmann, Hasbargen, Weigand, & Brändlein, 1985). These coefficients are a function of the radius of curvature of the inner race, outer race and ball surfaces which are in contact. The contact deformation (δ) is obtained based on the displacement of the bearing in the x- and y-directions.

A force balance is carried out on the components of the bearing assuming a two degree-of-freedom system as shown in Figure 1.



Figure 1. Schematic of two degree-of-freedom model of bearing system.

The governing equations of motion for this two degree-offreedom system are shown in (3)-(6). The subscripts b_1 and b_2 in these equations correspond to the bearing located on a shaft *s* as shown in Figure 2. The bearings are located in a bushing and are held in position by means of a spring and washer. The shaft supported by the bearings is driven by a brushless DC motor which can rotate at a maximum speed of 4800 rpm.

$$m_{b1}\ddot{x}_{b1} + k_s \left(x_{b1} - x_{b2} \right) + q_s \left(\dot{x}_{b1} - \dot{x}_{b2} \right) + f_{b1x} = 0 \quad (3)$$
$$m_{b2}\ddot{x}_{b2} + k_s \left(x_{b2} - x_{b1} \right) + q_s \left(\dot{x}_{b2} - \dot{x}_{b1} \right) + f_{b2x} = 0 \quad (4)$$

$$m_{b1}\ddot{y}_{b1} + k_s(y_{b1} - y_{b2}) + q_s(\dot{y}_{b1} - \dot{y}_{b2}) + f_{b1y} = l$$
(5)

$$m_{b2}\ddot{y}_{b2} + k_s(y_{b2} - y_{b1}) + q_s(\dot{y}_{b2} - \dot{y}_{b1}) + f_{b2y} = l \quad (6)$$

The mass of the bearing is represented by m, transverse stiffness and damping of the shaft due to the axial load supported by the bearing is given by k and q, and load acting on each bearing is represented by l.



Figure 2. Schematic of bearing assembled on a shaft.

Solving the governing equations (3)-(6) as a function of time, the displacement of the bearing is calculated, from which the contact deformation δ is obtained. The contact deformation is calculated for each rolling element as shown in Figure 3 when the rolling element enters the load distribution zone shown in Figure 1. The relationship between contact deformation and bearing displacement is given by the following relation (Sawalhi & Randall, 2008):

$$\delta = \delta_x + \delta_y = x_b \cos \varphi + y_b \sin \varphi \tag{7}$$

The angular position of the j^{th} ball after a time increment dt is calculated from the cage rotational frequency using (8).

$$\varphi_{j} = \frac{2\pi (j-1)}{n_{b}} + \left(1 - \frac{D_{b}}{D_{p}} \cos \alpha\right) \frac{\omega_{s}}{2} dt$$
(8)

where n_b is the number of balls, D_b is the ball diameter, D_p is the pitch circle diameter of the balls, α is the contact angle and ω_s is the shaft rotational frequency.



Figure 3. Relation between contact deformation (δ) and bearing displacement *x* and *y*.

In order to include the damping in the ball contact due to the presence of the lubricant, equation (1) is modified to include a viscoelastic damping contribution in addition to the elastic Hertzian component as shown below (Machado, Moreira, Flores, & Lankarani, 2012):

$$f_b = k_b \delta^n + \chi \delta^n \delta \tag{9}$$

where χ is the contact damping factor, $\dot{\delta}$ is the rate of change of contact deformation and n = 1.5 in the case of a ball bearing.

3. MODEL SIMULATION

The system of equations explained in the previous section is used to develop a model in Matlab/Simulink[®]. This model is solved to obtain the time domain acceleration signal using the ode4 solver which is based on the Runge-Kutta method. The bearing parameters which are used in this model for simulation are shown in Table 1. The operating load acting on each bearing is 0.69 N.

Table 1. Bearing parameters used for simulation

Value
6
1.588 mm
5.5 mm
10.4°
0.76 g
210 GPa
0.3

An under-lubricated condition of the bearing results in the bearing elements operating in a boundary layer lubrication regime. This is due to a reduction in the lubricant film thickness supporting the load acting on the bearing. This results in the contact of asperities during relative movement of the surfaces, which causes the Hertzian pressure distribution to rise to 1.5 times that observed in an ideal Hertzian contact (Stachowiak & Batchelor, 2013). The under-lubricated bearing operation is simulated in the model by increasing the bearing stiffness and at the same time decreasing the damping in the contact due to the reduced lubricant film thickness. The values for the bearing stiffness and damping were estimated by calibrating the model based on the vibration signals measured from the experiment, which is discussed in the next section.

4. EXPERIMENTAL SECTION

The bearings used in this study were mounted in a fixture as shown in Figure 2 and were held in place by a springwasher locking system. Vibration signals were measured while the bearings were operated at different speeds using a DC motor. The motor had a maximum speed of 4800 rpm. The speed of the cooling fan could be reduced down to 2160 rpm using a controller governed by a pulse width modulation (PWM) signal. Bearings which contained the nominal amount of grease as specified by the manufacturer are referred to as 100% bearings in this study. The same experimental set up was used to test specially manufactured bearings which contained a reduced amount of grease. Bearings containing half of the nominal amount of grease are referred to as 50% bearings, and bearings containing a quarter of the nominal amount of grease are referred to as 25% bearings. Analysis of the vibration signals was carried out to develop a procedure to distinguish the bearings containing the nominal amount of grease from the others. Figure 4 shows root mean square (rms) acceleration of the bearings for different operating speeds. The highest vibration level for the 100% bearing was observed at 3815 rpm. For the 50% and 25% bearing, the highest vibration level was shifted to 3960 rpm. Another trend which can be observed is that the vibration level of the 50% bearing is higher than that of the 100% bearing at 3960 rpm, whereas the vibration level of the 25% bearing is similar to that of the 100% bearing.



Figure 4. Box plot of rms acceleration at different bearing rotational speeds. The edges of the box at each data point are the 25th and 75th percentiles of the measurements and the whiskers correspond to $\pm 2.7\sigma$ assuming the data is normally distributed.

A feature for fault detection due to a reduction in the lubricant level of the bearing was developed based on the shift in the vibration level from one operating speed to another operating speed. The 100% bearing is used as a reference to develop this feature. The speed at which the maximum vibration level is observed is selected as the reference speed (3815 rpm from Figure 4). The speed at which the maximum vibration level is observed for the under-lubricated bearing is then selected to develop the fault feature, which is the ratio of the vibration level observed at 3815 rpm to the vibration level at the speed at which maximum vibration is observed for the underlubricated bearing. Figure 5 shows the fault feature used for classification. When this ratio is greater than 1 the bearing can be classified as a 100% bearing. A bearing with a ratio less than 1 can be classified as a faulty bearing. This fault feature can be used for classification of bearings with reduced amount of lubricant from that of the nominal bearings. This fault feature is quick to measure and can be readily implemented in an acceptance test scenario for bearings.



Figure 5. Fault feature for classification of amount of grease in a bearing

5. MODEL CALIBRATION

In order to explain the variations in vibration level with a reduction in the lubricant in the bearing, the bearing stiffness and damping values were calibrated in the model to identify the values which will generate the same vibration level as that observed in the experiment. The contact damping factor is a function of the coefficient of restitution of the elements in contact which can significantly change the vibration level in the bearing (Machado et al., 2012). The viscoelastic damping term in (9) is related to the coefficient of restitution, which can influence the vibration level of the bearing.

The stiffness and damping of the experimental set up was calculated by means of an impact test. Figure 6 and Figure 7



impact test

show the time domain and frequency domain response of the acceleration signal during the impact test. Since the acceleration signal is measured in only one direction, the stiffness and damping is calculated by treating the experimental setup as a single degree of freedom system. These values are included in the bearing model to incorporate the effects of the test structure in the simulation. Calibration of the bearing contact stiffness and bearing contact damping was carried out while simulating different rotational speeds of the bearing using the model.



Figure 7. Frequency domain of acceleration signal during impact test.

Model calibration carried out on bearing contact damping indicated that it did not cause any significant changes in the bearing acceleration level. However, bearing contact stiffness of bearings with reduced lubricant was higher than that of the 100% bearing as shown in Figure 8. Bearing stiffness values for the 50% and 25% bearings were fairly constant indicating the boundary layer lubrication regime is exerting a significant influence on the bearing contact stiffness. This contact bearing stiffness for 50% and 25% bearings was 1.5 times that of the 100% bearing on average, as shown in Figure 9. This is in agreement with the Hertzian contact stiffness increase for boundary lubrication in comparison with hydrodynamic lubrication (Stachowiak & Batchelor, 2013).

This increase in contact stiffness due to reduction of lubricant can be used to generalize the results of this study such that the fault feature can be developed for any bearing assembly. The first step in the fault feature development is to find the global maximum of the rms acceleration level for the 100% bearing within its operating speed range, which is the numerator of the fault feature developed in this study. The second step is to use the dynamic model developed in this study to determine the bearing contact stiffness for the 100% bearing. The third step is to simulate the underlubricated bearing case by increasing the bearing contact stiffness calculated in the previous step by a factor of 1.5. From this simulation, the global maximum of rms acceleration for an under-lubricated bearing can be identified, which is the denominator of the fault feature.



Figure 8. Bearing stiffness values for different lubricant levels and different rotational speeds



Figure 9. Ratio of bearing stiffness to the bearing stiffness of a 100% fan, at different operating speeds

Using this method, the fault feature can be developed for any bearing design, without the need to make measurements on under-lubricated bearings.

6. CONCLUSION

A fault characteristic feature to distinguish an underlubricated bearing from a bearing with the normal amount of lubrication has been developed in this study. This feature has been developed based on the observation that the operating speed at which the maximum vibration level of the bearing is observed shifts to a different operating speed with a variation in the lubricant quantity in the bearing. This feature can be measured quickly and non-destructively, making it suitable for applications in lot acceptance or screening. A dynamic model of a bearing was newly developed for this investigation, since existing models in the literature do not address the problem of under-lubrication in bearings. This model is used to identify the effect of the bearing contact stiffness and contact damping on the acceleration signal at various lubricant levels. Sensitivity analysis of bearing contact damping indicated that no significant changes in the bearing acceleration level are observed. The reason for this behavior could be due to the low external load acting on the bearing. Bearing contact stiffness was found to change with the reduction in the lubricant level of the bearing. The shift in vibration level with a reduction in the lubricant level in the bearing is due to the fact that the contact forces in the bearing change, resulting in a shift in the frequency domain characteristics of the dynamic system. This explained the patterns observed in the vibration level as a function of operating speed due to reduction in lubricant level in the bearing. For the 25% and 50% bearings this contact stiffness was found to be 1.5 times that of the 100% bearing. Future work anticipated on this topic will involve the validation of this classification procedure with different bearing designs and at various lubrication levels.

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REFERENCES

- Boškoski, P., Petrovčič, J., Musizza, B., & Juričić, Đ. (2010). Detection of lubrication starved bearings in electrical motors by means of vibration analysis. *Tribology International*, 43(9), 1683–1692. doi:10.1016/j.triboint.2010.03.018
- Eschmann, P., Hasbargen, L., Weigand, K., & Brändlein, J. (1985). *Ball and roller bearings: Theory, design, and application*. Munich, Germany: R. Oldenbourg.
- Kim, S., Vallarino, C., & Claassen, A. (1996). Review of fan life evaluation procedures. *International Journal of Reliability, Quality and Safety Engineering (IJRQSE)*, 03(01), 75–96. doi:10.1142/S0218539396000077
- Machado, M., Moreira, P., Flores, P., & Lankarani, H. M. (2012). Compliant contact force models in multibody dynamics: Evolution of the Hertz contact theory. *Mechanism and Machine Theory*, 53, 99–121. doi:10.1016/j.mechmachtheory.2012.02.010
- Morinigo-Sotelo, D., Duque-Perez, O., & Perez-Alonso, M. (2010). Assessment of the lubrication condition of a bearing using spectral analysis of the stator current. In 2010 International Symposium on Power Electronics Electrical Drives Automation and Motion (SPEEDAM) (pp. 1160–1165). doi:10.1109/SPEEDAM.2010. 5544958

- Nandi, S., Toliyat, H. A., & Li, X. (2005). Condition monitoring and fault diagnosis of electrical motors-a review. *Energy Conversion, IEEE Transactions on*, 20(4), 719 – 729. doi:10.1109/TEC.2005.847955
- Ribrant, J., & Bertling, L. (2007). Survey of failures in wind power systems with focus on Swedish wind power plants during 1997-2005. In *Power Engineering Society General Meeting*, 2007. *IEEE* (pp. 1–8). doi:10.1109/PES.2007.386112
- Sawalhi, N., & Randall, R. B. (2008). Simulating gear and bearing interactions in the presence of faults: Part I. The combined gear bearing dynamic model and the simulation of localised bearing faults. *Mechanical Systems and Signal Processing*, 22(8), 1924–1951. doi:10.1016/j.ymssp.2007.12.001
- Stachowiak, G., & Batchelor, A. W. (2014). *Engineering Tribology* (4th ed.). Oxford, U.K.: Butterworth-Heinemann.
- Tandon, N., & Choudhury, A. (1999). A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings. *Tribology International*, 32(8), 469–480. doi:10.1016/S0301-679X(99)00077-8

BIOGRAPHIES

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Vibration Based Blind Identification of Bearing Failures for Autonomous Wireless Sensor Nodes

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ABSTRACT

Despite all the attention received by maintainers, undetected roller bearings failures are still a major source of concern in relation with reliability losses and high maintenance costs. Because of that, bearing condition assessment through vibration monitoring remains an intensive topic of scientific research, focusing on the definition of monitoring strategies that allow early stage damage detection, failure causes identification and remaining life prediction. Next to the developments on signal processing, new opportunities of advanced monitoring platforms are devised as those based on Wireless Sensor Networks (WSNs). The combination of integrated sensing, embedded computing and wireless communication provides interesting elements on the development of a new generation of vibration monitoring systems. The algorithms for bearing assessment remain a crucial point for achieving a balance between efficient monitoring strategies and highly flexible monitoring platforms. Though current trends on signal processing for mechanical vibrations focuses on the development of robust techniques, the constraints of embedded processing in relation to energy and memory consumption hamper their implementation on WSN.

The present paper discusses the problem of bearing condition characterization from the basis of extraction of damage features associated with the specific stage of its deterioration process. This, other than data driven methods, allow to find the best compromise between robustness of the bearing assessment algorithm and the applicability of the algorithm on a WSN. Two cases are presented as validation of this approach: an artificial damage on a lab setup and a train bearing, for which the possibilities for detection, diagnostics and prognostics are discussed. The advantages and constraints of the use of autonomous wireless sensor nodes is discussed as final part of the paper.

1. MONITORING STRATEGIES

On the design and development Vibration Monitoring Systems (VMS), the authors (Sanchez et al, 2013) have proposed a design framework following a systems engineering approach. The framework is based on the hypothesis that the success of a VMS depends on the agreement among the choice of appropriate monitoring strategies that satisfy the maintenance requirements, and the physical components and algorithms that shape the monitoring platforms that carry out the selected strategies. In other words: to make a WSN based VMS a success, it is of crucial importance to revisit the physical characteristics of damage and vibrations in bearings.

According to the framework, a VMS is called to support on the damage detection (existence), diagnostics (origins) and remaining life prognostics (evolution). It is generally accepted that autonomous detection of abnormal vibration response can be achieved by a proper selection of alarm thresholds for vibration levels. Identifying the causes of the abnormal signals requires deeper understanding of the failure modes and failure mechanisms that may be taking place in the system. Lastly, the prediction of remaining useful life builds on top of the failure status diagnostics by the quantification of the actual loading as caused by the actual usage of the system (Tinga, 2013).

These VMS functions as described in the previous paragraph are of incremental nature. However this does not imply that all the VMS must fulfill the functions of detection, diagnostics and prognostics. For the case of bearings, accurate diagnostics becomes relevant when restoring maintenance actions (such as re-lubrication, balancing, etc.) can be taken for extending the bearing life. Prognostics becomes relevant for cases where no on-service restoring actions are possible, and bearing replacement is the only option left. Furthermore, prognostics is not only based on predicting the deterioration of the component, it also involves/requires the definition of safe vibration limits without compromising the operation and integrity of the machine.

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1.1. Failure Mechanisms and Bearing Life Prognostics

A physics approach on prognostics is defined by the balance between the load-carrying-capacity of a material and the actual loading experienced the system. Several bearing prognostics models, including the classical fatigue life rating of roller bearings follow similar reasoning, by using the bearing dynamic load for a rated fatigue life *C*, the equivalent load rating *P* and the life equation exponent *p* into the well-known L_{10} life equation Eq. (1).

$$L_{10} = \left(\frac{c}{p}\right)^p \tag{1}$$

Classical fatigue life is based on the traditional spalling due to subsurface fatigue, for which cracks are initiated below the surface and propagate towards the surface. As Lugt (2012) states "...the L_{10} basic rating life equation constitutes the foundation of all national and international standards for fatigue life rating of roller bearings, subsequent theories and developments." (pp 286)

Besides the material related failure mechanisms, surface initiated failures are significant contributors to bearing life shortening. Surface distresses generated by loaded asperities cause micro-spalling, while the over-rolled wear particles create dents in the surfaces leading to stress concentrations which again lead to spalls and fatigue. Lubricant rheological flow properties, as in the case of grease lubricated bearings, are also a main decisive factor on the bearing life, for which the lubricant life is expected to be considerable shorter than the material life (Lugt,2012).

1.2. Vibration as Failure Mode

Although the definition of developing failure mechanisms is central to life prognostics, in practice direct quantification of failure mechanisms is difficult, therefore practitioners must rely on indirect measures for its quantification. This poses the main justification of the use of vibration *response* as an "useful indicator" of the developing failure mechanisms. It must be noticed the word response is included for highlighting the fact that measured vibrations are due to the effect of a force on a system. Given the multiple forces acting on bearings and the complexity of the system itself, it is expected that discussion about the vibration response is everything but straightforward.

A functional approach as guideline for decomposing the vibration signal as support of the bearing deterioration assessment is proposed. Tinga (2012) defines failure mode as the manner in which a system or component functionally fails, that is, describing to what extent a certain function cannot be fulfilled anymore (pp 3). For the sake of

generalization, the case of bearings can be described by two simple functions. Firstly, to enable free relative motion between two components, named hereafter *free rotation*. The second function relates to ensuring the correct distribution of the concurrent forces, named as *structural support*. These two functions are considered as the basis of the vibration signal as descriptor of the bearing failure as presented in Table 1.

Table 1. Bearing Vibration Classification

Vibration Level	Failure mode	Description
Normal: Structural Support	Varying compliance (normal Vibrations)	Change in bearing stiffness and load asymmetry
Incipient: Free Rotation	Lubrication problems	Film thickness instabilities Mixed lubrication regimes Increase friction forces
Incipient: Structural Support	Short duration pulses due to metal- to-metal contact	Changes on local stresses due to local defect or increased loading
Moderate: Structural Support	Resonance due to Impulsive Response	Localized impacts due to cracks on races-rolling elements excite bearing structural modes
Severe: Structural Support	Surface deterioration becomes distributed due to extended superficial cracks and spalling.	Bearing functioning becomes instable and auto excited. Danger to compromise integrity of related components.

The starting point of the discussion on vibration response characterization is by recognizing that that even under perfect conditions, bearings are an intrinsic source of vibrations. As described by Liew and Lim (2005) the change of the number of rolling elements and their position in the load zone gives rise to periodical variation of the total stiffness of the bearing assembly, which leads to varyingcompliance vibrations. In other words, small levels of vibrations are acceptable, and for some cases even positive, as they act as the mechanism for lubricant replenishment on heavily starved contacts (Lugt,2012).

The free rotation function is of particular relevance for the new generation of bearings for low energy consumption and friction, which use thinner oils and grease lubrication. Instabilities on the lubrication film become very critical for the fulfillment of the free rotation function. Although the relation between vibration and shock loads for bearing lubrication is not fully defined, there is a general consensus that such loads may alter the film thickness and affect the contact dynamics of the rolling elements (Wijnant, 1998), and lead to some other failure mechanism such as fretting corrosion. Lubrication thickness disturbances have a direct effect on the rheological flow properties of the lubricant, and therefore the bearing life (Lugt, 2012).

The support function refers to distortions on the bearing load distribution due to defects on the bearing contact surfaces. The presence of surface defects such as superficial cracks or added material due to over-rolled wear particles has significant effects on the vibration response of the bearings. Local superficial defects cause abrupt changes on the contact stresses which generates short duration pulses at very high frequencies. As the severity of the defect progresses, the energy released by the impacts becomes higher, and therefore more sensible to be monitored. The accurate characterization of an impulse response relies on the identification of the natural frequencies and modes excited during the impact. These are valuable indicators of how the system responds to the effect of the loads. For instance, the rolling elements display natural frequencies in the range of hundreds of kilohertz (Swartjes, 1995) while for the bearings and machine components modes at lower frequencies are excited (Wensing, 1998).

As consequence of the discrete impact loading, wear develops throughout the contact element surfaces, which is typical of advanced bearing damage. Tandon and Choudhury (1999) state that variation in contact force between the rolling elements and raceways due to distributed defects result in an increased vibration level. Also the behavior of the signal changes. By increasing the occurrence of the impact loading, the leading edge of the impact response is buried in the delay of the previous impact. Therefore the superposition of impact responses turns into higher overall vibration levels with higher stochastic behavior. Figure 1 presents a comparison of the time signal between a discrete surface damage and distributed damage.



Figure 1. Time signal from bearings at incipient and advanced surface damage.

2. ALGORITHMS FOR BEARING EVALUATION

The complexity of bearing failure and the fact that the vibration signal captured at the bearing location may contain additional information regarding other machine components reflects the complexity of vibration analysis. The definition of appropriate steps for extracting information about the bearing deterioration from the vibration signal is presented in the following sections. The procedure is depicted on the Figure 2 and will be discussed in the next subsections.

2.1. Preliminary considerations

The failure evaluation of a bearing involves multiple factors such as the kinematic and dynamic characteristics of the system itself, the response to environment and the effects of developing failure mechanisms and failure modes. These factors are included in the proposed procedure depicted in Figure 1. All steps in this figure will be elaborated next.



Figure 2. Flowchart for steps on bearing evaluation

2.1.1. (Step 1) System Characterization

There is a wide range of signal processing techniques that can be used to decompose vibration signals from mechanical sources. Nevertheless, the application of such techniques without knowledge of the monitored system and specific criteria on the evaluation may be daunting. Step 1 refers to the specification of the monitored system, both for machines and structures. It includes the definition of operational conditions, kinematic data for participating mechanisms and the influence of environment. Existing knowledge of the particular failure mechanisms and failure modes expected through the operational life is also of valuable aid.

2.1.2. (Step 2) Signal Processing: Conditioning, Domains and Transformation

To support the choice of signal processing for enhancing the damage-related features within the vibration signal, the following criteria are proposed for selecting techniques and domain transformations to apply to the signal:

- i) Enhanced signal quality
- ii) Display the signal on the domain that represent the best its dominant characteristics
- iii) Decompose the signal according to the specifically sought features

Enhancing signal quality is fundamental for accurate characterization of different vibration phenomena, especially those associated to early damage. Although noise is usually highlighted as undesired for the signal, it should be realized that there are different sources of noise, such as: a) random noise, as caused by random excitation forces, b) mechanical noise due to the transmission path from the vibration source to the measurement point, and c) numerical noise due to the processing techniques. The first category can be actively reduced by using appropriate averaging techniques, while the second is inherent to the complexity of mechanical systems. Numerical noise has to be considered for each technique.

The following two criteria are satisfied by mathematical transformations, which are used for maximizing certain features of the vibration signals according to the intrinsic characteristics and the likelihood to identify a damage. There are several domain transformations involved in the monitoring problem, from the transduction of physical quantities (displacement, velocity, acceleration, strain, etc.) to voltages. Once the signal is digitalized, the starting domain is the time domain, for which the initially captured quantity, represented by a voltage, is presented as it occurs on time.

After the time domain, further domain transformation are used to extract particular features of the signal according to its changing nature (Randall, 2011). For instance Fast Fourier Transform (FFT) for constant frequency excitation; Short Time Fourier Transform (STFT) for slow fundamental frequency changes; the wavelet domain and Hilbert domain are employed for signals with high level of nonlinear and non-stationary behavior. The modal domain is an important transformation for the analysis of spatially distributed systems for which the principal coordinates define the prime motions of a body. Other types of transformation refer to the derivation of new signals within the domain. The derivation of analytic signals for Hilbert transform, Intrinsic Mode Functions (IMF) for Empirical Mode Decomposition (EMD) and residuals for Wavelet transformations are examples of transformations within the domain. Given the large range of algorithms and steps to consider, defining specific target features to base the analysis on results in a practical guide towards the signal decomposition.

2.2. Blind Identification Strategy - Features Extraction

Step 3 deals with the selection of specific features to aid in the problem of –understanding vibration signals and how these relate to the normal and abnormal functioning of a bearing.–Generally, multiple features have to be taken into account. All features must be monitored (blind identification), potentially leading to excessive resource requirements of a WSN. A smart way of performing this blind identification is therefore considered to be a crucial element in the VMS designTable 2 presents an overview of vibration features according to the machine characteristics, environment and damage influence.

2.2.1. (Step 3.1) Intrinsic features

Prior to the actual processing of the signal, one should ask what are the most relevant physical mechanisms that originate the signal observed. A first attempt to answer this lies the definition of the expected frequency components displayed on the signal. Four different types of vibration sources from mechanical machines can be distinguished: a) fundamental frequency, b) power related c) structural resonances d) random sources as presented on Table 2.

Table 2. Bearing Vibration Classification

	Feature	Example
Fundamental	Amplitude	High Forces
Frequency		
	Harmonic	Nonlinear Forces
	Distortion	
	Frequency Shift	Change operation
Mechanism	Harmonic	Unbalance.
related	Distortion	Nonlinear Forces
	Amplitude	Critical speed
	Modulation	(Compressor)
		Frequency Multiplication
		Beat phenomenon
	Frequency/Phase	Torsional Vibration
	Modulation	
Structure	Impulse Response -	Related to Resonance
Related	Excited	
Random	Broadband	Related to field
Vibrations	vibration	interaction

The fundamental frequency refers to the rotational speed of the shaft the bearing is supporting. This may be already difficult to identify for machines with transmissions or changing rotation speeds.

Power related frequencies relate to the power transferences happening at the machine. These can be due to punctual forces as in the case of gear transmission, for which the forces as concentrated on specific points of the mechanism. Other type of power-related frequencies are those due to distributed forces as in the case of rotors.

Structural frequencies are usually not excited under normal machine operation, however these are likely to be displayed during transient responses. Impact damages are the most common source of natural frequencies excitation. Recognition of natural frequencies from an operational vibration spectrum is in general a not a straight forward process.

2.2.2. (Step 3.2) Environmental Influence

The effect of environment on the normal behavior of the bearing response depends on the specific case. Environment can refer to the variation of the main input forces of the machine, both in a deterministic or non-deterministic fashion. Such changes can lead to nonlinear behavior of the features discussed in previous step.

A practical consideration of environment influence relates to the problem of alarm definition. For machines with continuously changing input forces, the signal response is often normalized for detection purposes. The vibration signature with environmental factors can also be updated by learning algorithms on the node or externally.

2.2.3. (Step 3.3a) Damage Features

Deviations on the vibration pattern that do not arise as consequence of environmental factors are presumed to be related to failure or damage on the system. The more knowledge available on the physics involved in the failure mechanism, the better the chances to find a relation with the vibration signal and its evolution. Some of the disturbances due to damage are listed below:

- Amplitude increment
- Fundamental frequency instabilities
- Harmonic distortion
- Amplitude modulation
- Frequency modulation
- Impulse response
- Broad band and narrow band noise

The specifics of how some of these features are related to bearing damage depend on the failure modes, however the specifics are largely influenced by the characteristics of the systems the bearings are contained in. Detailed explanation of the treatment of a particular damage feature is presented in section 3. The main advantage of defining specific features to base the monitoring strategy on is the possibility to reduce the signal complexity in discrete characteristics.

2.2.4. (Step 3.3b) Pattern Evolution

Once the signal is decomposed on specific signal features, such features have to be monitored independently. Tracking the evolution of distinctive features provides valuable information of the remaining life estimation, especially for the cases when it is normalized with the loading conditions.

2.2.5. (Step 4) Evaluation

The following steps provide the ground for gathering information on the bearing condition. The evaluation steps refer to the goals of the monitoring system, once again back to the detection, diagnostics or prognostics. Some of the possible results of the evaluation are:

- System operation is within acceptable levels.
- The system condition is stable, and there are no symptoms of accelerated deterioration.
- The system is underperforming, resetting of the system condition is required.
- System condition is worsening. Maintenance intervention must be planned according to usage expectations.

3. VALIDATION – CASE STUDIES

The proposed steps are applied for two bearing cases. The first one relates to artificial damage of a bearing running on an simple mechanical setup with little operational and environmental disturbances. This simple case highlights the classical failure modes of bearings referring to race damage and rolling elements damage. The second case refers to train bearing monitoring, which displays strong influence of the operation and environment.

3.1. Bearing with Artificial Damage

A simple bearing test setup was used for validation of impulsive behavior due to surface defects (Cisi. et al, 2013). The set of data composed by a pristine signal and three artificial defects on the inner race, outer race and rolling elements. The setup was run under stable conditions of load and speed, therefore the signals are expected to behave on a rather stationary manner. No environment disturbances were relevant during the data acquisition.



Figure 3. Feature treatment for signals with impulsive behavior.

Based on the discussion of superficial defect (section 1.2), the impulsive feature is used to elaborate the signal processing around it. Figure 3 presents the detailed treatment for the damage feature as presented in step 3.3a.

Figure 4 a, b, c, d presents the time data signal from the four cases. Figure 4.a corresponds with the bearing without defect or pristine condition. A reference line is extracted as an equivalent sinusoidal signal with the same peak to peak amplitude as the pristine condition (red line). Surface damage is introduced by creating a small scratch on the outer race (Figure 4.b) and inner race (Figure 4.c). Advanced damage is achieved by affecting the surface of the rolling elements (Figure 4.d). The time signals are very distinctive of the evolution of bearing damage as discussed in section 1.2.

The pristine condition shows low amplitude levels and no apparent damage feature is depicted on the time signal. Localized superficial defects lead to very distinctive impact response modulated by the bearing kinematic characteristics, namely the inner race and outer race failure frequencies. The amplitude of the vibration signal increases considerably at the moment of the impulse, as compared to the normal value represented by the red line of the pristine condition. For the advanced damage condition, although the impacts become less defined, the overall vibration in comparison with the pristine condition increases significantly.



Figure 4. Time domain signal for a) Pristine, b) Outer race damage, c) Inner race damage, d) Rolling element damage.

Table 3 presents some statistical quantities related to the signals. It can be seen that kurtosis, zero-peak and rms value can also be used as a measure for the impulsiveness of the signal. On actual signals, evaluating kurtosis for specific frequency ranges around structural frequencies is suggested (Randall, 2011).

		-	-	
Feature	Pristine	Inner	Outer	Rolling
		Race	Race	Element
Mean:	0.0595	0.0046	0.3665	0.013
Variance:	0.0056	0.3575	0.3665	4.247
Kurtosis	2.7642	5.2911	7.5950	3.871
Zero-Peak	0.298	3.062	1.605	10.11
rms	0.0738	0.59	0.313	1.027

Table 3. Summary Statistical Analysis

Subsequently, the frequency content of the signal is analyzed by performing an FFT on the time signal. For this case, the impact oscillating –carrier- frequency is identified as the highest peak of the frequency domain, around which a band pass filter is defined, see Figure 5. The filtered signal is subjected to an rectification and enveloping treatment as presented in Figure 6.a. The frequency displayed in the spectrum of the enveloped signal corresponds to the modulating frequency of the inner race as presented in Figure 6.b. Analysis of the signal displaying the rolling elements damage did not result in clear carrier and modulating frequencies as predicted for an adavanced damage stage.



Figure 5. Power Spectral Distribution for bearing signal displaying outer race defect.



Figure 6. a) Envelope from the rectified time signal for the outer race damage b) Fourier representation of the enveloped signal.

3.2. Train Wheel Bearing

The second validation case of the proposed bearing identification algorithm corresponds to the case of train bearings. Suspension bearings are very sensitive components since these are subjected to heavy loading from the train weight and dynamic loading due to the wheel-rail interactions. For this case, the bearings correspond to a CRB type from SKF which offer low friction characteristics and high clearance to withstand moderate impacts and changes on operational temperature. They also contain good lubrication conditions to protect against fretting corrosion (Railways SKF, 2012). From the monitoring perspective, train bearings display several challenges because of the difficulty in separating the influence of operation (weight of the wagon, speed), environment (wheel-rain interaction) and the bearing condition itself.





Figure 7. a) Train Bearing 1 at 5.3 m/s, b) Train Bearing 1 at 13m/s c) Train Bearing 4 at 5.3m/s

Figure 7 present three typical vibration signals from two different bearings of the same wagon. Figure 7.a and Figure 7.b correspond to the same bearing but during different train speeds (5.4m/s and 13.2m/s respectively). Figure 7.c corresponds to a suspected bearing during the captured at the same time as the first signal. For this signal it is already possible to see the increment on the overall vibration values and the peak amplitude. For the analysis, small periods from the signal are taken for further study, as indicated by the colored bands in the spectra. Table 4 presents a summary of the events for the analysis of rms and kurtosis values.

3.2.1. Detection

Following the proposed methodology, the signal is subjected to feature extraction, for which the normal operational conditions and the influence of the environment are analyzed.

Table 4. Rms and Kurtosis for different events for the train bearing signals

for the train bearing signals					
	Description	Train Speed [m/s]	Rms (g)	Kurtosis	
а	Random Excitation	5	0.53	5.72	
b	Stable response	5	0.15	3.18	
c	Impact	5	0.49	15.81	
d	Impact	13	3.15	4.95	
e	Stable response	13	0.48	2.92	
f	Repetitive Impact	5	0.71	21.82	
g	Repetitive Impact Random Excitation	5	1.72	5.71	

Step 3.1 - Operational Influence

Events b and e are used for comparison of the rms and kurtosis values of the bearing 1 under stable operation.

Although there is a significant increment on the rms value (0.15g - 0.48g), the kurtosis levels remains relatively stable (3.18 - 2.9). The comparison of the spectral density at the both events (Figure 8) shows a correlation on the energy distribution but with marked amplitude differences.



Figure 8. PSD comparison for stable operation of bearing 1 at 5m/s and 13 m/s.

Step 3.2 – Environment Influence

For understanding the environment influence, two different type of events are analyzed. The first influence relates to a random excitation as shown in event (a), for which both rms and kurtosis change relatively much in comparison to the stable response (rms 0.53g, K 5.72). The power spectral density shows in Figure 9 the increment of the vibration response at frequencies above 6000Hz.



Figure 9. Environmental disturbance of stochastic nature for bearing 1.

The second type of environmental influence refers to the moderate impact loading due to several phenomena in the wheel-rail contact. The characteristics of the impulse response are valuable to understand the impact of such sudden loads for exciting natural frequencies of the system. Figure 10 a, b, c relate to the impact events c (rms 0.49g, K 15.81)), d (rms 3g, K 4.9) and f (rms 0.71g, K 21).



Figure 10. Environmental disturbance of impulsive behavior for a) bearing 1 at 5m/s b) bearing 1 at 13 m/s, c) bearing 4 at 5m/s.

From the comparison of the different events, again the strong influence of environment on the kurtosis level of the signal can be seen. However, the impact occurrence on the third case is an important indicator that the impact behavior is related to an intrinsic damage of the bearing.





Figure 10 Cont. Environmental disturbance of impulsive behavior for a) bearing 1 at 5m/s b) bearing 1 at 13 m/s, c) bearing 4 at 5m/s.

Step 3.3 – Bearing Damage

After completing the assessment of the occurrence of impacts due to bearing damage, a demodulation procedure is performed (Figure 11). The envelope spectrum reveals a modulation at 19.34Hz with harmonics, which corresponds to the circular frequency of each rolling element as it spins also known as Ball Spin Frequency (BSF). This was calculated for a CRB Bearing with pitch diameter of 136.186mm, rolling element diameter of 18.158mm, number of rolling elements 21 and rotational speed of 320rpm (SKF, 2014).

3.2.2. Step 4. Evaluation

The last step on the strategy aims at the evaluation of the bearing condition in relation to the possible damage. From the analysis of impact response at events c, d and f, it becomes interesting to look at the frequencies excited during the impact response. Those relate to how the system is responding to the sudden loads, both intrinsic and extrinsic.



Figure 11. Enveloping analysis for suspect bearing .

Figure 12 present the signal decompositions using a filter of 500Hz, for low band-pass (red) and high band-pass (blue). It is up to the specialist on train dynamics to analyze the incidence of those signals for the quantification of load-carrying-capacity and actual loading.



Figure 12. Signals decomposition. Red-below 500Hz, blue above 500Hz. a) bearing 1 at 5m/s b) bearing 1 at 13 m/s, c) bearing 4 at 5m/s.

4. IMPLICATIONS FOR AUTONOMOUS WIRELESS SENSOR NODES

The case of the train bearing highlights the particularities of using Autonomous Wireless Sensors for vibration monitoring. For this application, the possibility to sample at 25.6KHz allows very detailed analysis of local resonances above the structural range. Therefore the possibility of detecting incipient damages in bearings is increased.

Furthermore, the definition of simple features to base the evaluation strategy upon provides a guideline for selecting signal processing algorithms adaptive to the signal current characteristics. Features-based algorithms are suitable for optimization of for efficient usage of the node processing and energy resources.

High sampling and specialized algorithms for bearing evaluation derive into inexorable high energy load and increasing complexity for such autonomous nodes. To enable its execution using embedded platforms, the nodes must incorporate smart operation management systems suitable to tune the power and memory requirements for signal acquisition and processing and communication.

5. CONCLUSION

The term *blind identification*, does not imply that physics knowledge of the monitored object is no longer required. On the contrary, a blind identification strategy for bearing assessment on WSN relies on concise understanding of the bearing failure process and associated mechanisms that allows the identification of the current damage state although some specific or historic data may be missing.

From the general understanding of the failure mechanisms taking place during the deterioration process, the more specific failure modes that are likely to be displayed due the intrinsic design features, operation and environment disturbances associated to a specific bearing application can be understood.

The present article discusses the multiple physical phenomena related to bearing degradation. It has been shown that it is unlikely that a unique signal processing technique could capture such complexity. Instead, the authors propose the construction of a monitoring strategy based on fundamental features of the vibration signal, which are modified by the effect of loading, environment or damage. The simplicity of such distinctive features enables the design of flexible, but yet robust monitoring systems, bringing the implementation of VMS based on wireless sensor networks within reach.

The feature used for the case of bearing assessment is impact behavior, both as a response to extrinsic factors such as in the case of environment loading, and due to bearing intrinsic surface damage. Although the phenomenological description exhibits similarities for those cases, the effects on the system are particularly different. Still, the identification of the natural frequencies excited by the impact is a valuable indicator of the impact loading on the general system.

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REFERENCES

- Sanchez Ramirez, A; Loendersloot, R., Jauregui, J. M., & Tinga, T. (2013). Design Framework for Vibration Monitoring Systems for Helicopter Rotor Blade Monitoring using Wireless Sensor Networks. In International Workshop on Structural Health Monitoring (pp. 1023 – 1030). September 10-12. Stanford University. California.
- Tinga, T. (2013). Principles of Loads and Failure Mechanisms. London: Springer London. doi:10.1007/978-1-4471-4917-0
- Lugt, P.M. (2012). Grease Lubrication in Rolling Bearings. New York: John Wiley & Sons. ISBN: 978-1-118-35391-2
- Wijnant. Y.H. (1998). Contact Dynamics in the field of Elastohydrodynamic Lubrication. Ph.D. Thesis. University of Twente. The Netherlands.
- Liew and Lim (2005). Analysis of time-varying rolling element bearing characteristics. *In Journal of Sound and Vibration* 283. Pg 1163-1179.
- Swartjes, M. (1995) Resonant Ultrasonic Spectroscopy: measurement system for detection of cracks in rolling elements. Master Thesis. University of Twente. The Netherlands
- Wensing, J.A. (1998). *On the dynamics of ball bearings*. Ph.D. Thesis. University of Twente. The Netherlands.
- Tandon. N. & Choudhury. A. (1999). A review of vibration and acoustic measurement methods for the detection of defects in rolling elements bearings. *Tribology International 32.* Pg 469-480.
- Alessandro Cisi, Alessandro Zanella, Giuseppe D'Angelo. (2013). Rolling Element Bearing Fault Detection Based on Orthogonal Hilbert-Huang Transform, In Tenth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM and MFPT, June 18-20, Poland
- Randall, R.B. Vibration- Based Condition Monitoring. Industrial, Aerospace and Automotive Applications. New York: John Wiley & Sons. ISBN: 978-0-470-74785-8

- Railways SKF (2012). Bearing designs Cylindrical roller bearings and units. Railway technical handbook, Vol 1, Ch 4, Pg 88-95.
- SKF Engineering Calculator. www.skf.com. Retrieved March 2014.

BIOGRAPHIES

Andrea Sanchez Ramirez obtained her master degree Cum Laude in Mechanical Engineering, research group of Applied Mechanics (2009) and her master degree of Business Administration (2010), both at the University of Twente in the Netherlands. Previously she obtained the bachelor degree (2004) at the Universidad Nacional de Colombia. From 2005 onwards she has been working on vibration monitoring topics at different industries, including oil industry in Colombia and Trinidad and Tobago, industrial sector as part of the Condition Monitoring division of SKF for Latin America and Wind industry in the Netherlands. Currently she is pursuing her PhD at the University of Twente in the Chair of Dynamics Based Maintenance on the topic of Advance Vibration Monitoring Systems.

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Richard Loendersloot obtained his master degree in Mechanical Engineering, research group Applied Mechanics, at the University of Twente in 2001. His MSc assignment was in collaboration with DAF trucks and concerned a sound radiation problem. He continued as a PhD student for the Production Technology, researching the flow processes of resin through textile reinforcement during the thermoset composite production process Resin Transfer Molding. He obtained his PhD degree in 2006, after which he worked in an engineering office on high end FE simulations of various mechanical problems. In 2008 he returned to the University of Twente as part time assistant professor for the Applied Mechanics group, where he combined his knowledge on composites and dynamics. From September 2009 on he holds a fulltime position. His current research focus is on vibration based structural health and condition monitoring, being addressed in both research and education.

Accelerated life tests for prognostic and health management of MEMS devices

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ABSTRACT

Microelectromechanical systems (MEMS) offer numerous applications thanks to their miniaturization, low power consumption and tight integration with control and sense electronics. They are used in automotive, biomedical, aerospace and communication technologies to achieve different functions in sensing, actuating and controlling. However, these microsystems are subject to degradations and failure mechanisms which occur during their operation and impact their performances and consequently the performances of the systems in which they are used. These failures are due to different influence factors such as temperature, humidity, etc. The reliability of MEMS is then considered as a major obstacle for their development. In this context, it is necessary to continuously monitor them to assess their health status, detect abrupt faults, diagnose the causes of the faults, anticipate incipient degradations which may lead to complete failures and take appropriate decisions to avoid abnormal situations or negative outcomes. These tasks can be performed within Prognostics and Health Management (PHM) framework.

This paper presents a hybrid PHM method based on physical and data-driven models and applied to a microgripper. The MEMS is first modeled in a form of differential equations. In parallel, accelerated life tests are performed to derive its degradation model from the acquired data. The nominal behavior and the degradation models are then combined and used to monitor the microgripper, assess its health state and estimate its Remaining Useful Life (RUL).

1. INTRODUCTION

Current maintenance strategies have progressed from breakdown maintenance, to preventive maintenance, then to condition based maintenance CBM (Aiwina, Sheng, Andy, & Joseph, 2009). CBM is a maintenance program that recommends maintenance decision based on the information collected through condition monitoring. It consists of three main steps: data acquisition, data processing and maintenance decision making. The key process of CBM is Prognostic and Health Management (PHM), an approach that estimates the Remaining Useful Life (RUL) of systems based on their current health state and their future operating conditions. Prognostic approaches can be categorized into three classes, namely model-based (also called physics-based approach), data-driven and hybrid prognostic approaches (Jay et al., 2014).

Model-based prognostics deal with the prediction of the RUL of components by using mathematical or physical models to describe the degradation phenomena. Data-driven prognostics aim at transforming sensory data into relevant models of the degradation behavior (Medjaher, Tobon-Mejia, & Zerhouni, 2012). In general, hybrid prognostic approach benefits from both categories to overcome their drawbacks, for example, (Hansen, Hall, & Kurtz, 1995) proposed an approach which fuses the outputs from model-based and data-driven approaches. Prognostic results obtained from this approach are claimed to be more reliable and accurate (Jay et al., 2014). PHM approaches can be applied to MEMS to improve the reliability and availability of systems in which they are utilized, to avoid failures and to reduce maintenance costs. However, the miniaturization of these microsystems makes the implementation of PHM approaches more specific.

This paper presents a hybrid prognostic method applied to microgripper MEMS. Firstly, in section 2, an overview of different categories of MEMS and their common degradation/failure mechanisms are given. In section 3, the proposed method which aims at assessing the health state of MEMS and estimating their RUL is introduced. In addition, the description, modeling of an electrostatic micro-gripper and the results of accelerated life tests are provided in section 4. From the obtained experiments, an empirical model of the microgripper degradation is learned. This model is then combined with the analytical behavior model of the microgripper to as-

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sess its health state and estimate its RUL. Finally, a conclusion is given in section 5.

2. OVERVIEW OF MEMS AND THEIR FAILURE MECHA-NISMS

MEMS are introduced in 1989 when Professor Howe (Howe, 1989) from university of California at Berkeley first used the acronym to describe the hybrid use of microelectronics and mechanical components to piezo-actuate and create electrical signals. A MEMS is a system that integrates several mechanical, optical, thermal and fluidic elements using electricity as an energy source in order to perform measurement and / or actuating functions in structures having micrometric dimensions. MEMS devices have the ability to sense, control and actuate on the micro scale, and generate effects on the macro scale. They can be grouped in four main categories (D. Tanner, 2009)

- Class 1: no moving parts (pressure sensors and microphones).
- Class 2: moving parts with no rubbing or impacting surfaces (gyroscope, accelerators and RF oscillators).
- Class 3: moving parts with impacting surfaces (micromirror).
- Class 4: moving parts with impacting and rubbing surfaces (micro-motors).

MEMS technology has grown from laboratory research projects to global commercialization (Walraven, 2005) and thanks to their miniaturization, low power consumption and tight integration with control and sense electronics (Shea, 2006), MEMS are more and more utilized in numerous applications as shown in Table 1.

Categories	Examples
Micro-sensors	Pressure sensors, accelerometers, gyroscopes, thermal sensors, op- tical sensors, micro-bolometers, magnetometer, and microphones.
Micro-actuators	Electrostatic, piezoelectric, ther- mal, magnetic.
RF MEMS	Metal contact switches, tunable capacitors, tunable filters, RF switches, micro-resonators.
Optical MEMS	micro-mirrors, optical switches, Optical reflectors, attenuators.
Fluidic MEMS	Pumps, valves.
Bio MEMS	DNA chips, microsurgical in- struments, intra-vascular devices, mchip, microfluidic chips.

Table 1. MEMS applications and examples.



Figure 1. Failure mechanisms illustration: (a) stiction of the finger on the substrate, (b) stiction in electrothermal actuator, (c) contamination in a comb-drive, and (d) finger fracture (D. M. Tanner et al., 2000), (Dardalhon, 2003), (Mir, Rufer, & Dhayni, 2006)

Most of MEMS are designed with some basic parts such as cantilever beams, membranes, springs, hinges, etc (Merlijn van Spengen, 2003). These parts are subject to degradation and failure mechanisms due to several influence factors (temperature, humidity, vibration, noise, etc). Common failure mechanisms identified and known until now concern stiction, wear, fracture, creep, delamination, contamination, adhesion, fatigue, degradation of dielectrics, and electrostatic discharge (D. Tanner, 2009), (Merlijn van Spengen, 2003), (Shea, 2006), (McMahon & Jones, 2012), (Matmat, 2010), (Huang, Vasan, Doraiswami, Osterman, & Pecht, 2012), (Zaghloul et al., 2011), (Li & Jiang, 2008). Figure 1 shows some of these failure mechanisms.

MEMS failure modes can be classified according to two strategies: they can be categorized as failures related to manufacturing or to utilization (Matmat, 2010), or as mechanical, electrical and material based failures (Shea, 2006), (McMahon & Jones, 2012), (Ruan et al., 2009), (Müller-Fiedler, Wagner, & Bernhard, 2002). The two classifications are shown in Tables 2 and 3.

3. PROPOSED METHOD

The main steps of the proposed method are summarized in Figure 2.

This method can be applied to different categories of MEMS, it aims at combining both degradation and nominal behavior models in order to detect and diagnose faults, estimate their health state and predict their RUL. The degradation model is obtained experimentally through accelerated life tests ((Ruan et al., 2009), (Shea, 2006)) and the nominal behavior model is derived by writing the corresponding physical equations.



Figure 2. Main steps of the proposed hybrid prognostic method.

Mechanical	Electrical	Material
Delamination	Degradation of	Stiction
_	dielectrics	
Fracture	Electrostatic dis-	Contamination
	charge ESD	
Fatigue	Electro-migration	
Creep	Electrical short	
	circuit	
Wear	Electrical stiction	
Stiction		
Plastic deforma-		
tion		
Adhesion		

Table 2. Mechanical, electrical and material based failure modes.

The estimated health state which can be represented by the parameter values is compared to the failure threshold which is obtained experimentally by observing the response of the MEMS when performing accelerated life tests to calculate the RUL. As shown in Figure 3, the RUL value corresponds to the difference between the failure time and the current time.



Figure 3. RUL estimation.

Related to utilization	Related to manufactur-
	ing
Stiction	Stiction
Delamination	Contamination
Fatigue	Fracture
Creep	Electrical short circuit
Wear	
Electro-migration, ESD	
Adhesion	
Electrical short circuit	
Fracture	

Table 3. Failure modes related to manufacturing or to utilization.

4. EXPERIMENTAL SETUP AND RESULTS

4.1. Description of the experiments

The experimental platform designed to perform accelerated life tests of three microgripper MEMS is shown in Figure 4. The microgripper FT-G100 used in this application and shown



Figure 4. Overview of the experimental platform.

in Figure 5 is designed by the Swiss company Femtotools based in Zurich. The main feature of the FT-G100 is the ma-

nipulation of micro and nano objects with two arms (the first is moving, the second is static). The initial opening of the two arms is 100 μ m and can be controlled with nanometer precision. The maximum actuation voltage of the microgripper is 200 V. This device consists of two mechanisms: an electrostatic actuation mechanism containing a comb-drive actuator and an actuated finger. In addition, a sensory mechanism comprises a capacitive force sensor. The comb-drive actuator contains 1300 electrodes: 650 moving electrodes and 650 static electrodes. The shuttle is the moving part of the actuator. The capacitive sensor consists of 400 electrodes.



Figure 5. Microgripper FT-G100 used in the accelerated life tests.

In response to a voltage V_{in} applied to the comb-drive actuator, an electrostatic force F_{elec} is generated. This force is proportional to the square of the input voltage and its analytical expression is given by Eq. (1):

$$F_{elec} = \frac{N_a.e.h_z}{2.g}.V_{in}^2 \tag{1}$$

where $N_a = 1300$ is the number of electrodes in the combdive, $e = 8.85 \ pF/m$ is the air permittivity, $h_z = 50 \ \mu m$ is the thickness of the electrodes and $g = 6 \ \mu m$ is the gap between the fixed and the mobile electrodes.

The platform is constituted of a voltage source (an ARDUINO device which generates a square signal of 5 V magnitude and frequency equal to 25 Hz), a voltage amplifier, a distributor for supplying the voltage to the three microgrippers, an interferometer and a micrometric adjustment support to fix the MEMS when taking measurements. The acquisition of measurements is the same for the three microgrippers and for each one of them the following steps are applied: (a) fix the microgripper on the support, (b) adjust the interferometer reflection (50 % minimum), (c) the reflected signal is acquired at a frequency equal to 25 kHz, with 16384 points, (d) store the result in different files in a dedicated computer for later use.

4.2. Physics-based model and parameters identification

The time response obtained experimentally from a new microgripper is shown in Figure 6. It corresponds to a second order dynamic system. The microgripper can then be modeled as a



Figure 6. Time response of a new microgripper.

The governing equation of such a system is given in Eq. (2).

$$F_{elec} = M\ddot{x} + f\dot{x} + kx \tag{2}$$

where F_{elec} is the electrical force actuating the mobile arm, x is the displacement, f is the friction coefficient, k is the stiffness of the arm and M is its mass. By applying the Laplace transform on Eq.(2) and by putting $U(t) = V_{in}^2(t)$, one gets the canonical transfer function given in Eq.(3):

$$H(p) = \frac{X(p)}{U(p)} = \frac{\frac{\eta}{k}}{1 + \frac{f}{k}p + \frac{M}{k}p^2} = \frac{K}{1 + \frac{2\xi}{w_n}p + \frac{1}{w_n^2}p^2}$$
(3)

In Eq. (3), $K = \frac{\eta}{k}$ is the static gain of the microgripper, $w_n = \sqrt{\frac{k}{M}}$ its natural frequency and $\xi = \frac{f}{2.\sqrt{k.M}}$ its damping coefficient.

According to Eq. (3), the parameters which can vary are the natural frequency w_n , the friction coefficient f and the stiffness k. The variation of the two first parameters depends on k which can vary significantly due to cycling. In the next subsections, and in order to study the degradation of the MEMS, only the variation of its stiffness will be studied.

4.3. Experimental results

This subsection is devoted to the presentation of experimental results, the degradation model and RUL estimation.

The experiment remained running for more than two months. During the accelerated life tests, the measurements were per-

mass-spring-damper (MSD) system.

formed every 2 160 000 cycles and at each measurement the value of the stiffness k is estimated from the time response of the corresponding microgripper. At the end of each accelerated life test, which duration is more than 140 million cycles, the evolution of the stiffness k is plotted as a function of number of cycles as shown in Figure 7.

The experimental measurements are performed for three microgrippers in the same conditions to ensure the repeatability of the parameter k. The first 20 million cycles are considered as a transient phase (interesting to study for infant mortalities but is not considered here for the prediction of RUL) and can be neglected in the model identification. Figure 7 shows the low standard deviation between the values of the stiffness k of the three microgrippers.

Before starting the identification of the degradation model, the averages of k are plotted as a function of number of cycles as shown in Figure 8.



Figure 7. Experimental results.

4.3.1. Degradation model

The experimental measurements are approximated by a sixth order polynomial which better represents the shape and gives more accurate as shown in Figure 8. The mathematical equation of the green curve is estimated by using Matlab (Eq. 4).

$$k(n) = \sum_{i=0}^{6} (a_i . n^i) \tag{4}$$

where k is the stiffness, a_i the constants of the approximated polynomial (Table 4) and n is the number of cycles.

Equation (4) represents the polynomial degradation model of the microgripper. This model will be used in the next subsection to estimate the RUL.



Figure 8. Six order polynomial approximation.

i	a_i	i	a_i
0	7.18	4	-6.03×10^{-30}
1	4.55×10^{-7}	5	3.35×10^{-38}
2	$-2.24 imes10^{-4}$	6	-7.12×10^{-47}
3	5.02×10^{-22}		

Table 4. Numerical values of the polynomial coefficients.

4.3.2. RUL results and discussion

The polynomial degradation model obtained experimentally through accelerated life tests is combined with the nominal behavior model of the microgripper in order to monitor its health state and estimate its future state. The time responses shown in Figure 9(a) are given by injecting the number of cycles in the nominal behavior model. The parameters of the system such as the settling time, the static gain, the natural frequency and the damping coefficient can be estimated. To assess the health state of the MEMS, only the settling time t_s is studied. Table 5 shows the values of k and t_s for different number of cycles n. The settling time is estimated from the time responses (Figure 9(a)) and is plotted as a function of number of cycles as shown in Figure 9(b).

$n(10^6)$	k(N/m)	$t_s(s)$
70	10.7367	0.102
100	9.4625	0.106
130	8.3890	0.109
150	7.8573	0.111

Table 5. Stiffness and settling time values.

The failure time T_f is obtained by fixing a settling time limit, which corresponds in this application to 150 million cycles. The RUL is then calculated as the difference between T_f and the current time t (Eq. 5). Figure 10 shows the stochastic estimation of RUL.

$$RUL = T_f - t \tag{5}$$



Figure 9. Time response for different values of k and settling time variation.



Figure 10. RUL estimation.

5. CONCLUSION

In this paper, a hybrid prognostic method of microgripper MEMS has been proposed. It is based on the combination of two models: an analytical behavior model obtained by writing the physical equations and a degradation model derived from accelerated life tests. The method is applied to assess the health state of the MEMS and estimate its RUL. By injecting the degradation model in the nominal behavior model, the time response is given and its parameters can be estimated. The latter information are then used to assess the health state of the MEMS, define a failure threshold and calculate the RUL.

The proposed method has been applied on a set of only three MEMS with constant operating conditions. It can be improved by performing experiments with more MEMS and varying the influence factors (temperature, humidity, vibration, etc) to have a degradation model which can be more representative, reliable and accurate.

REFERENCES

- Aiwina, H., Sheng, Z., Andy, C. T., C, & Joseph, M. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, 23, 724-739.
- Dardalhon, M. (2003). Contribution à l'analyse de la fiabilité de microsystèmes: prise en compte des contraintes liées à l'environnement spatial. Unpublished doctoral dissertation, Montpellier 2, Université des Sciences et Techniques du Languedoc.
- Hansen, J., R, Hall, L. S., D, & Kurtz, K. (1995). New approach to the challenge of machinery prognostics.

Journal of Engineering for Gas Turbines and Power, 117, 320-325.

- Howe, R. T. (1989). Microsensor and microactuator applications of thin films. *Thin Solid Films*, *181*, 235-243.
- Huang, Y., Vasan, A. S. S., Doraiswami, R., Osterman, M., & Pecht, M. (2012). Mems reliability review. *Device* and Materials Reliability, IEEE Transactions on, 12, 482-493.
- Jay, L., Fangji, W., Wenyu, Z., Masoud, G., Linxia, L., & David, S. (2014). Prognostics and health management design for rotary machinery systems reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42, 314-334.
- Li, Y., & Jiang, Z. (2008). An overview of reliability and failure mode analysis of microelectromechanical systems (mems). In *Handbook of performability engineering* (p. 953-966).
- Matmat, M. (2010). Pour une approche complète de l'évaluation de fiabilité dans les microsystèmes. Unpublished doctoral dissertation, INSA de Toulouse.
- McMahon, M., & Jones, J. (2012). A methodology for accelerated testing by mechanical actuation of mems devices. *Microelectronics Reliability*, 52, 1382-1388.
- Medjaher, K., Tobon-Mejia, D. A., & Zerhouni, N. (2012). Remaining useful life estimation of critical components with application to bearings. *Reliability, IEEE Transactions on*, 61, 292-302.
- Merlijn van Spengen, W. (2003). Mems reliability from a failure mechanisms perspective. *Microelectronics Re*-

liability, 43, 1049-1060.

- Mir, S., Rufer, L., & Dhayni, A. (2006). Built-in-self-test techniques for mems. *Microelectronics journal*, 37, 1591-1597.
- Müller-Fiedler, R., Wagner, U., & Bernhard, W. (2002). Reliability of mems-a methodical approach. *Microelectronics Reliability*, 42, 1771-1776.
- Ruan, J., Nolhier, N., Papaioannou, G., Trémouilles, D., Puyal, V., Villeneuve, C., ... Plana, R. (2009). Accelerated lifetime test of rf-mems switches under esd stress. *Microelectronics Reliability*, 49, 1256–1259.
- Shea, H. R. (2006). Reliability of mems for space applications. In *Moems-mems 2006 micro and nanofabrication*.
- Tanner, D. (2009). Mems reliability: Where are we now? *Microelectronics reliability*, 49, 937-940.
- Tanner, D. M., Smith, N. F., Irwin, L. W., Eaton, W. P., Helgesen, K., Clement, J., ... others (2000). Mems reliability: infrastructure, test structures, experiments, and failure modes. SANDIA report, 155–157.
- Walraven, J. A. (2005). Failure analysis issues in microelectromechanical systems (mems). *Microelectronics Reliability*, 45, 1750-1757.
- Zaghloul, U., Papaioannou, G., Bhushan, B., Coccetti, F., Pons, P., & Plana, R. (2011). On the reliability of electrostatic nems/mems devices: Review of present knowledge on the dielectric charging and stiction failure mechanisms and novel characterization methodologies. *Microelectronics Reliability*, *51*, 1810-1818.

Methodology for Integrated Failure-Cause Diagnosis with Bayesian Approach: Application to Semiconductor Manufacturing Equipment

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ABSTRACT

Semiconductor Industry (SI) is facing the challenge of short product life cycles due to increasing diversity in customer demands. As a result, it has transformed into a high-mix low -volume production line that requires sustainable production capacities. However, significant increase in the unscheduled equipment breakdowns, limits its success. It is observed that in a high-mix low-volume production, product commonality is inversely proportional to failure occurrences and number of corrective actions in each failure. This provides evidence of misdiagnosis for equipment failures and causes. Moreover, equipment is believed to be the only source for product quality drifts that increase the unscheduled breakdowns and result in unstable production capacities. In this paper, we propose two defense lines against increasing unscheduled equipment breakdowns due to misdiagnosis. We argue that product quality drift can be traced to product itself, process and maintenance events, besides equipment. The Bayesian Belief Network (BBN) is proposed using symptoms, collected across drift sources, that improves equipment breakdown decisions by accurately identifying the source of product quality drift. The misdiagnosis of equipment failures and causes, if equipment is found as a source of drift, is another significant factor for increasing unscheduled equipment breakdowns. Existing failures and causes diagnosis approaches, in the SI, model equipment as a single unit and use fault detection and classification (FDC) sensor data. We also argue that these are the key reasons for the misdiagnosis because of neglected facts that production equipment is composed of multiple modules and FDC sensors undergo reliability issues in a high-mix low-volume production line. Therefore, to improve these misdiagnosis, another BBN is proposed that uses statistical information,

collected from the equipment database, at the module level. These BBN models are evaluated in a thermal treatment (TT) workshop at the world reputed semiconductor manufacturer. The BBN model for the identification of the source of product quality drift (failure mode) demonstrates 97.8% prediction accuracy; whereas, module level BBNs for equipment failures and causes diagnosis are found 45.7% more accurate than equipment level BBN.

1. INTRODUCTION

The SI has revolutionized our daily lives with integrated circuit (IC) chips and on the average we use more than 250 chips and 1 billion transistors per day per person. These chips are installed in almost all the equipment around us ranging from dish washer, microwave ovens and flat screens to office equipment. The sales revenues in the SI are characterized with cyclic demand patterns and positive compound annual growth rate (CAGR) of 8.78% (Figure 1). This ensures that demand driven downfalls will follow a cumulative growth. It also motivates the SI to continuously introduce new technologies and improve their existing processes to address the challenge of high-mix low-volume production and capture maximum market share.



Figure 1 - Global sales revenues of SI¹

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¹ The data is collected from the well known technology research centers (i) Gartner {www.gartner.com} and (ii) isuppli {www.isuppli.com}

The demand for integrated circuits (ICs) is mainly driven by end-user markets from electronics industry (EI) e.g. data processing, automotive industry, consumer electronics, communications and industrial sector (Ballhaus, Pagella, & Vogel, 2009). The SI forms a part of this complex interaction among these multiple industrial sectors (Yoon & Malerba, 2010; Kumar, 2008). Wireless communication and consumer electronics are leading market segments whereas automotive is a potential emerging segment. At present, the automotive market is only 8% of the total SI market but is expected to dominate in near future. Demand is continuously increasing not only in volume but also in diversity. This diversity has witnessed significant growth that ultimately leads to short product life cycles (Shahzad, Hubac, Siadat, & Tollenaere, 2011).



Figure 2 - Product mix, commonality and differentiation vs. equipment utilization²

The Figure 2 above presents equipment utilization for a thermal treatment (TT) workshop at the world reputed semiconductor manufacturer. This data is aggregated at the quarter level and spans over last six years (2008Q1 to 2014 Q1). It is also manipulated for the confidentiality purposes; however, scale is kept constant to keep the original trends. It can be seen that during 2008Q1 and 2012Q2, production capacities are significantly larger than both scheduled and unscheduled breakdowns (Figure 2a). In this period, we can observe a slight increase in the product mix that decreases production capacities. The data till 2014Q1 shows that with the fluctuation of the product-mix, the production capacities

suffers unstability and a notable decline. The Figure 2b presents the impact of product differentiation and commonality for two consecutive quarters on the equipment utilization. The difference in product mix is plotted on secondary v-axis. This can be positive or negative and ranges from -25% to +38%; whereas, product commonality is plotted on the primary y-axis for each current quarter, that ranges from 49% to 92%. It can be observed that production capacities increase with an increase in product commonality and are inversely related to unscheduled breakdowns. Therefore, the production learning curves against demand diversity can be improved by reducing not only unscheduled breakdowns but also by stabilizing them. In last two years, high product mix and short product life cycles that result in product differentiation has reduced TT workshop production capacities to 30%. It is because of unscheduled equipment breakdowns that result in the waste of resources and global productivity due to interruption in the time constraint production schedules. However, corrective maintenance due to these breakdowns is unavoidable.



Figure 3 - Failure counts, durations and occurrences

Further analysis on the failure durations (primary y-axis), occurrences, and number of repair actions (secondary y-axis) in each failure are plotted and presented in Figure 3, using data collected from TT equipment. The data is plotted for two significant failures: (a) elevator boat rotation and (b) OCAP_SPC and it is manipulated due to confidentiality. It can be seen that failure occurrence are inversely proportional to product commonality. However, OCAP (out of control action plan) failure occurrence is relatively higher (30%)

² The production line data from thermal treatment (TT) production line is manipulated with a constant for confidentiality while not losing the insight in reduced production capacities.

than elevator boat rotation. The increase in number of repair actions in a failure occurrence provides significant evidence for misdiagnosis that is one of the key factor for increasing unscheduled equipment breakdowns in a high-mix lowvolume production lines e.g. SI.

In addition to equipment failures and causes misdiagnosis, we also argue that misdiagnosis can occur while identifying the source of product quality drifts. In a highly complex production environment as SI, we believe that the source of such drifts can be equally traced to other elements such as products, process, equipment and maintenance; however, at present it is believed to be the equipment. This paper is divided in 4 sections. Section-2 presents related literature review on equipment failure-cause diagnosis in general and specially in the SI, and the evidence that equipment is taken as the only source of product quality drift. The proposed methodology and the case study are presented in section-3 whereas BBN models and analyses results are presented in section-4. Finally, we conclude this paper with discussion and perspectives.

2. LITERATURE REVIEW

For clear orientation, we refer to the SEMI standard definition³ of failure as an unplanned event that changes an equipment (system) to a condition where it cannot perform its intended function. Whereas, cause or fault is the reason behind the occurrence of failure in the equipment. It is different than the source of product quality drift, referred as failure mode (FM), in this paper. The FM is the category of cause behind a product quality drift. For example, due to the type of TT equipment (batch cluster) where multiple lots are processed together; a drift might occur due to the influence of different product combinations. In such situation, the FM is the product and not equipment; therefore, equipment must not be stopped for the failures and causes diagnosis, and associated corrective maintenance actions. In this regard, section 2.1 presents analysis on the product quality drift sources. The section 2.2 presents the existing equipment failure-cause diagnosis in the SI and section 2.3 presents the choice of BBN as our target approach for modeling the FM identification and equipment failures and causes diagnosis.

2.1. Source of Product Quality Drift Analysis

Analysis of the source of product quality drift can be related to Root Cause Analysis, a study to diagnose the sources of problems in processes for directing counteractive actions (Rooney & Heuvel, 2004). Doty (1996) and Smith (2004) used the classification by Ishikawa and Loftus (1990) to divide the root causes into six assignable categories of Man, Machine, Method, Material, Measure and Environment to explain abnormal situations in statistical process control strategies. It is a qualitative method, used frequently in the diagnosis domain, but requires long brainstorming sessions with experts and is performed on the occurrence of each new excursion. Therefore, it cannot be used in the complex production environment. Weidl, Madsen, and Israelson (2005) model industrial process and product failure control system using generic object oriented Bayesian Network that proposes corrective maintenance actions with explanation of root causes. Their set of root causes contains all possible hypotheses on failure sources or conditions coming from equipment sensors and process operations. Sarkar (2004); Demirli and Vijayakumar (2010) have combined cluster analysis with engineering knowledge to classify big set of equipment failure events into small number of categories and use the knowledge to identify root causes for each cluster.

These above researches are important as they provide the possibility of finding the true source of product quality drift. However, the problem for process and product is always associated to an equipment and then further investigation is made to find other probable causes. As a matter of fact, in the SI, a product quality drift is associated to a failure in the equipment; whereas, in reality, it can be traced to other assignable causes as demonstrated by Ishikawa diagram. We suggest to combine the advantages of the qualitative method (Ishikawa diagram) with probabilistic approach (BBN) to improve decisions on equipment stoppage against product quality drifts. This will act as a first line of defense to accurately identify the source of product quality drift and reduce unscheduled equipment breakdowns. The details can be found in sections 3.1 and 4.1.

2.2. Equipment Failure and Cause Diagnosis in the SI

Recent IT revolutions have enabled huge data volumes with improved artificial intelligence (AI) techniques for failure diagnosis. The commonly used techniques to optimize the production operations are advanced process control (APC) methods that include run to run (R2R) loops, statistical process control (SPC) and fault detection and classification (FDC). Chen and Blue (2009) have proposed an approach using EWMA (exponentially weighted moving average) chart as a function of variance and covariance of relevant parametric distributions to classify the bad equipment. It is comparable to FDC approach that uses SPC to model temporal patterns and to monitor and detect shifts or drifts in the equipment signals (Yue & Tomoyasu, 2004; Lacaille & Zagrebnov, 2007; He & Wang, 2007). This approach is objectively different than the above approaches as it integrates all sensors to generate one single index that reflects the overall equipment health against product quality. (Chang, Song, Kim, & Choi, 2012) proposed a fault detection and classification methodology for the SI using a sequential SVDD (support vector data description) classifier

³SEMI International Standards: Compilation of terms (Updated April 2014), retrieved on 4th June 2014 from: http://www.semi.org/en/sites/semi.org/files/docs/CompilationTerms0414.p df

algorithm. It is a probabilistic modeling used in addition to statistical approach

A careful analysis of the existing approaches, methods and techniques, highlights that till today, to model a failure and cause diagnosis, sensors data are used. In addition, above discussion also highlights that the diagnosis models model equipment as a single unit for failures and causes diagnosis; whereas, an equipment is composed of multiple modules.

2.3. Bayesian Belief Network (BBN) as Modeling Tool

The methods used for failure and cause diagnosis range from univariate and multivariate statistical to artificial intelligence (AI) and machine learning (ML) methods. There do exist hybrid methods; however, most promising and suitable technique found in literature is the BBN. The advantage of using Bayesian network is its inherent ability for deduction and inter-causal reasoning (Kjærulff & Madsen, 2006). The deductive (causal) reasoning takes into account the causal links between variables, from causes to effects using dynamic detection evolution. The inter-causal reasoning is interesting and powerful ability of BBN where evidence on one possible cause disapproves other possible causes. In addition to their ability to represent causal relationships, BBN has the capacity to perform data learning efficiently in uncertain environments, involving small amount of data and short temporal change of states. It can be used to represent compact joint probability distributions (Margaritis, 2003).

The Bayesian network based approach has recently become focus for dynamic maintenance management and failure diagnosis in the SI. Yang and Lee (2012); Bouaziz, Zamaï, and Duvivier (2013) applied BBN for diagnostics and prognostics in the semiconductor manufacturing with an objective to investigate the causal relation among equipment conditions and their affects on product quality. Moreover, there do exist published methods and algorithms to adapt the BBN to fit to specific case studies in the SI (Roeder, Schellenberger, Schoepka, Pfeffer, Winzer, Jank, & Pfitzer, 2011). In the process industry, Isham (2013) proposed a BBN to compute dynamic probabilities and update the Fault Semantic Network. Its focus is on predicting real time risk based accident forecasting in oil and gas sector. Another important use of BBN is as a classifier and isolater of faults (Verron, Li, & Tiplica, 2010). Weber and Jouffe (2006) present a detailed review of BBN application in the domains of reliability, risk analysis and maintenance.

A traditional BBN consists of a set of nodes representing random variables (V), set of arcs (A) connecting these nodes to form a directed acyclic graph (DAG) (equation 1) and conditional probability distributions (CPD) tables to quantify the probabilistic relationships between nodes. The BBN is a graphical representation of joint probability distribution (equation 2) that represent dependent and conditionally independent relationships.

Directed Acyclic Graph,
$$G = (V, A)$$
 (1)

$$P(X_1 = x_1, ..., X_n = x_n) = \prod_{i=1}^{n} P(X_i = x_i | Parents(X_i))$$
(2)

This probabilistic representation of a system in a graphical form allows monitoring relationships among different variables. The CPD table is constructed based on the Bayes rule (equation 3) which states that for given 2 events A and B, the probability of A given B is the function of conditional dependence of B to A and respective probabilities of having A and B events together. It is an efficient feature to model causal relationships between a set of event.

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$
(3)

The distribution changes when the states of the nodes in G experience a change of events (called evidence). Propagation algorithm is used to fuse and propagate the impact of new evidence and beliefs through BBN so that each proposition eventually will be assigned a certainty measure, consistent with the axioms of probability theory (Pearl, 1988).

It is a powerful method for probabilistic knowledge representation and inference under uncertainty. The maintenance personnels make decisions to stop the production equipment, in case of product quality drift, under uncertainty. Therefore, BBN is the approach that offers probabilistic contextual information to make accurate decisions. It must be noted that every bad decision adds to unscheduled equipment breakdowns.

In this paper we focus on presenting a methodology to :

- *I*dentify the failure modes (source of product quality drift) as either product, process, equipment or maintenance. Therefore, we first develop a BBN that identifies the failure modes (section 4.1), accurately.
- Develop integrated failure-cause diagnosis BBN models at the module and equipment level (sections 4.2 and 4.3). The existing equipment level BBNs are based on FDC sensors data that is no more reliable due to high-mix low-volume production.
- Use product, process, maintenance and equipment data/information. The key advantage of this data is that it is not subjected to reliability issues like FDC sensors (Blue, Roussy, Thieullen, & Pinaton, 2012).

3. PROPOSED METHODOLOGY

In this section, we elaborate the proposed methodology used to achieve the previously discussed objectives, followed by the description of case study, data processing and a brief presentation of BBN learning strategies.

3.1. Proposed BBN Based Methodology

In step-1, we start with the classification of potential symptoms from product, process, equipment and maintenance databases. The FDC sensor signals within equipment database are not directly used as symptoms; however, decisional data/information based on these signals is used as potential symptoms, failures and causes. It is due to the fact that emerging sensor reliability issues are linked with high-mix low-volume production and could result in unstable models. The FM are modeled as a function of symptoms and resulting BBN for FM identification serves as first defense against unscheduled equipment breakdowns. It help equipment engineers to make accurate decisions on stopping the equipment if the product quality drift is not related to product, process or maintenance. The step-2 in this methodology advocates to model equipment failures and causes as a function of symptoms using module level BBNs. We also model the equipment level BBN in step-3 to assess the assumption that module level BBNs are more accurate in failure-cause diagnosis than the equipment level model. The equipment level BBN is modeled and proposed to be updated upon new excursions where any structural change between two consecutive equipment level BBNs will be used as the signal to revise the module level BBNs, with expert's intervention. This loopback step is not completed in this case study; however, diagnosis results from module and equipment level models are compared based on their accuracies as the final step of this methodology.



Figure 4 - Proposed 4-step methodology for integrated failures-causes diagnosis

3.2. Description of the Case Study for Thermal Treatment (TT) Workshop

As a case study, we consider TT workshop equipment, used to grow oxide and deposit nitride layers on the surface of silicon wafer as dielectric, respectively. This equipment uses low pressure chemical vapor deposition (LPCVD) as the technique to deposit nitride layers. It is also used for annealing (heat treatment) after production steps to stabilize the crystalline structure of a silicon wafer, prior to the next steps. The equipment type in this production line is batch cluster with two process chambers known as reactors (Figure 5). The structure of the TT equipment is presented in Figures 5a and 5b, below. The reactor, wafer handling robot (WHR) and work in progress (WIP) are the three main modules. Each of these modules is further composed of many sub modules (Figure 5b). In this case study, we consider three modules Reactor1, Reactor2 and Mainframe for demonstration with an assumption that these constitute the whole equipment. The integrated failure-cause diagnosis BBN models at module and equipment levels are therefore developed for these equipment modules.



Figure 5 - View of the vertical LPCVD (Selen, Timmermans & Bolscher, 2009)

3.3. Data Processing

The dataset used in this case study spans six months (from week 27^{th} to week 52^{nd} of 2013) and are collected across product, process, equipment and maintenance databases for TT equipment. These are used in symptoms, failures and causes identification. The symptoms are classified into four categories and are used to generate the BBN to accurately identify the FM as the function of symptoms (section 4.1) as well as the development of an integrated failure-cause diagnosis BBN models at the module and equipment level (sections 4.2 and 4.3).

3.4. Bayesian Belief Network Learning

The BBN networks can be obtained either through experts knowledge or based on data learning. In the proposed methodology, the latter option is used. The BBN models are learned with BayesiaLab 5.3 using equivalence class (EQ), Taboo and Taboo order algorithms that use minimum description length (MDL) as an objective function. The brief summary of BBN learning with these methods is presented in Table 1. The models are learned first using EQ followed by optimization with Taboo and Taboo order. The model with lowest MDL score is accepted for further analysis. All BBN models are learned and tested using 75-25 cross validation strategy. The evaluation of BBN networks performance is presented in section 4.

Function	А	lgorithm	S	Strength	References			
BBN structure building	Equival	lence Class (EQ)	Reduce sea	rch space efficiently	(Chickering, 2002; Munteanu & Bendou, 2001)			
BBN structure optimization	Taboo	Taboo Order	Capacity to refine a developed model	Ability for exhaustive search with accurate results (given additional time)	(Glover, 1986)	(Teyssier & Koller, 2005)		
BBN structure choice (function objective)	Minim Ler <u>Target</u>	um Description ngth (MDL) : Lowest MDL score	Tradeoff between application to multi	accuracy and complexity : ply connected belief network	(Lam &	Bacchus, 1994)		

Table 1 - Learning Bayesian network structure with BayesiaLab

4. MODELLING AND ANALYSIS RESULTS

In this section, we present the modeling and analysis results of BBN models as proposed in the methodology (section 3.1).

4.1. Classification of Symptoms and FM Identification (Step-1)

The identification and classification of potential symptoms from the database is the most difficult and complex task. It is because one needs to have multidisciplinary expertise from product, process, equipment and maintenance domains. This difficulty was addressed by a task force with experts from each discipline. The brainstorming sessions resulted in the formalization of well known Ishikawa (a.k.a. Fishbone) diagram (Ishikawa & Loftus, 1990) to find potential symptoms across product, process, equipment and maintenance areas. The results are presented in Figure 6.

Symptoms are classified in four axes as product, process, equipment and maintenance. The TT equipment is of batch cluster type; hence, they process multiple lots in a given step. Therefore current/previous product combinations might influence the product quality. Number of reworks, wait time before process and defect distribution from previous steps are also identified as key product symptoms linked with product quality drift. The process capability (Cp) and process capability index (Cpk) are the key process symptoms. It is also identified that not only current recipe but also previous recipe and their respective process steps combinations could be strongly linked with product quality. The FDC sensor signals from equipment database are not directly considered; however, decisional information based on these signals is a good candidate for potential symptoms. The key symptoms are equipment capability (Cm) and equipment capability index (Cmk); however, overall equipment efficiency (OEE) indicators and counters are the additional symptoms included . The counters are the meters associated with equipment modules (process chambers and mainframe), used for triggering preventive maintenance. The last category of symptoms is the maintenance where reliability, availability and maintenance (RAM), and failure indicators are identified as the key symptoms. The data is collected for these symptoms against product quality drifts. The data for OEE, RAM, process and equipment capability, and failure indicators are aggregated on weekly basis whereas rest of the data is instantaneous for a given product and process step.



Figure 6 - Classification of symptoms

The BBN to identify potential failure modes (equipment, product, process and maintenance) is learned with BayesiaLab, using symptoms as recognized in Figure 6. The model is presented in Figure 7 where FMs are modeled as

the function of symptoms. In this paper, the concept of prediction is used to represent inference results of a target node.



Figure 7 - BBN model for FM identification

The symptoms in this model are grouped into four categories as differentiated with different colors. The green, pink, yellow and light brown represent process, product, equipment and maintenance related symptoms, respectively. The target node is the failure mode. The objective of showing this graph (Figure 7) is to present the complexity of resulting network. The proof of concept and few results are presented in Figures 8 and 9. It can be seen that, BBN identifies product (64%) or maintenance related (36%) for a given set of symptoms as shown in the Figure 8. Hence, in this situation, maintenance personals should not stop the equipment.



Figure 8 - Proof of concept: product as the FM

Similarly, the Figure 9 shows that maintenance is found as the only reason against given symptoms; hence, BBN model suggests to stop the equipment for further investigation on failures and causes. The precision and reliability matrices of the BBN model to identify the FM are presented in Figure 10. It can be seen that this model offers 97.8% precision on 75-25 cross validation strategy. In this strategy, 75% data is used to learn the model whereas 25% data (randomly selected) is used for precision and reliability measures.



Figure 9 - Proof of concept: maintenance as the FM

Value (Precision)	Equipment (1533)	Maintenance (1417)	Process (1015)	Product (1035)	
Equipment (1533)	100%	0%	0%	0%	
Maintenance (1338)	0%	94.42%	0%	0%	
Process (1043)	0%	0%	100%	2.71%	
Product (1086)	0%	5.58%	0%	97.29%	
Value (Deliability)	Equipment (1E22)	Maintonena (1417)		Dec duct (102E)	
value (Reliability)	Equipment (1555)	Maintenanc (1417)	FIOCESS (1015)	FIOUUCI (1055)	
Equipment (1533)	100%	0%	0%	0%	
Maintenance (1338)	0%	100%	0%	0%	
- (1010)	00/	0%	97.32%	2.68%	
Process (1043)	0%	070	5710270		



Figure 10 - Precision and reliability of FM BBN

Figure 11 - Prediction accuracy with ROC curves

Figure 11 shows FM prediction accuracy evaluation using receiver operating caracteristic (ROC) curves, a graph to plot true positive rate (Y-axis) against false positive rate (Xaxis). Its index represents the surface under the ROC curve divided by the total surface and in this graph it represents an 99.88% average accuracy with 0.02% of false positive prediction. The capability of FM identification model with gain curves is presented in Figure 12. The yellow line (Figure 12c) presents that 31% of the test cases have 'equipment' as FM whereas the red curve represents the capability to predict them correctly in comparison with random prediction represented by the blue curve. The x-axis represents rate of individual cases taken into account for prediction whereas v-axis represents rate at which they are predicted accurately with target failure mode. The Gini index represents the gain over random model and is computed by dividing the area below red curve and above blue curve with the area under blue curve. The FM identification capability for product and process are higher than the equipment and maintenance. The relative Gini index is computed by dividing the area within triangle formed due to crossing of red, blue and yellow lines with area under blue curve.



Figure 12 - FM identification model capability with gain curves

4.2. Module Level Failures-Causes Diagnosis BBN Models (Step-2)

The FM identification model, presented in previous section, is the first step towards reducing unscheduled equipment failure breakdowns. This is complemented by failures and causes diagnosis through BBN model, developed at module level where data on failure and causes are collected from the world reputed semiconductor manufacturer for the LPCVD process equipment (sections 3.2 and 3.3). For demonstration, we have used three modules (i) Reactor1, (ii) Reactor2 and (iii) Mainframe. The reactors are the process chambers where multiple lots are processed together for annealing, oxidation or metrication depositions (section 3.2). The Mainframe module is also referred as WIP module (see Figure 5).

The BBN model for Reactor1 is presented below in the Figure 13 whereas BBN models for other modules are not presented due to space restrictions. The target nodes Failure Code1 and Failure Code2 are modeled as the function of symptoms; however, causes are also allowed to be directed from these symptoms. The color scheme for symptom classes is same as presented in section 4.1 whereas causes and failure codes are added with new colors (orange and blue respectively). The nodes not connected in these models are found with zero influence on either failure codes or causes.



Figure 13 - Failure-Cause BBN diagnosis models for Reactor1

The example as proof of concept from the learned models is shown below in the Figure 14 for Reactor1. The equipment failures-causes diagnosis made by BBN model is presented as the function of symptoms in green rectangle.



Figure 14 - Result from module level Reactor1 model

The prediction capability for learned models are presented below in Figure 15. The results show that learned models have high precision and accuracy. Besides this, it can also be observed that accurate prediction capabilities are also very high in terms of Gini indices.



Figure 15 - Gain curves for BBN models

4.3. Equipment Level Failures-Causes Diagnosis BBN (Step-3)

To find out, whether module level BBN models are more accurate than equipment level BBN model, we developed an equipment level diagnosis model to find failure and causes. The symptoms from FM identification model (section 4.1) plus failures and causes from module level BBNs (section 4.2) are used to develop equipment level BBN model. Besides this, we add one node 'Module' to diagnose failure for a given module in the equipment. The model is presented below in the Figure 16. It can be seen that all nodes are connected. The nodes that have zero influence in module level BBNs, appear connected in this network that add confusion and influence the equipment level failurescauses diagnosis. Confusion is also caused by the given fact that similar modules, Reactor1 and Reactor2 share common failures such as OCAP_SPC. Each module have different occurrences of OCAP SPC but in this network, they overlap. It is also observed from the proof of concept that

for given symptoms, all modules have 33.33% probability of occurrence that confirms the added confusion.



Figure 16 - Failure-Cause diagnosis BBN model at equipment level

Some of the prediction accuracy results for the equipment level BBN model are presented in Figures 17 with gain and ROC curves. The results clearly show the declined gain and increasing false positive that significantly reduces the diagnosis capability of the equipment level BBN model.



Figure 17 - Gain and ROC curves for equipment Level BBN model

4.4. Comparison of Diagnosis Accuracy for Equipment vs. Model Level BBN Models (Step-4)

The diagnosis accuracy from equipment and module level BBNs are presented in Figure 18. The accuracy is computed

as an average of reliability and precision for each BBN model. It shows that module level BBN has almost overall 99.7% prediction accuracy in comparison to 54% for equipment level model. The gain obtained in diagnosis with module level BBNs is 45.7% that is significant and can help in reducing unscheduled equipment breakdowns. The likely reason for misdiagnosis by equipment level BBN is the commonality in failures between different modules that add confusion. Hence, it's evident to get accuracy over equipment level BBNs when failures-causes diagnosis are modeled at module levels.



Figure 18 - Gain in prediction accuracy for module level BBNs over equipment level

5. DISCUSSION AND PERSPECTIVES

Above results advocate the hypothesis that misdiagnosis is the reasons for increased unscheduled breakdowns. It is due to the fact that existing failure diagnosis approaches model equipment as a single unit and use FDC sensor data. These approaches also make an assumption that product quality drifts are due to equipment failures, but in actual practice, the causes can equally be traced to maintenance, product or process. In the SI, equipment are composed of multiple modules that share symptoms, failures and causes. Besides this fact, the variability of sensor data could easily trigger a misdiagnosis and result in unstable model.

In the proposed methodology, we first modeled the failure modes against product drifts as a function of symptoms. It is the first step towards reducing unscheduled breakdowns. Then failure and cause diagnosis is modeled at module level. An equipment level BBN model is also learned in the same way and is found to be less accurate in comparison with the module level BBNs. It provides clear evidence that failure-cause diagnosis must be modeled at module level and produces more accurate results when used with data other than FDC in high-mix low-volume production lines.

The BBN models, developed in this paper as a proof of concept, are static in nature; however, real advantage lies in transforming these models into dynamic BBNs. The developed BBN models can also be used with FDC sensors data as complimentary indicators when faced with a situation where BBN model for FM identification give equal probability to all failure modes (product, process, equipment and maintenance). Therefore, it is possible to extend this work in future. The cost of maintaining these models for a

complete workshop and ultimately a production line could be very high. Therefore, we believe that generalization of these models can be made for similar type of equipment with common failure behaviors.

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REFERENCES

- Ballhaus, W., Pagella, A., & Vogel, C. (2009). A change of pace for the semiconductor industry. *Technical report, German Technology, Media and Telecommunications*, Nov. 2009.
- Blue, J., Roussy, A., Thieullen, A., & Pinaton, J. (2012). Efficient FDC based on hierarchical tool condition monitoring scheme. 23rd Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC) (pp. 359-364), May 2012.
- Bouaziz, M. F., Zamaï, E., & Duvivier, F. (2013). Towards Bayesian network methodology for predicting the equipment health factor of complex semiconductor systems. *International Journal of Production Research* (*IJPR*), 51(15), 4597-4617.
- Chang, H. J., Song, D. S., Kim, P. J., & Choi, J. Y. (2012). Spatiotemporal pattern modeling for fault detection and classification in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 25(1), 72-82.
- Chen, A., & Blue J. (2009). Recipe-independent indicator for tool health diagnosis and predictive maintenance. *IEEE Transactions on Semiconductor Manufacturing*, 22(4), 522-535.
- Chickering, D.M. (2002). Learning equivalence classes of Bayesian-network structures. *The Journal of Machine Learning Research*, 2, 445-498.
- Demirli, K., & Vijayakumar, S. (2010). Fuzzy logic based assignable cause diagnosis using control chart patterns. *Information Sciences*, 180(17), 3258-3272.
- Doty, L. A. (1996). *Statistical process control (2nd ed.)*. NY, USA: Industrial Press.
- Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers and Operations Research*, 13(5), 533-549.
- He, Q.P., & Wang J. (2007). Fault detection using the k-nearest neighbor rule for semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing*, 20(4), 345 ± 354 .
- Isham, M.U. (2013). *Real time safety verification in the process industry using fault semantic networks (FSN)*. Doctoral dissertation. Institute of technology, University of Ontario.
- Ishikawa, K., & Loftus, J. H. (1990). Introduction to quality control (Vol. 98). Tokyo: 3A Corporation.
- Kjærulff, U.B., & Madsen A.L. (2006). Probabilistic Networks for Practitioners – A Guide to Construction and Analysis of

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Bayesian Networks and Influence Diagrams, Department of Computer Science, Aalborg University, HUGIN Expert A/S.

- Kumar, R. (2008). Fabless semiconductor implementation. New York: McGraw-Hill.
- Lacaille, J.,& Zagrebnov, M. (2007). An unsupervised diagnosis for process tool fault detection: The flexible golden pattern. IEEE Transactions on Semiconductor Manufacturing, 20(4), 355-363.
- Lam, W., & Bacchus, F. (1994). Learning Bayesian belief networks: An approach based on the MDL principle. Computational intelligence, 10(3), 269-293.
- Margaritis, D. (2003). Learning Bayesian network model structure from data. Doctoral dissertation. University of Pittsburgh.
- Munteanu, P., & Bendou, M. (2001). The EQ framework for learning equivalence classes of Bayesian networks. Proceeding IEEE International Conference on Data Mining (ICDM), (417-424).
- Pearl, J. (1988). Probabilistic reasoning in intelligent systems: networks of plausible inference. Morgan Kaufmann.
- Roeder, G., Schellenberger, M., Schoepka, U., Pfeffer, M., Winzer ,S., Jank, S., & Pfitzner L. (2011). Approaches for Implementation of Virtual Metrology and Predictive Maintenance into Existing Fab Systems. Retrieved from http://convegni.unicatt.it/miproco/meetings_Roeder2011_06 13 Statistical Workshop Milan final.pdf on 3rd January 2014.
- Rooney, J. J., & Heuvel, L. N. V. (2004). Root cause analysis for beginners. Quality progress, 37(7), 45-56.
- Sarkar, P. (2004). Clustering of event sequences for failure root cause analysis. Quality engineering, 16(3), 451-q460.
- Selen, L. J. M., Timmermans, E. A. H., & Bolscher, G. (2009). U.S. Patent No. 7553516 B2. Washington, DC: U.S. and Trademark Office. Retrieved Patent from http://www.google.fr/ patents/US7553516 on 21st March 2014
- Shahzad, M. K., Hubac, S., Siadat, A., & Tollenaere, M. (2011). An Extended Business Model to Ensure Time-to-Quality in Semiconductor Manufacturing Industry. International Conference on Enterprise Information Systems, Portugal.
- Smith, G. M. (2004). Statistical process control and quality improvement (5th ed.). NJ, USA: Pearson/Prentice Hall.
- Susto, G., Pampuri, S., Schirru, A., & Beghi, A. (2012). Optimal tuning of epitaxy pyrometers. Proceeding of 23rd IEEE/SEMI Advanced Semiconductor Manufacturing Conference (ASMC), (294–299).
- Teyssier, M. & Koller, D. (2005). Ordering-based search: A simple and effective algorithm for learning Bayesian networks. Conference in Uncertainty of Artificial Intelligence (UAI).
- Verron, S., Li, J., & Tiplica, T. (2010). Fault detection and isolation of faults in a multivariate process with Bayesian network, Journal of Process Control, 20(8), 902-911.
- Weber, P., and Jouffe, L., (2006), Complex system reliability modeling with Dynamic Object Oriented Bayesian Networks (DOOBN). Reliability Engineering and system Safety, 91, 149-162.
- Weidl, G., Madsen, A. L., & Israelson, S. (2005). Applications of object-oriented Bayesian networks for condition monitoring, root cause analysis and decision support on operation of

complex continuous processes. Computers & chemical engineering, 29(9), 1996-2009.

- Yang, L., & Lee, J. (2012). Bayesian Belief Network-based approach for diagnostics and prognostics of semiconductor manufacturing. *Robotics* and Computer-Integrated Manufacturing, 28, 66-74.
- Yoon, M., & Malerba, F. (2010). Technological interrelatedness, knowledge generality and economies of scale in the evolution of firm boundaries: A history-friendly model of the fabless ecosystem. International Conference on Opening Up Innovation: Strategy, Organization and Technology.
- Yue, H.H. & Tomoyasu, M. (2004). Weighted PCA and its applications to improve FDC performance. Proceeding 43rd IEEE Conference on Decision and Control, (4262–4267).

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A Bayesian network based approach to improve the effectiveness of maintenance actions in Semiconductor Industry

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ABSTRACT

The Semiconductor Industry (SI) is facing the challenge of high-mix low-volume production due to increasing diversity in customer demands. This has increased unscheduled equipment breakdowns followed by delays in diagnosis and ineffective maintenance actions that reduce the production capacities. At present, these challenges are addressed with mathematical approaches to optimize maintenance actions and their times of intervention. However, few studies take into account the ineffectiveness of maintenance actions, which is the key source for subsequent breakdowns. Hence, in this paper, we present a methodology to detect poorly executed maintenance actions and predict their consequences on the product quality and/or equipment as the feedback for technicians. It is based on the definition of maintenance objectives and criteria by experts to capture information on the extent to which the objective is fulfilled. Data collected from maintenance actions is then used to formulate Bayesian Network (BN) to model the causality between defined criteria and effectiveness of maintenance actions. This is further used in the respective FMECA defined for each equipment, to unify the maintenance knowledge. The key advantages from the proposed approach are (i) dynamic FMECA with unified and updated maintenance knowledge and (ii) real time feedback for technicians on poor maintenance actions.

1. INTRODUCTION:

The SI is characterized by fastest change in smallest period of time and has become a 300+ B\$ industry in less than 60

years (Stamford, 2012; Dale, 2012). The demand in SI is mainly driven by end-user markets (Ballhaus, Pagella, and Vogel, 2009); hence, increasing diversity in customer demands with short product life cycles has resulted into a high-mix low-volume production. It increases unscheduled equipment breakdowns followed by delays in diagnosis and ineffective maintenance actions that reduce production capacities. This fact is shown in Figure 1, where unscheduled equipment breakdown is plotted against product mix using data collected from a world reputed semiconductor manufacturer for 2013. The blue curve represents number of different products whereas red curve is unscheduled equipment breakdown duration, in second. It can be seen that the variation of product mix has an important impact on production capacities; therefore, it is necessary to reduce variability of unscheduled breakdowns due to this fluctuation.



Figure 1. Product mix vs unscheduled breakdown

This complexity is treated in literature with mathematical approaches to optimize maintenance actions and their times of intervention. Vassilis and Christo (2013) used a Bayesian

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classifier to recommend problem types based on historical case associated to specific event using sensor data. Multiagent based approaches are also used in maintenance to dynamically schedule the actions (Aissani, Beldjilali, and Trentesaux, 2009). Weber and Jouffe (2006); Weild, Madsen, and Israelson (2009); Yang and Lee (2012); and Efthymiou, Papakostas, Mourtzis, and Ghyryssolouris (2012) present an application of Bayesian network for dynamic condition monitoring and diagnostic in order to support condition based maintenance (CBM) in the complex SI and aircraft industries. However, none of these above approaches take into account the effectiveness of the maintenance actions performed by technicians that serve as key source for variability in production capacities. Medina-Oliva and Weber (2013) proposed probabilistic relational model (PRM) with key performance indicators (KPIs) to monitor and report human effectiveness against maintenance strategies. The proposed approach, in this article, is different as we predict consequences of poorly executed maintenance actions as feedback to technicians, on product quality and equipment.

In this paper, we introduce the notion of defined criteria for maintenance functions based on equipment and maintenance types by experts. These are updated in failure mode effect and criticality analysis (FMECA) followed by maintenance checklists. The responses collected from technicians, while executing maintenance actions, serve as the knowledge base to model the consequences due to ineffective actions. This proposed methodology is implemented in dielectric (DIEL) workshop at the world reputed semiconductor manufacturer. The data is used to develop Bayesian network (BN) with an unsupervised learning that models causality between criteria and effectiveness of maintenance actions. The key benefits of the proposed approach are (i) dynamic FMECA to unify the maintenance knowledge and (ii) real time feedback to technicians on poorly executed maintenance actions. It also helps to renew experts' knowledge on equipment against increasing unscheduled due to fluctuations in product mix. This approach is not limited to SI and can be applied to any production line facing the challenges of reduced production capacities due to unscheduled equipment breakdowns.

This paper is divided in 3 sections. Section 2 presents a literature review on existing approaches and methods. The proposed methodology based on BN, case study and results are presented in section3. We conclude this article with the discussion and perspectives in section 4.

2. LITERATURE REVIEW

The review has been performed across three axes: (i) maintenance strategies, (ii) maintenance actions predictions and (iii) approaches to take into account the human factor during maintenance in the SI and complex production lines.

2.1. Design and Manufacturing Operations in SI

The design and manufacturing process of integrated circuit (IC) chip is presented in Figure 2 (Shahzad, Hubac, Siadat, and Tollenaere, 2011). In this process, customers request new products that go through a complex design using CAD tools and design libraries (reusable blocks of circuits). These are simulated to assess their compliance with technology specifications. Upon validation, design moves to the mask preparation step. These masks are glass plates with an opaque layer of chrome carrying target chip layout. They transfer product layout on silicon wafer through repetitive sequence of deposition, lithography, etching and polishing steps. The next step is called frontend manufacturing where thousands of transistors are fabricated on the silicon surface along with a network of interconnected wires to form an IC chip. The silicon wafers are then tested, cut, packaged and shipped to customers a.k.a. backend process. This complex manufacturing process consists of approximately 200+ operations, 1100+ steps and 8 weeks of processing time,. The cost of a production facility in SI with 600 production and metrology equipments is around 3.5 billion US dollars (Shahzad, Tollenaere, Hubac, and Siadat, 2011). The production capacity of a SI production line is measured in wafers manufactured per week. The case study performed in this paper is completed in 12 inches wafer production facility.



Figure 2. Design and manufacturing process for an IC chip

2.2. Maintenance Strategies

In the SI environment, maintenance is a key issue to keep such a high level of production and control capacity. The common maintenance practices in the manufacturing domain are corrective (run to failure), preventive (time and usage based) and predictive maintenances (Mili, Bassetto, Siadat, and Tollenaere, 2009). The corrective maintenance strategy is not suitable for the semiconductor manufacturing because it destabilize the production system; however, till now, the SI has relied on preventive maintenance (PM) as an alternative maintenance strategy to optimize capacities while ensuring product quality. The key disadvantages of PM are over and under maintenance. It decreases capacities due to maintenance when equipment is still in good health and adds additional costs due to delayed maintenance. Besides these strategies, a new strategy known as predictive maintenance (PdM) is proposed, where maintenance actions are triggered depending on the condition of the equipment and in anticipation (prediction) of potential failure before they occur. This strategy has evolved in two forms as (i) non-predictive condition based maintenance (CBM) and (ii) predictive CBM. The non-predictive CBM is similar to the PM strategy but with the difference that maintenance decisions are taken based on surpassing thresholds on the key parameters used to monitor the health of equipment, instead of time based or usage based approach (Susto, Pampuri, Schirru, and Beghi, 2012); (Krishnamurthy, Adler, Buonadonna, Chhabra, Flanigan, Kushalnagar, Nachman, and Yarvis, 2005). The predictive CBM is far superior to PM and non-predictive CBM. It is because the maintenance actions are based on continuously monitoring equipment health followed by failure predictions and pre-failure interventions.

At present, unscheduled breakdowns are addressed with the mathematical approaches to optimize maintenance actions and their intervention time. Vassilis et al. (2013) employed Bayesian classifier to recommend problem types based on historical cases associated to specific event with sensor data. Weber and Jouffe (2006); Weild et al. (2009); Yang and Lee (2012); Efthymiou et al. (2012); and Bouaziz, Zamai, and Hubac (2012) used BN for dynamic condition monitoring and diagnostic to support condition based maintenance (CBM) in complex (e.g. SI and aircraft) industries. Mili et al. (2009) implemented dynamic FMECA based method to unify maintenance actions and prevent risks with qualitative information. Hubac and Zamai (2013) presented dynamic adjustment of maintenance policies based on CBM strategy approach allow to dynamically control and quantify equipment reliability in high mix flow industry. This shows that CBM is the dominant maintenance strategy being used to optimize maintenance actions. The mathematical and BN approaches are also found to be used for modeling purposes. However, none of these approaches take into account the effectiveness of maintenance actions that has emerged as a source of variability in dynamic environment like SI.

2.3. Maintenance Actions Predictions

In the past, it was very difficult to predict equipment failures due to the unavailability of fault detection and classification (FDC) and maintenance data; however, today its availability with artificial intelligence (AI) techniques has enabled the failure prediction. There are several PdM based maintenance approaches proposed in recent papers for the SI e.g. classification methods (Baly & Hajj, 2012), filtering and prediction approaches (Susto, Beghi, and DeLuca, 2011); (Schirru, Pampuri, and DeNicolao, 2010) and regression methods (Hsieh, Cheng, Huang, Wang, and Wang, 2013); (Susto, Pampurin, Schirru, and Beghi, 2012). An innovative approach, integrated failure prediction (Susto, McLoone, Pagano, Schirru, Pampuri, and Beghi, 2013), is presented with the hypothesis that the data collected is based on full maintenance cycle runs in compliance with runs to failure policy. Here, the objective is to capture the evolution of failures from initial safe conditions. However, this approach does not take into account the influence of parent-child relation between different equipment modules and suggest to model failure evolution for each module. It is also adapted from support vector machine (SVM) technique, a very well know classification method in machine learning (ML). Not all the equipment monitoring parameters are relevant in predicting a specific failure; hence, different approaches are used for the combination of relevant parameters e.g. discriminated analysis to get linear combination of parameters (Gertsbakh, 1977). Similarly, a linear combination function of parameters with the maximum contribution to the tool condition can also be found with principal component analysis (PCA) or singular value decomposition (Stamatis, Mathioudakis, and Papailiou, 1992). The predictive CBM needs accurate model for equipment failure predictions. The most commonly used techniques are AI and ML based predictive CBM with different types of data; however, none of them use effectiveness of maintenance actions as criteria for prediction.

2.4. Human Factor in Maintenance

This paper highlights the importance of such factors to implement an effective predictive maintenance process. There are few studies that use effectiveness of actions in the equipment maintenance. Trucco, Cagno, Ruggeri, and Grande (2007) focus more on risk analysis associated to human and organizational factors and in their study used a fault tree analysis (FTA) with BN model. In this framework, Léger, Weber, Levrat, Duval, Farret, and Iung (2009) also proposed a methodology to integrate operator and human actions for probabilistic risk assessment. Medina-Oliva et al. (2013) takes into account the notion of human effectiveness. They propose a probabilistic relational model (PRM) to integrate maintenance system interactions with enabling system, and impact of maintenance strategies and human effectiveness on production line performance.

Our approach is different as we focus on detecting poorly executed maintenance actions and predicting their consequences on the product quality and equipment, as feedback to technicians. It provides an opportunity for continuous improvement. This approach also offers dynamic unification of maintenance knowledge as well as a source to renew knowledge of maintenance experts. The BN is taken as the target modeling method due to its structural ability for causality. This study is based on hypothesis that ineffective maintenance actions is one of the reason for decreasing unscheduled equipment breakdowns in the SI, challenged with high-mix low-volume production. The next section will detail our proposal approach.

3. PROPOSED METHODOLOGY

The proposed 3-step methodology is presented in Figure 3 below. In this methodology, step-1 corresponds to the criteria and consequence definition for maintenance actions, depending on the effectiveness of human by maintenance experts. The checklists for the target equipment and maintenance type are modified to capture information on the extent to which the associated objectives are fulfilled. The initial BN between maintenance functions, objectives, criteria, failure modes, effects and causes is developed using experts' knowledge from FMECA. Moreover, updated checklists are deployed on the production line to capture qualitative and quantitative information as evidence to evaluate the believed causality by experts. The BN is then learned from this collected data with supervised learning in step-2. This is compared with the knowledge based BN and any structural changes found are fed to step-1 for knowledge unification and renewal in the FMECA. The learned BN is continuously updated with the new evidence collected from the production line and is fully capable to detect and notify not only the effect of product mix, but also feedback to the technicians as potential consequences.



Figure 3. Proposed three-step methodology

3.1. Including Human Factors with Proposed Extension in FMECA (Step-1)

The FMEA approach was initially conceived by US military (MIL-18372) to find failure modes of system components,

evaluate effects and propose counter measures. The formal description of FMEA is given by the New York Academy of Sciences (Coutinho, 1964). This was further extended as the FMECA by NASA to ensure desired reliability of the space systems (Jordan, 1972). There are different diversifications of this approach (Reifer, 1979) as software failure mode and effects analysis (SWFMEA), design FMEA, process FMEA and system or concept FMEA etc. The traditional 5-step FMECA process is presented in Figure 4, below.



Figure 4. Proposed FMECA with objectives and criteria

It starts with clear description of the scope e.g. maintenance type (preventive maintenance) followed by important functions identification for further analysis (step-1) by experts. The potential failure modes, effects and causes are listed along with occurrences, severity and detection (step-2). We propose the inclusion of objectives and criteria definition for each identified function and inclusion of criteria levels while calculating risk priority number (RPN). The severity, occurrence and detection are multiplied followed by division with criteria level for RPN (step-3). It is because RPN decreases if a criterion linked to the defined objectives is fulfilled at highest criteria level, a.k.a. objective fulfillment index (OFI). The RPN is assigned with threshold that triggers the priority to select failure modes for operational fixes (step4). The results are finally evaluated and reviewed (step-5). This 5-step process is repeated until RPN number falls below the threshold.

The proposed approach is implemented and tested in one of the eight workshops (dielectric DIEL) in SI production line. In this production area, a thin film of electrical insulation is deposited on the wafers. These layers serve to insulate different zones with transistors and interconnections. This deposition is completed with chemical vapor deposition (CVD) process using plasma technology at temperature < 400°C to avoid structural changes in previous layers. This workshop is one of the critical workshops in SI production line and is often turn into bottleneck with reduced production capacities and increasing unscheduled equipment breakdowns. Hence, the role of effective maintenance actions becomes critical. The DIEL equipments use multiple recipes and chemical gases due to high-mix low-volume production that destabilizes the equipment. The FMECA analysis is done on all equipment by experts for each type of maintenance. In this case study, we have selected PM-FMECA in DIEL workshop to clean process chamber, for the purpose of demonstration. Each FMECA is then translated into checklist that comprises a sequence of maintenance actions. The key functions in this PM are equipment and personal security, ventilation of the process chamber, dismantling foreline, leak test with helium etc. We present FMECA analysis for PM procedure to clean process chamber (Figure 5). In this analyses, we presented only normalized RPN* is computed with and without OFI that clearly reflects the decrease in the associated risk due to human actions effectiveness (Figure 6). In this figure, failure modes are plotted along x-axis and normalized RPN* on y-axis for confidentiality reason. The three functions in FMECA analysis are associated to an objective, whereas each objective is linked with multiple fulfillment criteria and levels to capture the effectiveness of maintenance actions. The criteria are defined at chamber or equipment

	Title : PM procedure for cleaning Process chamber> Actual Risk (FMECA Analyses)																									
Function	Objective	Cri	teria Definition	Criteria Levels	Potential Failure Mode	Potential Effects of Failure	Potential Cause/ Mechanism of Failure	Current Controls Prevention	Current Controls Detection	(S) SEV	00 000	(D) DET	OFI	Current RPN = (S*O*D)	Knowledge based RPN = (S*O*D) / OFI											
nt Security	nst mishandling	el	Sequence of checklist actions is respected	No=1, Yes=2	Actions execution order is mixed based on the experience of technician	Contamination of process chamber	Technicians are not provided with the feedback of consequences of random execution of actions	Trainings and certifications	No detection	8	7	6	2	336	168											
and Equipme	of machine agai	Equipment Lev	Only the screen described in the procedure are used	No=1, Yes=2	Prescribed screen is not conculted during the maintenance operation	Contamination of equipment	Technicians prefer their expeirence then using prescribed actions as FMECA and respective checklists are considered static	No control for prevention	No detection	6	7	5	2	210	105											
Personal	Protection (Action on the equipment is carried out without training and certification'	No=1, Yes=2	Some maintenance actions are executed without training and certification	Risk to damage equipment due to poorly executed actions	Urgence, lack of trained maintenance professionals or undermining the importance of formal training and need	Trainings and certifications	No detection	9	7	7	2	441	221											
							<i>(a)</i>																			
			plasma?	On=1, Off=2	Plasma ON	defectivity	RF on	see prevetion for RF on	alarm equipement alarm E-star	7	3	1	2	21	11											
			backstreaming?	Yes=1, No=2		defectivity/abort	TV regulation problem	see prevention for PTV regulation pb	alarm equipement alarm E-star	8	3	1	2	24	12											
	off plasma by products	r Level	Chamber at right temperature?	ight >80°C =1, = 80°C =2, <80°C = 3	Backstreaming	defectivity/abort	Wrong TV opening set up	hardware capability respect	alarm equipement alarm E-star	9	1	2	3	18	6											
		ambe	Flush with He?	No=1, Yes=2	Chamber too cold		Step time too long	Recipe creation	Infilm	9	4	1	2	36	18											
Purge		с,	Chamber pressure?	<7torr=1, =7torr=3, >7torr=2		deposition rate HS	He flow too high	Recipe creation	Infilm	7	3	1	2	21	11											
Не	Switch Evacuat		Chamber SCCM settings?	<2000sccm=1, =2000sccm=3, >2000sccm=2	No flush with neutral gaz	defectivity/abort	MFC failure	see prevetion for MFC failure	alarm equipement alarm E-star	2	4	2	3	16	5											
		tLevel	RF?	On=1, Off=2	RF ON	abort	communication failure, bug soft	NA	alarm equipement alarm E-star	4	3	2	2	24	12											
		Equipmen	Equipment	Mass flow controller (MFC) failure?	Yes=1, No=2	MFC failure	Flow not at setpoint	Communication or hardware issue	MFC calibration after PM	alarm equipement alarm E-star	7	4	2	2	56	28										
							<i>(b)</i>																			
	umbe	Chamber Level				defectivity	pumping step too long	NA	Infilm	8	2	2		32												
	ng (chei		Chamber Level	oer Level	ber Level	ber Level	ber Level	ber Level	ber Level	ber Level	ber Level	ber Level	ber Level	Back streaming?	Yes=1, No=2	Backstreaming	defectivity/abort	TV regulation problem	see prevention for PTV regulation pb	alarm equipement alarm E-star	7	3	1	2	21	16
tion.	utgazi													ber L	ber L	ber L	ber L	ber Le				defectivity/abort	Wrong TV opening set up	hardware capability respect	alarm equipement alarm E-star	9
ventilat	sidual or			Purge all gas lines	Yes=2, No=1	Gas lines not purged	Residues in gas line	Base pressure too high	NA	alarm equipement alarm E-star	8	4	1	2	32	16										
hamber	s and re: lin		PTV regulation problem?	Yes=2, No=1	PTV regulation pb	Residues in gas line	Communication or hardware issue	PTV replaced during PM	alarm equipement alarm E-star	7	3	1	2	21	11											
D	Purge all gaz line:	Equipment Leve	Pump failure?	No=2, Yes=1	Pump failure	Pressure not at setpoint / equipment abort	Communication or hardware issue	Pump replaced in PM	Supervision available for pump & abatement support to detect / alarm equipement alarm E-star	9	4	1	2	36	18											

(c)

Figure 5. FMECA analysis on PM procedure to clean process chamber

three functions (*i*) personal and equipment security (Figure 5a), (*ii*) HE (helium) purge (Figure 5b) and (*iii*) process chamber ventilation due to space limitations (Figure 5c). However, the severity, occurrence and detection values have been changed due to confidentiality.

The objectives (functions), criteria definition and criteria levels are the columns added in addition to traditional FMECA columns, by the experts. The defined criteria levels (1 to 3) are the objective fulfillment indices (OFI) which are judged and responded by technicians during PM. The

levels, where applicable. It can be observed that, for the PM procedure under discussion, detection is already optimized with strong preventive controls where risk values, range from 1-2 and 1-4, respectively, for functions 2 and 3 (see Figure 6).

However, these are quite high for function 1. It is because, this function depends on the effectiveness of maintenance actions performed by technicians. The proposed approach enables us to reduce the risk associated with human factor for all maintenance action in a given maintenance

^{*} The RPN values are normalized for confidentiality purposes.

procedure. The benchmarked target RPN* with OFI are modest, whereas effective RPN* with OFI actually achieved in the case study are highly significant and result in optimizing the production capacities due to unscheduled equipment breakdowns (see section 4).



Figure 6. Comparison of normalized RPN* and RPN*/OFI

FMECA is very effective in collecting experts' knowledge and risk quantification; however, its static nature cannot predict in real time the failure modes and their effects on the equipment and products. For this reason, Bayesian network modeling approach is selected as the target method due to its inherent abilities to model causal relations between variables from FMECA (Garcia & Gilbert, 2011). The effectiveness of FMECA structure to build causal nets like Bayesian network is also demonstrated by (Lee, 2001) and (Weber, Suhner, and Iung, 2001). The BN is an artificial intelligence (AI) technique for probabilistic reasoning under uncertainty (Kjærulff & Madsen, 2006); (Jensen and Nielsen, 2007); (Pourret, Naïm, and Marcot, 2008). Bayesian networks are institutive approach for modeling human like decision-making problem with probabilistic reasoning under uncertainty. The Bayesian network (graph) comprises of the nodes (random variables) and directed edges (links, arcs) between nodes. The directed edges represent the influence of nodes in the network.

The conditional probabilities computed from the input data corresponds to the quantitative part of the Bayesian model. The structure of the Bayesian network (graph) is the qualitative model that represents causal dependence and inter-dependence between variables. The name "Bayesian" is conceived from Mr. Thomas Bayes' surname (Peter, 2012), who proposed formulae to compute conditional probabilities (a.k.a. Bayes theorem) (equation 3.1). The formalism is read as probability of an event A knowing the evidence on the occurrence of event C and is also referred as "Bayes condition".

$$P(A \mid C) = \frac{P(A, C)}{P(C)} = \frac{P(C \mid A)P(A)}{P(C)}$$
 3.1

In the BN, prior probabilities are provided in the absence of evidence, whereas conditional probabilities are dynamically updated with new information as input to a network, a.k.a. a posteriori probabilities. For n variables, 2n-1 joint probabilities result in huge numbers; however, resulting Bayesian network encodes knowledge so that key and less important information is easily identified (Pearl, 2000). The Bayesian network is developed with minimum computations and is easy to understand (Kjærulff & Madsen, 2006). It is an efficient method, because of inherent assumption of interdependence about variables; hence, it requires expert intervention for the definition of the structure (directed edges).

The advantages of using Bayesian network is its inherent ability to deduce the inter-causal reasoning (Kjærulff & Madsen, 2006). The Bayesian network is gaining popularity due to its graphical structure with probabilistic networks to express causal interactions and direct/indirect relations. The notion of causality empowers Bayesian network with the human like reasoning under uncertainty. The ability of the Bayesian networks to handle causal independence, results in efficient inference even with large number of variables. They have superiority over rule based systems (RBS) due to their capabilities for deductive, abductive and inter causal reasoning. The Bayesian network is an interesting choice for statistical modeling due to its efficient learning and inference algorithms (Zou & Bhanu, 2005).



Figure 7. Experts' knowledge based BN model

Initial BN model is developed based on experts' knowledge from FMECA file. The data collected to build initial BN, presented in Figure 7, are three principle PM objectives, the criteria to fill each objective, failure modes and their effects on equipment and products. As per proposed methodology (Figure 2), this static knowledge based BN structure will be compared with the learned BN model using data collected from the production line maintenance operations. The expert knowledge based BN model is divided into four classes of nodes with different colors as maintenance objectives (red), criteria (orange), failure modes (green) and effects (SandyBrown). It is based on the a priori probabilities which are computed from severity, occurrence and detection values, and the prior from experts. In this BN model, solid nodes are discrete variables whereas dotted nodes e.g. chamber temperature, SCCM (see figure 6-b) and pressure are continuous variables which are discretized. The direction of the associations is drawn as per knowledge from FMECA. This BN is implemented using Bayesialab 5.0 and for demonstration purposes the chamber pressure node is set as the target variable for interactive inference, as presented in Figure 8. This figure contains an example to exploit the experts knowledge modeled as a static BN model.

The Figure 8a predicts potential failure modes for a given set of values for objective and criteria nodes. It shows that, in the presence of backstreaming, pressure <7.5 Torrs, temperature <80, and SCCM between 1500 and 2001, the likely failure modes are cold chamber, backstreaming error and RF errors. Similarly, figure 8b presents that, for the same criteria and objective settings, likely effects are defectivity, abort and high deposition rate. The experts can interactively change the probabilities to analyze the knowledge discovery by this static BN model. Moreover, this model is based on initial experts judgment and do not take into account the effect of changing equipment behaviors due to changing high-mix of products. In next section, we learn this BN from the data collected across the production line in DIEL workshop.



Figure 8. Experts' knowledge based BN model

3.2. BN Model for Effectiveness of Maintenance Actions and Analyses Results (Step-2)

The PM checklist modified form the revised FMECA (Figure 6). It is approved and deployed on the production line as a pilot case study for four months prior. In this period, revised PM checklist is executed 223 times on 15 equipments in the DIEL workshop. The historic data of maintenance checklist executions, equipment states and parameters such as RF, pressure and chamber temperature, and product measurements like defectivity and deposition rate are collected to learn new model. In order to learn new BN structure using these data, three unsupervised learning algorithms (EO, Taboo and Taboo order) were used working on a set of heuristics to reduce the search space. The objective function used in these algorithms is the minimum description length (MDL). It takes into account "correlation" plus structural complexity of the causal network and establishes "automatic significance thresholds" (Rissanen, 1978); (Bouckaert, 1993). These algorithms result not only in the network, but also in the associated conditional probabilities. The MDL score is used as a criteria to select the lowest score network.

The equivalence class (EQ) is an efficient algorithm for structural learning as it significantly reduces search space. It is based on the assumption that two BN structures are said to be equivalent if the set of distributions that can be represented with one of those structures are identical to the set of distributions that can be represented with the other (Chickering, 2002); (Munteanu & Bendou, 2001). The Taboo search algorithm is useful in refining the network based on a given structure; hence, it gives better results when initial structure is developed with experts' knowledge or using some other unsupervised learning algorithm. This algorithm also has the capability to learn network from scratch but in this case, it is less efficient than EQ. Therefore, we use it in combination with EQ where EQ provides an initial structure followed by Taboo to improve it based on the MDL score. Taboo order (Teyssier & Koller, 2005) is an exhaustive search algorithm that offers more accurate results, but takes more time than simple Taboo search. This method searches the space in the order of Bayesian network nodes by choosing parents of a node between nodes appearing before it, in the considered order.

The learned network serves as a reference network and is cross validated using 50 randomly generated datasets, based on the distribution of responses collected through survey from employees with added noise. As a result, we retain the network with best fit. The threshold in our case is 75%. The learned BN along with its contingency fit are presented in Figures 9a and 9b. The learned BN using unsupervised learning in Bayesialab is presented below in Figure 9. The dataset is divided into randomly selected 75 and 25% rows for learning and testing. The contingency fit is observed to be 77 and 72%, respectively. The threshold of 75% is used as a criteria to accept the model.



Figure 9. BN learned from Data using unsupervised learning

3.3. Knowledge Discovery: (Step-3)

The structural difference in experts' knowledge (Figure 7) and learned (Figure 9a) BN models is presented below in Figure 10. The learned BN model shows new knowledge as new arcs from potential failures to causes. It must be noticed that the checklist flow execution error/failure in the BN model learned from production line data results in chamber and equipment contaminations. The plasma and backstream error are found to be correlated with defectivity. It is important to note that while learning BN model from data, certain arcs were forbidden. e.g. arcs from criteria, failure modes and effects are not allowed to loopback towards objectives. Similarly, the arcs from failure modes and effects towards criteria are also not allowed. The color of each node in this new BN model corresponds to its respective class (objectives, criteria, failure modes, effects).



Figure 10. Structural difference in BN models and knowledge discovery





Figure 11. Learned BN model for knowledge exploitation and feedback to technicians

The newly learned BN model based on data collected from production line is set to similar test settings as presented in Figures 8a and 8b, above. Figure 11a predicts plasma error, backstreaming, cold chamber, MFC and RFC failures against backstreaming and cold chamber as identified by static BN model for the same objective and criteria settings. Figure 11b predicts defectivity, abort, flow setpoint issue and high deposition rate as potential effects against abort, defectivity, and high deposition rate. The new knowledge generated from this learned BN models (Figure 10) serves dual purpose as it provides continuous renewal of experts' knowledge and updates FMECA. This BN model also generates feedback with predictions on likely failure modes and effects based on the level of fulfillment of defined criteria.

4. CONCLUSIONS, DISCUSSION AND PERSPECTIVES

The new BN model was deployed on the production line to provide feedback to technicians during maintenance, on potential failure modes and effects, if the expected criteria level is not reached. The data collected on failure occurrence and normalized RPN* upon subsequent deployment of this methodology, over a four months experiment, is presented in Figures 12a and 12b. RPN* has greatly decreased because the said BN model has improved not only detection, but also reduced failing actions occurrences by providing feedback to technicians.





(b)

Figure 12. Impact of proposed BN based methodology on risk and failure occurrences

The proposed methodology demonstrates that effectiveness of maintenance actions by technicians has a strong impact on the subsequent risk, failure occurrences and ultimately on the equipment unscheduled breakdowns. This study has also concluded that providing feedback to maintenance personals on the consequences of their actions improves failure occurrences that have direct impact on the production capacities. It also highlights the need to renew experts' knowledge with high-mix low-volume impacting the equipment behaviors.

There remain some open ended issues e.g. what is the learning time or excursion frequency, before the BN model predictions and structural changes are used to renew experts and FMECA knowledge? Similarly, it should be interesting to introduce a multi-agent based technology to share the knowledge, captured through BN model on one equipment, for other similar equipments in the same workshop. We still need to find an answer that the proposed BN model should be developed at an equipment level or one generic model for all the equipments in a production line would be efficient. These questions are presently investigated by the authors.

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REFERENCES

- Aissani, N., Beldjilali, B., & Trentesaux, D. (2009). Dynamic Scheduling of Maintenance Task in the Petroleum Industry: A reinforcement approach. Engineering Applications of Artificial Intelligence, vol. 22, pp. 1089-1103. doi: 0.1016/j.engappai.2009.01.014
- Baly, R., & Hajj, H. (2012). Wafer Classification Using Support Vector Machines. *IEEE Transactions on Semiconductor Manufacturing*, vol. 25(3), pp. 373-383.
- Ballhaus, W., Pagella, A., & Vogel, C. (2009). A change of pace for the semiconductor industry. Germany, Technology, Media and Telecommunications. Retrieved from <u>http://maltiel-</u> <u>consulting.com/Semiconductor Industry After Econo</u> <u>mic_Upheaval_maltiel_semiconductor.pdf</u>
- Bouaziz, M. F., Zamaï, E., & Hubac, S. (2012). Modélisation de l'état de santé d'un équipement de fabrication par une méthode probabiliste. *Proceedings* of 9th International Conference on Modeling, Optimization and SIMulation.
- Bouckaert, R. R., (1993). Probabilistic Network Construction Using The Minimum Description Length Principle. In Lecture Notes in Computer Science, vol. 747, pp. 41-48.
- Chickering, D. M., (2002). Learning Equivalence Classes of Bayesian-Network Structures. *Journal of Machine Learning Research*, vol. 2, pp. 445-498.

- Coutinho, J. S., (1964). Failure effect analysis. Trans. *New York Academy. Sci.*, vol. 26(II), pp. 564–584.
- Dale, F., (2012). Intel's semiconductor market share surges to more than 10-year high in 2011, March 2012.
- Efthymiou, K., Papakostas, N., Mourtzis, D., & Ghyryssolouris, G. (2012), On a Predictive Maintenance Platform for Production Systems. *Proceedings of CIRP conference on manufacturing systems*, pp. 221-226.
- Gertsbakh I. B., (1977). *Models of preventive maintenance. Amsterdam*, The Netherlands: North-Holland Pub. Co
- Garcia, A., & Gilabert, E. (2011). Mapping FMEA into Bayesian Netoworks. *International Journal of Performability Engineering*, vol. 7(6), pp. 525-537.
- Hubac, S., & Zamai, E. (2013). Politiques de Maintenance Equipement en Flux de Production Stressant -Equipment Maintenance Policy in Stressed Manufacturing Flow (Technology or Product). Edition TI (Technique de l'ingenieur) [AG 3535].
- Hsieh, Y. S., Cheng, F. T., Huang, H. C., Wang, C. R., Wang, S. C., & Yang, H. C. (2013). Vm-based Baseline Predictive Maintenance Scheme. *IEEE Transactions on Semiconductor Manufacturing*, vol. 26, pp. 132-144.
- Jensen, F. V., & Nielsen, T. D. (2007). *Bayesian Networks* and *Decision Graphs*. Second Edition, New York, USA: Springer Verlag
- Jordan, W. E., (1972). Failure modes, effects and criticality analyses. *In Proc. Annu. Reliability Maintainability Symp.*, pp 30-37.
- Kjærulff, U. B., & Madsen, A. L. (2006), Probabilistic Networks for Practitioners - A Guide to Construction and Analysis of Bayesian Networks and Influence Diagrams. Department of Computer Science, Aalborg University, HUGIN Expert A/S
- Krishnamurthy, L., Adler, R., Buonadonna, P., Chhabra, J., Flanigan, M., Kushalnagar, N., Nachman, L., & Yarvis, M. (2005). Design and deployment of industrial sensor networks: Experiences from a semiconductor plant and the north sea. *Proceedings of the 3rd international conference on Embedded networked sensor systems*, November 02-04, San Diego, California, USA
- Lee, B., (2001). Using Bayes Belief Networks in Industrial FMEA Modelling and Analysis. In Proc. Annual RELIABILITY and MAINTAINABILITY Symposium. vol. 15(4), pp. 281-293.
- Léger, A., Weber, P., Levrat, E., Duval, C., Farret, R., & Iung, B. (2009). Methodological Developments for Probabilistic Risk Analyses of Socio-Technical Systems. *Journal of Risk and Reliability*, vol. 223, pp. 313-332.
- Medina-Oliva, G., & Weber, P. (2013). PRM-based patterns for Knowledge Formalization of Industrial Systems to Support Maintenance Strategies Assessment. *Reliability Engineering and system Safety*, vol. 116, pp. 38-56.
- Mili, A., Bassetto, S., Siadat, A., & Tollenaere, M. (2009). Dynamic Risk Management Unveil Productivity

Improvements. Journal of Loss Prevention in the Process Industries, vol. 22, pp. 25-34.

- Munteanu, P., & Bendou, M. (2001). The EQ Framework for Learning Equivalence Classes of Bayesian Networks. *First IEEE International Conference on Data Mining (IEEE ICDM)*, San José
- Pearl, J., (2000). Causality: Models, Reasoning and Inference. New York, USA: Cambridge University Press, vol. 19, pp. 675-685.
- Peter, M. L., (2012). *Bayesian Statistics: An Introduction*. Wiley & Sons, Inc
- Pourret, O., Naïm, P., & Marcot, B. (2008). Bayesian Networks: A Practical Guide to Applications. Chichester, England: John Wiley & Sons, Inc
- Reifer, D. J., (1979). Software Failure Modes and Effects Analysis. *IEEE Transactions on Reliability*, vol. 28(3), pp. 247-249.
- Rissanen, J., (1978). Modeling by Shortest Data Description. *Automatica*, vol. 14(5), pp. 465-658. doi:10.1016/0005-1098(78)90005-5
- Schirru, A., Pampuri, S., & DeNicolao, G. (2010). Particle filtering of hidden gamma processes for robust predictive maintenance in semiconductor manufacturing. *Proceedings of* 6^{th} *IEEE CASE*.
- Shahzad, M. K., Hubac, S., Siadat, A., & Tollenaere, M. (2011). An Extended Business Model to Ensure Timeto-Quality in Semiconductor Manufacturing Industry. *International Conference on Enterprise Information* Systems. Portugal
- Shahzad, M. K., Tollenaere, M., Hubac, S., & Siadat, A. (2011). Extension des Methodes DFM pour l'industrialisation de produits microelectroniques. 9^e Congrès International de Genie Industriel. Montréal, Canada
- Stamatis, A., Mathioudakis, K., & Papailiou, K. (1992). Optimal Measurement and Health Index Selection For Gas Turbine Performance Status and Fault Diagnosis. *Journal of Engineering for Gas Turbines and Power*, vol. 114, pp. 209-216.
- Stamford, C., (2012). Market share analysis: Total semiconductor revenue, worldwide, April 2012. http://www.gartner.com/newsroom/id/2405215
- Susto, G., Beghi, A. & DeLuca, C. (2011). A predictive maintenance system for silicon epitaxial deposition. *Proceedings of IEEE Conference on Automation Science and Engineering (CASE)*, pp. 262–267.
- Susto, G., Pampuri, S., Schirru, A., & Beghi, A. (2012). Optimal tuning of epitaxy pyrometers. Proceedings of 23rd IEEE/SEMI Advanced Semiconductor Manufacturing Conference, pp. 294-299.
- Susto, G. A., McLoone, S., Pagano, D., Schirru, A., Pampuri, S., & Beghi, A.(2013). Prediction of Integral Type Failures in Semiconductor Manufacturing through Classification Methods. *Proceedings of IEEE 18th Conference on Emerging Technologies & Factory Automation* (ETFA).

- Teyssier, M., & Koller, D. (2005). Ordering-based search: A simple and effective algorithm for learning Bayesian networks. Proceedings of 21st Conference on Uncertainty in AI (UAI). pp. 584-590.
- Trucco, P., Cagno, E., Ruggeri, F., & Grande, O. (2008). A Bayesian Belief Network Modeling of Organizational Factor in Risk Analysis: A Case Study in Maritime Transportation. Reliability Engineering and system Safety, vol. 93, pp. 823-834.
- Vassilis, K., Vassilis, P., & Christos, E. (2013). A Bayesian Approach for Maintenance Action Recommendation. International Journal of Prognostics and Health Management, ISSN 2153-2648, 2013 034
- Weber, P., & Jouffe, L. (2006), Complex System Reliability Modeling with Dynamic Object Oriented Bayesian Networks (DOOBN). Reliability Engineering and system Safety, vol. 91, pp. 149-162.
- Weber, P., Suhner, M. C., & Iung, B. (2001). System approach-based Bayesian Network to Aid Maintenance of manufacturing process. Proceedings of 6^{th} IFAC Symposium on Cost Oriented Automation, Low Cost Automation. October 8-9, Berlin, Germany
- Weild, G., Madsen, A. L., & Israelson, S. (2005). Application of Object-Oriented Bayesian Networks for Condition Monitoring, Root Cause Analysis and Decision Support on Operation of Complex Continuous Process. Computer and Chemical Engineering, vol. 29, pp. 1996-2009.
- Yang, L., & Lee, J. (2012). Bayesian Belief Network-based Approach for Diagnostics and Prognostics of Manufacturing. **Robotics** and Semiconductor Computer-Integrated Manufacturing, vol. 28, pp. 66-74.
- Zou, X., & Bhanu, B. (2005). Tracking Humans using Multi-modal Fusion. Proceedings of Computer Society Conference on Computer Vision and Pattern Recognition (CVPRW'05). San Diego, California, USA

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A Particle Filtering-Based Approach for the Prediction of the Remaining Useful Life of an Aluminum Electrolytic Capacitor

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ABSTRACT

This work focuses on the estimation of the Remaining Useful Life (RUL) of aluminum electrolytic capacitors used in electrical automotive drives under variable and nonstationary operative conditions. The main cause of the capacitor degradation is the vaporization of the electrolyte due to a chemical reaction. Capacitor degradation can be monitored by observing the capacitor Equivalent Series Resistance (ESR) whose measurement, however, is heavily influenced by the measurement temperature, which, under non-stationary operative conditions, is continuously changing. In this work, we introduce a novel degradation indicator which is independent from the measurement temperature and, thus, can be used for real applications under variable operative conditions. The indicator is defined by the ratio between the ESR measured on the degraded capacitor and the ESR expected value on a new capacitor at the present operational temperature. The definition of this indicator has required the investigation of the relationship between ESR and temperature on a new capacitor by means of experimental laboratory tests. The prediction of the capacitor degradation and its failure time has been performed by resorting to a Particle Filtering-based prognostic technique.

1. INTRODUCTION

The aluminium electrolytic capacitor is one of the most critical components of electric systems, leading to almost 30% of the total number of failures in such systems Marco Rigamonti et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

(Wolfgang, 2007). Its main failure mode is caused by the vaporization of the contained electrolyte, which involves a loss of functionality, and produces a reduction of the capacity and an increase of the Equivalent Series Resistance (ESR) of the component: for this reason, the ESR is typically used as degradation indicator. This degradation mechanism is driven by the temperature experienced by the component: higher the temperature, faster the degradation. Generally the failure threshold of the capacitor is defined as the double of the initial ESR value, and a physical model of the ESR evolution has been proposed for capacitors working at constant temperature (Perisse et al., 2006, Abdennadher et al., 2010, Gasperi, 1996).

In this work, we consider capacitors used in Fully Electrical Vehicles (FEVs), which are characterized by continuously changing operative conditions, also of temperature, so that the measured value of the capacitor ESR is continuously changing. Thus, we propose a new degradation index for the electrolytic capacitor, which is based on the ratio between the ESR measured on the degraded capacitor and the ESR expected value on a new capacitor at the present operational temperature. Its computation has required to perform a series of laboratory experiments for the identification of the relationship between the ESR and the temperature in a new capacitor. The main advantage of this new degradation index is that it is independent from the measurement temperature and, thus, can be used for real applications under variable operative conditions. The physical degradation model and the novel proposed degradation index have been exploited for the prediction of the RUL of a capacitor under non-stationary operative conditions by means of a particle filtering algorithm.

The remaining part of the report is organized as follows: in Section 2 the capacitor degradation model is presented; Section 3 shows the particle filtering model for the RUL estimation; in Section 4, the experimental test setup for the parameters estimation and the obtained results are presented; in Section 5 the developed methodology is applied to a case study; finally, in Section 6 some conclusions and remarks are drawn.

2. CAPACITOR DEGRADATION MODEL

The aluminum electrolytic capacitor is one of the most critical components of electric systems: thus, its failure modes and degradation mechanisms have been deeply investigated in literature (Perisse et al., 2006, Abdennadher et al., 2010, Ma & Wang, 2005, Gasperi, 1996, Celaya et al., 2011). In particular, in Abdennadher et al. (2010) a physical model describing the evolution of the health state of the component is presented.

2.1. Degradation indicator

The degradation of the capacitor is mainly due to the chemical reactions occurring inside the component, which cause the vaporization of the contained electrolyte, leading to a loss of functionality. Component degradation can be identified by monitoring the ESR: higher the degradation, higher the measured ESR value.

2.2. ESR evolution equation

According to Abdennadher et al. (2010), the ESR for a capacitor aging at constant temperature T^{ag} is given by:

$$ESR(t, T^{ag}) = ESR_0(T^{ag})e^{C(T^{ag})t}$$
(1)

where $ESR_0(T^{ag})$ represents the initial ESR value of the capacitor at temperature T^{ag} , *t* the age of the capacitor and $C(T^{ag})$ a temperature-dependent coefficient which defines the degradation speed of the capacitor. In particular, the temperature coefficient $C(T^{ag})$ can be expressed as:

$$C(T^{ag}) = \frac{\ln 2}{\underset{k}{\text{Life}_{nom}(T_{nom})\exp[\frac{E_a}{k}\frac{(T_{nom}-T^{ag})}{T_{nom}\cdot T^{ag}}]}}$$
(2)

where $Life_{nom}$ represents the nominal life of the capacitor aged at the constant nominal temperature (T_{nom}), and the temperatures are expressed in Kelvin degrees. A detailed description of the semi-empirical procedure adopted for the definition of the macro-level physical model of Eqs. (1) and (2) can be found in Perisse et al. (2006).

It has to be emphasized that the measured ESR value depends on the measurement temperature: this means that if we measure the ESR value on the same degraded capacitor at a temperature T^{me} different from that at which the capacitor is degrading (T^{ag}), the measured value of ESR will be different. The relationship between the initial ESR for a

new capacitor and the ESR measurements temperature T^{me} for a new capacitor is (Abdennadher et al., 2010):

$$ESR(0, T^{me}) = ESR_0(T^{me}) = \alpha + \beta e^{-T^{me}/\gamma}$$
(3)

where α , β and γ are parameters characteristics of the capacitor.

3. A PF APPROACH FOR RUL ESTIMATION

Unfortunately, the relationship defining the influence of the measurement temperature T^{me} on the ESR for a degraded capacitor is unknown. Thus, since the FEV capacitor typically works at variable temperatures, the ESR cannot be directly used as degradation indicator for a capacitor experiencing different operational conditions such as those of FEV. For this reason, in order to define a degradation indicator which is independent from the temperature, in the present work we introduce a new degradation indicator defined by the ratio between the ESR measured at temperature T^{me} and its initial value at the same temperature T^{me} :

$$ESR_{norm}(t) = ESR(t, T^{me}) / ESR_0(T^{me})$$
(4)

where $ESR_0(T^{me})$ is computed by using Eq. (3). Notice that, according to this new degradation indicator, if we consider a degraded capacitor and we measure its ESR value at different temperature, we obtain exactly the same ESR_{norm} value, which is independent from the temperature of the measurement and it expressed as a percentage. The failure threshold, i.e. a value of ESR_{norm} such that if it is exceeded the capacitor is considered failed, is set equal to $ESR_{norm} =$ 200%. The rationale behind this choice is that the failure threshold for any capacitor is typically defined as the double of its initial ESR value (Venet et al., 1993). The new degradation indicator allows overcoming the lack of knowledge on the relationship between the temperature and the measured ESR for a degraded capacitor. Thus, it is now possible to represent the degradation process as a first order Markov Process between time steps t_{k-1} and t_k ; the new degradation equation is, then, defined as:

$$ESR_{norm}(t_{k}) = ESR_{norm}(t_{k-1})e^{C(T_{k-1}^{ag})} + \omega_{k-1}$$
 (5)

where T_{k-1}^{ag} represents the aging temperature at time t_{k-1} and ω_{k-1} models the process noise.

Eq. (5) represents the degradation state evolution and is independent from the measurement temperature T^{ae} . There is only a dependence from the temperature T^{ag} experienced by the capacitor in the coefficient $C(T^{ag})$ defining the speed of degradation, which can be computed by using Eq. (2). The equation linking the measured ESR and *ESR*_{norm} is:

$$\text{ESR}(t_k, T_k^{\text{me}}) = \text{ESR}_{\text{norm}}(t_k) \cdot \left(\alpha + \beta e^{-\frac{T_k^{\text{me}}}{\gamma}}\right) + \eta_k \qquad (6)$$

where T_k^{me} represents the measurement temperature at time t_k and η_k represents the measurement noise.

Figure 1 sketches the PF approach to prognostics based on the following three steps:

- 1. the estimation of the equipment degradation state at the present time based on a sequential Monte Carlo method; the state of the system is defined by the ESR_{norm} value. The PF approach requires the definition of a process equation, which in this case is given by Eq. (5), and a measurement equation, which is given by Eq.(6)
- 2. the prediction of the future evolution of the degradation state by Monte Carlo simulation
- 3. the computation of the equipment RUL.



Figure 1. Sketch of the PF approach to fault prognostics

More details on the application of the PF approach to prognostics can be found in Baraldi et al., (2013).

Notice that we resort to a PF instead that to a classic Kalman Filter framework because in Eq. (5) we cannot express the noise as a Gaussian additive term. In practice, the Gaussian noise, to which the aging temperature T^{ag} is subject, affects the aging coefficient $C(T^{ag})$ (Eq. (2)) and, then, Eq. (5), thus becoming a non Gaussian additive term.

4. PARAMETER ESTIMATION

According to the Particle Filtering model described in Section 3 and used for the RUL prediction, we need the relationship between the initial ESR and the temperature for a new capacitor described by Eq. (3). Since the parameters α , β and γ of Eq. (3) are characteristic of the particular type of capacitor, we have performed experimental tests in order to identify the α , β and γ values for the considered capacitor.

4.1. Experimental Design

We considered a capacitor of the ALS30 series in pristine conditions. ESR measurements have been taken using a FLUKE PM6306 RLC meter directly connected to the capacitor in a Votsch Industrietechnik climatic chamber.

The experimental test procedure has been based on the following three steps:

- Setting of the desired temperature
- Once the stationary conditions are reached in the chamber, the temperature is maintained for 20 minutes in order to allow the internal layers of the capacitor to heat up.
- The ESR is measured at different frequencies, between 10 kHz and 1 MHz.

The procedure has been repeated at different temperatures in the range [12°C, 110°C], which is expected to be experienced by the FEV capacitor. The ESR measurements have been performed at steps of 15° C.

4.2. Results

The obtained experimental laboratory results are shown in Figure 2, where the ESR measurements performed on a new capacitor at different temperatures and frequencies are reported.



Figure 2. Experimental curve describing the variation of the initial ESR value $\text{ESR}_0(\text{T}^{\text{me}})$, in Ohm, at different measurement frequencies

Notice that the ESR at a given temperature tends to increase when the frequency is increased from 10 kHz to 20 kHz, whereas further increasing of the frequency does not modify numerically the ESR measurements. Since the degradation index ESR_{norm} defined in Eq. (4) is based on the ratio between the measured value of ESR and its initial value at the corresponding temperature, the most advantageous choice would be the measurement frequency with the highest associated absolute values of the ESR, which in this case corresponds to the 20 kHz curve. The rationale behind this consideration is that if we assume the same measurement noise, then its influence would be lower for the largest absolute values of the ESR.

Then, by resorting to an exponential regression method we have identified the following values for the experimental parameters α , β and γ :

$$\alpha = 0.0817 \Omega$$
 $\beta = 0.037 \Omega$ $\gamma = 30.682^{\circ}C$ (7)

Notice that these values can be used for modelling the degradation of the tested capacitor (ALS30 Series Electrolytic capacitors from KEMET) and cannot be employed on different types of capacitors.

5. CASE STUDY

In this Section, the application of the method described in Sections 3 and 4 to the degradation process of a capacitor used in a FEV is discussed. Since, at the present time, real ESR data collected on a degrading capacitor operating on a FEV are not available, the developed method has been applied to a numerically simulated capacitor life. Notice that laboratory experiments are being performed at CEIT facilities within the European Project HEMIS (www.hemiseu.org), whose objective is the development of Prognostics and Health Monitoring System (PHMS) for the most critical FEV components. The objective of the tests is to collect data describing the capacitor degradation process in environmental conditions similar to those of a FEV (Celaya et al., 2012).

5.1. Simulation of the temperature profiles experienced by a FEV

Since real data describing the temperature profile experienced by a capacitor in a FEV are currently not available, we have simulated possible temperature profiles. According to the suggestions of motor experts, we have considered that the temperature variations experienced by the capacitor during its life are mainly caused by the variation of the environmental external temperature. The temperature profile simulations are based on the following assumptions:

• the FEV is operating 4000 hours in a year (1000 hours each season);

- the seasonal mean temperatures experienced by the FEV capacitor depend from the season and are: T_{winter}=70°C, T_{spring}=85°C, T_{summer}=95°C, T_{autumn}=80°C;
- in order to take into account temperature oscillations, the real temperature value experienced by the FEV is sampled from a Gaussian distribution with mean value equal to T_{winter} , T_{spring} , T_{summer} , T_{autumn} depending on the season, and standard deviation equal to 2°C for all cases.



Figure 3. Average Temperature Profile

5.2. Simulation of a capacitor life

According to the above assumptions, considering the ALS30 Series electrolytic capacitor, whose nominal life at the nominal aging temperature of 85 °C is reported to be of 20000 hours, we have simulated a capacitor life which will be considered as the "real" degradation trajectory. In practice, starting from the initial value $ESR_{norm}=100\%$, by using Eq. (5) and the simulated temperature profile we have numerically simulated the time evolution of the capacitor degradation (ESR_{norm}) until the failure time, i.e., according to Section 3, the time at which the ESR of the capacitor reaches the double of its initial value. In Eq. (5), the process noise ω_k is due to the intrinsic uncertainty of the physical degradation process, and it is a normally distributed random variable with mean set equal to zero and standard deviation set equal to 2%. Furthermore, we have simulated the values of 7 ESR and T^{me} measurements during the capacitor life (taken every 2500 hours, starting from t=3000 h to t=18000 h). The measured ESR values have been obtained by applying Eq. (6) to the numerically simulated degradation indicator values ESR_{norm}, considering the measurement noise η_k as a normally distributed random variable with mean equal to zero and standard deviation equal to 0.02 Ω . The measurement temperature values T^{me} have been simulated by adding an artificial Gaussian noise ($\mu = 0^{\circ}$ C; $\sigma = 2^{\circ}$ C) to the expected temperature profile shown in Figure 3. Figure 4 shows the simulated values of the considered 7 ESR measurements. The obtained simulated capacitor life will be referred to as the "true" capacitor life, considering the numerically simulated ESR measurements as the real available ESR measurements.



Figure 4. Numerical simulation of the measured ESR value $\text{ESR}(t, T^{\text{me}})$

5.3. Application of the method and results

The prognostic method described in Section 3 has been applied to the simulated capacitor life of Section 5.2 described by the 7 ESR and temperature measurements. The application of the PF method has been done with fixed number of particles equal to 1000; the process noise ω_k and the measurement noise η_k have been sampled from Gaussian distributions characterized by ($\mu = 0\%$; $\sigma = 2\%$) and ($\mu =$ 0Ω ; $\sigma = 0.02\Omega$), respectively. The prognostic method provides a prediction of the RUL in the form of a probability density function.



Figure 5. Evolution of the RUL prediction pdf according to the measurement number

In Figure 5, the real RUL of the component is represented by the solid line. Notice that the range of variability of the predicted RUL is clearly reducing from a large width at the first measurement (t=3000 h) to a narrow width at the last measurement (t=18000 h). This reduction of the RUL uncertainty is due to the acquired knowledge of the degradation provided by the ESR measurements, which allows updating the degradation probability distribution and leads to a more accurate assessment of the component degradation state. This can be clearly observed in Figure 5, where the evolution of the RUL pdf as time passes is shown. It is also interesting to notice in Figure 6 that the expected RUL value (dark solid line) remains close to the true RUL value (black dashed line), indicating the accuracy of the method, and that the true RUL value is always within the 10th and the 90th percentiles of the distribution (light solid lines). It is worth noting that the predicted RUL is closer to the 10th percentile than the 90th percentile: this is due to the fact that the Gaussian measurement noise to which the aging temperature T^{ag} is subject causes a non-symmetric non-gaussian effect on the coefficient $C(T^{ag})$ in Eq. (5).



Figure 6 RUL prediction uncertainty representation

6. CONCLUSION

In this paper, we have addressed the problem of predicting the RUL of an aluminum electrolytic capacitor used in FEVs. Given the non-stationary operative conditions and the varying operational temperature experienced by capacitors in FEVs, we have proposed a new degradation index independent from temperature. The index is defined by the ratio between the ESR measured at temperature T^{me} and its initial value at the same temperature T^{me} . In order to compute the proposed degradation index ESR_{norm} , experimental tests have been expressly designed and performed for the estimation of the parameters of the physical relationship between the temperature and the initial value of the ESR for a new capacitor. Resorting to the ESR physical evolution model, we have then applied a particle filtering framework to predict the capacitor RUL. The obtained results encourage a further development of the method in order to allow its application to the prediction of the RUL of a capacitor operating in FEVs. Once the proposed framework will be completely developed, we intend to compare its performance with respect to different machine learning techniques in order; finally, a sensitivity analysis will be performed for the complete characterization of the proposed method.

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Reference

- Abdennadher, K., Venet, P., Rojat, G., Rétif, J.-M., Rosset, C., (2010). A real-time predictive-maintenance system of aluminum electrolytic capacitors used in uninterrupted power supplies, *IEEE Transactions on Industry Applications 46 (4)*, art. no. 5512800, pp. 1644-1652, 2010.
- Baraldi, P., Cadini, F., Mangili, F., & Zio, E., (2013). Model-based and data-driven prognostics under different available information, *Probabilistic Engineering Mechanics 32*, pp. 66 - 79
- Celaya, J., Kulkarni, C., Biswas, G. & Goebel, K., (2011). A model-based prognostics methodology for electrolytic capacitors based on electrical overstress accelerated aging, *Proceedings of Annual Conference of the PHM Society*, September, pp. 25.
- Celaya, J.R., Kulkarni, C., Saha, S., Biswas, G. & Goebel, K., (2012). Accelerated aging in electrolytic capacitors
for prognostics, *Reliability and Maintainability Symposium (RAMS)*, Proceedings - Annual, pp. 1.

- Gasperi, M. L., (1996). Life prediction model for aluminum electrolytic capacitors, *Conference Record - IAS Annual Meeting* (IEEE Industry Applications Society) 3, pp. 1347-1351.
- Ma, H., & Wang, L., (2005). Fault diagnosis and failure prediction of aluminum electrolytic capacitors in power electronic converters, *Industrial Electronics Society*, IECON 2005, 31st Annual Conference of IEEE, pp. 6.
- Perisse, F., Venet, P., Rojat, G. & Rétif, J.M., (2006). Simple model of an electrolytic capacitor taking into account the temperature and aging time, *Electrical Engineering*, 88 (2), pp. 89-95.
- Venet, P., Darnand, H., & Grellet, G., (1993). Detection of faults of filter capacitors in a converter. Application to predictive maintenance, in *Proc. Int. Telecommun. Energy Conf.*, pp. 229–234.
- Wolfgang, E., (2007). Examples for failures in power electronics systems. ECPE Tutorial on Reliability of Power Electronic Systems.

BIOGRAPHIES



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A Joint Predictive Maintenance and Spare Parts Provisioning Policy for Multi-component Systems Using RUL Prediction and Importance Measure

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ABSTRACT

The paper presents a joint predictive maintenance and spare parts provisioning policy for gradually deteriorating multicomponent systems with complex structure. The decisionmaking process related to maintenance, spare parts ordering, as well as inspections scheduling is based on both RUL prediction and structural importance measure. Moreover, economic dependency between components is studied and integrated in decision rules. In addition, the impacts of the system structure on components deterioration process are also investigated. This dependency may have a significant influence on the RUL estimation of components. In order to evaluate the performance of the proposed joint predictive policy, a cost model is used. Finally, a numerical example of a 6component system is introduced to illustrate the use and the advantages of the proposed joint maintenance and spare parts provisioning policy.

1. INTRODUCTION

Maintenance involves preventive and corrective actions carried out to retain a system or restore it to an operating condition. Optimal maintenance strategies aim to provide optimum system reliability/availability and safety performance at lowest possible maintenance costs. In recent years, condition monitoring and prognostic information are new trends being exploited for maintenance optimization. The use of prognostic information is often dedicated to estimate/predict the remaining useful life (RUL) that may be more advantageous for making decisions related to maintenance, spare parts ordering, as well as inspections scheduling. Several joint maintenance and spare parts inventory strategies using RUL prediction have been introduced in the literature. However, they are applicable to a limited class of systems such as mono-component systems (Elwany & Gebraeel, 2008; Boudhar, Dahane, & Rezg, 2013; L. Wang, Chu, & Mao, 2008), series structures systems with identical components (W. Wang, Pecht, & Liu, 2012; Van Horenbeek, Scarf, Cavalcante, & Pintelon, n.d.; L. Wang, Chu, & Mao, 2009; Xie & Wang, 2008). Today, with the development of industrial manufacturing, the structures of systems become more and more complex in inter-connections with a large number of different components. The inter-connections could be a mixture of well-known basic connections. The above problem remains widely open.

To face with this issue, the aim of this paper is to propose a joint predictive maintenance and spare parts provisioning policy for gradually deteriorating multi-component systems with complex structure. The decision-making associated with maintenance, spare parts ordering, and inspections scheduling is based on both components RUL and their corresponding importance measure. In fact, RUL provides the information about the future health of a component, while the structural importance measure gives a structural importance ranking of a component in the system. Both information should be taken into account in spare parts provisioning and maintenance decision-making. Moreover, economic dependency between components is studied and integrated in decision rules. In addition, the impacts of the system structure on components deterioration process are also considered. This may significantly influence on the components RUL estimation (Nguyen, Do Van, & Grall, 2013a, 2013b). In order to evaluate the performance of the proposed policy, a cost model is used. Furthermore, a simulation approach is developed to find the optimal decision values of the system's inspection time,

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of preventive maintenance and spare part ordering thresholds corresponding to each component.

This paper is organized as follows. Section 2 is devoted to the system description and deterioration modeling. The reliability/RUL prediction of components and their structural importance are described and discussed. Section 3 focuses on the description of inspection, maintenance, spare part ordering operations and related costs. The proposed joint predictive maintenance and spare parts provisioning policy is described in Section 4. In order to evaluate the performance of the proposed joint policy, a cost model is presented in Section 5. Section 6 is devoted to illustrate the use and the advantages of the proposed joint policy for 6-component system with complex structure. Some numerical results are, in addition, discussed here. Finally, the last section presents the conclusions drawn from this work.

2. SYSTEM DESCRIPTION AND PREDICTIVE RELIABIL-ITY CALCULATION

2.1. Deterioration modeling framework

This paper considers a multi-component system whose components are non-identical, inter-connected according to a complex configuration which could be a mixture of several common basic connections (i.e. connection in series, in parallel, in k-out-of-n), and deteriorate gradually as shown in Fig. 1. To study such systems, the concepts of minimal cut sets, critical and non-critical components should be introduced. The definitions are given as follows:

- 1. A Minimal cut set (MCS) is a minimal set of components for which when all components of the set are failed, the system is then failed (Rausand & Høyland, 2004);
- 2. A component is said to be "critical" if a failure of the component, while the other components being in functioning state, lead to a failure of the system and "non-critical" otherwise.

Additionally, in order to model the deterioration of each component i (i = 1, 2, ..., N) of the system, the following general assumptions are considered:

- The deterioration level of the component *i* at time *t* can be measured and described by a scalar random variable *X_tⁱ*. Without any maintenance operation on the component *i*, the deterioration trajectory, (*X_tⁱ*)_{t≥0}, is a stochastic process and increases monotonically over time;
- 2. The initial deterioration level, X_0^i , is equal to zero, then the component *i* is considered as new one. The higher X_t^i , the closer the component *i* to failure. The component *i* is considered to be failed if X_t^i exceeds a predefined critical threshold D^i and its failure time is then expressed by $T_f^i = \inf\{t \in \mathbb{R}^+ | X_t^i \ge D^i\}$. The D^i can be seen as a deterioration level which must not be exceeded for economical or security reasons;

3. The deterioration increments considered between any two consecutive instants, Δx^i , are supposed to be stationary, nonnegative, and statistically independent.



Figure 1. Description of the deterioration process $(X_t^i)_{t\geq 0}$ for component *i* without maintenance activities.

In this study the deterioration of each component of the system is assumed to be evolved like a homogenous Gamma process, whose characteristic is clearly monotonically increasing. It has been used widely to describe the degradation behaviors in several physical degradation process, e.g. (Grall, Dieulle, Bérenguer, & Roussignol, 2002; Van Noortwijk, 2009). For the Gamma deterioration process, the random increment Δx^i which is considered between two consecutive inspected times, t and s (t > s), follows a Gamma probability density function (pdf), $f_{\alpha_i}(t-s),\beta_i(x)$, with shape parameters α_i and scale parameter β_i , with $\alpha_i, \beta_i \in \mathbb{R}^{+*}$:

$$\frac{1}{\Gamma[\alpha_i(t-s)]} \beta_i^{\alpha_i(t-s)} x^{\alpha_i(t-s)-1} e^{-\beta_i x} \mathbb{I}_{\{x \ge 0\}}$$
(1)

where: $\Gamma(t) = \int_0^{+\infty} u^{t-1} exp(-u) du$ denotes the Euler Gamma function. The parameters α_i and β_i can be estimated from monitored degradation information of the component *i*. The mean deterioration rate and variance are determined by α_i/β_i and α_i/β_i^2 , respectively. Various deterioration behaviors from almost-deterministic to very-chaotic can be modeled by such a stochastic process.

Finally, as mentioned above, if a non-critical component (that is present in the MCS of order greater 1) fails, it does not lead the system to a failure. However, if the component is not replaced as soon as possible, this may be cause to conduct some other components to idle states. More precisely, these components are disabled even if they are not failed. It is also supposed that the degradation level of components being idle state remains unchanged (Nguyen et al., 2013a).

2.2. Predictive reliability calculation

At time t, the reliability $R^{i}(t)$ of component i is defined as the probability that the component i is in an operational state between times 0 and t:

$$R^{i}(t) = \mathbb{P}[T_{f}^{i} > t] = 1 - \mathbb{P}[T_{f}^{i} \le t] = 1 - \int_{0}^{t} f_{i}(u)du, \quad (2)$$

where: T_f^i is the random variable of time of failure of component *i* and $f_i(u)$ is its pdf. For the time-based reliability, an item is only considered in two states functioning or failed. Such a consideration only reflects average characteristics of the reliability; it cannot take into account information related to the condition (i.e. deterioration level) of the item during its operating process. Assume now that component *i* is functioning at time *s*, let $R^i(t|X_s^i = x_s^i)$ be a conditional reliability of the component *i* at instant *t* given its deterioration level at instant s < t, $X_s^i = x_s^i$. It can be determined by:

$$R^{i}(t|x_{s}^{i}) = \mathbb{P}[X_{t}^{i} < D^{i}|x_{s}^{i}] = 1 - \int_{D^{i}-x_{s}^{i}}^{+\infty} f_{\alpha_{i}}(t-s), \beta_{i}(x)dx$$
$$= 1 - \frac{\Gamma\left[\alpha_{i}(t-s), \beta_{i}(D^{i}-x_{s}^{i})\right]}{\Gamma[\alpha_{i}(t-s)]},$$
(3)

where $\Gamma(\alpha, \sigma) = \int_{\sigma}^{+\infty} x^{\alpha-1} exp(-x) dx$ is incomplete Gamma function. $R^i(t|x_s^i)$ or $R^i(t|s)$ is also called the predicted reliability and computed at time s. Model parameters (α_i, β_i) can be estimated from complex data, see e.g. (Do Van, Levrat, Voisin, Iung, et al., 2012; Le Son, Fouladirad, Barros, Levrat, & Iung, 2013). The predicted reliability will be used for decision making in maintenance as well as spare part provisioning. Detail description will be presented in Section 4.

2.3. Importance measure

The importance of each component in a multi-component system may be assessed by the measure of structural importance which was proposed by (Birnbaum, 1969). It allows taking into account the topology importance of the logic position of components in a multi-component system to perform various decisions (Nguyen et al., 2013b). The structural importance measure is defined as follows:

Let v_i be a binary variable that describes the state of component i, (i = 1, ..., N), such that $v_i = 1$ if the component i is operating and 0 otherwise; and let $\mathbf{v} = (v_1, ..., v_i, ..., v_N)$ be the state vector of the considered system. Then, the system state can be described by a binary/structure function $\Psi(\mathbf{v}) = \Psi(v_1, ..., v_i, ..., v_N)$. Where, $\Psi(\mathbf{v}) = 1$ if the system is operating and $\Psi(\mathbf{v}) = 0$ if the system is in a failed state.

The structural importance measure expresses the relative proportion of the 2^{N-1} possible state vectors which are critical state vectors for component *i* and is denoted I_B^i . A state vector is considered as critical for component *i* if for this state vector a change in the value of v_i causes a change of the structure function value. I_B^i is defined for component *i* as:

$$I_B^i = \frac{\delta_{\Psi}(i)}{2^{N-1}},\tag{4}$$

where:

1. $\delta_{\Psi}(i)$ is the total number of critical state vectors for component *i*, i.e.

$$\delta_{\Psi}(i) = \sum_{(\cdot_i, \mathbf{V})} \left[\Psi(1_i, \mathbf{v}) - \Psi(0_i, \mathbf{v}) \right]$$

(hence $1 \le \delta_{\Psi}(i) \le 2^{N-1}$);

2. $(._i, \mathbf{v})$ represents all the possible 2^{N-1} state vectors when the state of component *i* is fixed and can be either $(1_i, \mathbf{v})$ component *i* is running or $(0_i, \mathbf{v})$ if it has failed.

In this paper, the structural importance measure is used to make decisions related to maintenance and spare parts ordering. Detail descriptions are presented in Section 4.

3. MAINTENANCE AND SPARE PARTS ORDERING OPER-ATIONS, AND RELATED COSTS

Inspection operation

In this framework, we assume that a failure of a component is instantaneously revealed by the self-announcing mechanism (e.g. by using smart-sensor) and the deterioration level of working components in system can only be known through periodic inspections at dates $t_k = k\delta t$, with δt is a fixed inter-inspection interval and $k \in \mathbb{N}$. The inspection operation is assumed instantaneous, perfect, non-destructive, and is incurred a cost c_{ins} for each component.

Maintenance operations

Two possible maintenance activities upon each component are preventive replacement (PR) before a failure and corrective replacement (CR) after a failure, which can restore completely the component to "as good as new" state. Both PR and CR activities can be performed at either inspection times or opportunistic maintenance times (i.e. system shutdown times). Also concerning maintenance time, each maintenance activity usually takes a time interval however it is often very small with respect to the time interval between two consecutive inspections. Therefore, in this work the maintenance durations are assumed to be negligible. In some cases, the failed system should be restored as soon as possible. So, some failed components are needed to be replaced immediately. An emergency order with negligible lead-time is then required if spare parts of the failed components are not available. As a result, an emergency ordering cost c_e is incurred for each component in these cases. In other cases, the system should be left in failed state to wait for the arrival of spare parts. Then, a system downtime may appear from the system's failure occurrence time until restored system time. Hence an unavailability cost rate, $c_{d,f}$, is incurred for every unit time when the system elapsed in failed state.

1. When performing a PR on component *i*, a PR cost, C_p^i , is incurred and calculated by:

$$C_p^i = c_p^i + c_{ms},\tag{5}$$

where: c_p^i represents a specific PR cost; c_{ms} is the fixed set-up cost for maintenance, incurred once a time for all PR/CR activities. The set-up cost can be composed by the preparation costs (e.g. rent tools, labors, dissemble, etc.) and the cost of crew traveling. This cost depends on the characteristic of each system. It can be shared when several components are replaced at the same time.

2. Similarly, when performing a CR on component *i*, a CR cost, C_c^i , is incurred and calculated by:

$$C_c^i = c_c^i + c_{ms} + c_e \mathbb{I}_e^i, \tag{6}$$

where: c_c^i is a specific CR cost. A failure can have disastrous consequences, not only on the incurred cost due to unplanned interventions for example, but also on the environment as well as humans impact, hence it is reasonable to be assumed that $c_c^i > c_p^i$; c_e represents the emergency ordering cost of spare part for a component; \mathbb{I}_e^i is indicator function to indicate that if $\mathbb{I}_e^i = 1$, spare part of component *i* is emergently purchased and if $\mathbb{I}_e^i = 0$, spare part of component *i* is not requested.

Spare parts ordering

The spare parts provisioning operation is of continuous time (S-1, S) type of inventory policy which was been applied in several reports in the literature (Moinzadeh & Schmidt, 1991; Armstrong & Atkins, 1996). S is maximum stocking level. The inventory policy is suitable for systems for which demand rate is low but components are expensive (Moinzadeh & Schmidt, 1991). In our work, the studied system consists of N non-identical components which request N independent inventory policies (S - 1, S) corresponding to each component. We assume that the maximum number of spare parts is only one. It is either available in stock or present on an outstanding order for each component of the system at any time. This means that the maximum stocking level is S = 1 for each component at every time. Under this policy, a possible normal order (upon an inspection cycle) with a lead-time Lis regularly placed just after each inspection time t_k for all components of the system. It is assumed that the lead-time Lis constant and much lower than the inter-inspection interval. Spare parts of the normal order is delivered at two different dates that are named date1 and date2, respectively. Date1 includes a time interval L after t_k (i.e. at $t_k + L$) and date2 is at the next inspection time t_{k+1} . Let $n_1 \ge 0$ denote the number of spare parts at date1 and $n_2 \ge 0$ denote the number of spare parts at date2, with $n1 + n2 \le N$. Then, total cost for a normal order per an inspection cycle including set-up cost for placing an order, specific ordering costs, and transportation costs is determined as follows:

$$C_{o} = \left[c_{os} + \left(\sum_{i=1, i\neq j}^{n_{1}} c_{o}^{i} + c_{1,ship}\right) \mathbb{I}_{\{n_{1}>0\}}^{i}\right] + \left(\sum_{j=1, j\neq i}^{n_{2}} c_{o}^{j} + c_{2,ship}\right) \mathbb{I}_{\{n_{2}>0\}}^{j} \mathbb{I}_{\{n_{1}+n_{2}>0\}},$$
(7)

where:

- c_{os} is the set-up cost for taking an order;
- cⁱ_o or c^j_o is the specific ordering cost of component i or component j, with i ≠ j;
- c_{1,ship} and c_{2,ship} are transportation costs corresponding to ordered spare parts delivered at date1 and date2, respectively. Where, c_{(.),ship} is calculated by:

$$c_{(.),ship} = \begin{cases} c_{0,ship} + c_{d,ship}(n_{(.)} - n_0) & \text{if } n_{(.)} > n_0, \\ c_{0,ship} & \text{for otherwise} \end{cases}$$
(8)

where: (.) can be 1 or 2; $c_{0,ship}$ is minimal transportation cost (deterministic cost) for one delivery time; n_0 is the minimal number of spare parts at which a minimal transportation cost $c_{0,ship}$ is incurred; $c_{d,ship}$ is transportation cost per spare part. It is calculated for spare parts only if their package exceeds the minimal number n_0 .

In addition, after the ordered spare parts have been delivered, some of them may be utilized immediately for PR and/or CR activities, and the remainder is kept in the stock. For spare parts being in the stock, their deterioration is assumed to remain unchanged, that means they are kept "as-good-as-new". The inventory holding cost for each spare part corresponding to each component per a time unit is $k_h c_o^i$, where k_h is inventory holding rate per a spare part per a time unit.

4. JOINT POLICY OF PREDICTIVE MAINTENANCE AND SPARE PARTS PROVISIONING

At each time $t_k = k \, \delta t$ with $k \in \mathbb{N}$, the inspection is made on all functioning components of the system except components which have been selected for PR at the latest inspection time but have not been preventive replaced until the current inspection time. Thank to inspection operations, the deterioration level of each component can be measured. More precisely, for each component *i*, its the deterioration level at inspection times $t_k, X_{t_k}^i = x_{t_k}^i$, is determined.

The main idea of the proposed joint predictive maintenance and spare parts provisioning policy is to use jointly the structural importance measure and predictive reliability/RUL for selecting the spare parts provisioning and preventive maintenance actions. In fact, at each inspection time the decision rules for component *i* spare part ordering threshold R_o^i and PR threshold R_p^i are determined based on both structural importance and predictive reliability/RUL of the component. In this way, it is reasonable to be assumed that $R_o^i \ge R_p^i$. Consequently, parameters of the proposed joint policy are needed to be optimized including δt , R_p^i and R_o^i , with i = 1, ..., N.

4.1. Maintenance policy

Maintenance activities can only be performed at inspection times (planned maintenance) or when system fails (unplanned maintenance) given that the necessary related spare parts are available. Each planned or unplanned maintenance date is considered as a maintenance opportunity for executing together several preventive and/or corrective maintenance actions. In fact, at each maintenance opportunity, all functioning preventive components which have been selected for PR action and failed components are maintained together if their corresponding spare part (SP) are available. In this way, different maintenance decision rules are proposed for both preventive and corrective maintenance activities.

Maintenance decisions at t_k

Each inspection time $t_k = k \, \delta t$ (with k = 1, 2...) the inspection and maintenance decisions for each component i (i = 1, ..., N) are the following:

- If component *i* has already failed, it is correctively replaced if its SP is available;
- If component *i* is functioning, an inspection operation is firstly carried out, i.e. the deterioration level of the component is measured, $x_{t_k}^i$. Secondly, the predictive reliability of the component *i* $R^i(t_{k+1}|x_{t_k}^i)$ is estimated (see again subsection 2.2). The main idea to build preventive maintenance decision rules for component *i* is to jointly consider its structural importance and predictive reliability. To this end, a fixed PR thresholds, R_p^i ($0 < R_p^i \le 1$), is introduced as follows:

$$R_p^i = K_p I_B^i$$
, with $0 < K_p \le \frac{1}{\min_{i=1,\dots,N} (I_B^i)}$, (9)

The coefficient K_p is the same for all components. I_B^i is the importance measure of component *i* and is calculated by Eq. (4).

Finally, the preventive maintenance decision rules is the following:

- If $R^i(t_{k+1}|x_{t_k}^i) \leq R_p^i$, then component *i* is selected for preventively replacement action. It is immediately replaced if its spare part is available otherwise the component will be replaced at a maintenance opportunity when its SP is available; - If $R^i(t_{k+1}|x_{t_k}^i) > R_p^i$, no maintenance action is carried out on component *i*.

Maintenance decisions between (t_k, t_{k+1})

This is concerned with unplanned maintenance which could occur randomly between (t_k, t_{k+1}) (i.e. the system fails). If the failure of component *i* does not lead the system to failed state, then no corrective maintenance action on the failed component *i* is carried out and the decisions related to this component will be placed at the next maintenance opportunity. Otherwise, if the failure of component *i* leads the system to failed state, then the decision rules of the system restoration are the following:

- If the component *i* is critical one, and
 - if its spare part is available, a corrective replacement is immediately carried together then the system is immediately restored;
 - if the spare part of *i* is present on an outstanding order, then the system is left in failed state and will be restored as soon as when the ordered spare part of *i* is delivered;
 - if the spare part of *i* neither available nor present on an outstanding order, then an emergency order is placed for the spare part of *i*. The system will be restored right away the arrival of this spare part;
- If the component *i* is non-critical one, and
 - if there is at least one spare part of a MCS that contains the component *i* which is available, then the system is immediately restored;
 - if there is not any spare part of the MCS (that contains the component *i*) available; but if at least one spare part of this MCS is present on an outstanding order, then the system is left in failed state and will be restored as soon as possible when the ordered spare parts is delivered.
 - if there is not any spare part of the MCS available or present on an outstanding order, then the spare part of *i* is emergently ordered. The system will be restored immediately the arrival of this spare part.

4.2. Spare parts provisioning policy

At every time, it is assumed that the maximum number of spare parts is only one which is either available in stock or presenting on an outstanding order for each component of the system. By inspection operations, a normal order is placed right away after the time t_k for the (k + 1)-th inspection cycle, in which a spare part if any of a component can only be delivered at either date1 or date2. The delivery is illustrated in Figure 2.

At time t_k , spare parts ordering rules are as follows:

1. If component *i* has failed and if its spare part is not available, spare part of *i* will be delivered at date1;



Figure 2. Illustration of delivery of a normal order.

- 2. If operating component *i*, but $R^i(t_{k+1}|x_{t_k}^i) \leq R_p^i$ and its spare part is not available, then spare part of *i* will also be delivered at date1;
- 3. If the predictive reliability $R^i(t_{k+1}|x_{t_k}^i)$ is higher the PR threshold R_p^i but lower or equal the ordering threshold R_o^i , then spare part of *i* will be delivered at date2. The ordering threshold introduced here is formulated as:

$$R_o^i = K_o I_B^i$$
, with $0 < K_o \le \frac{1}{\min_{i=1,\dots,N} (I_B^i)}$, (10)

Each I_B^i only depends on the system configuration and remains unchanged with time. Therefore, the optimal PR threshold R_p^{i*} and the optimal ordering threshold R_o^{i*} for each component *i* can be determined from the global optimal coefficients K_p^* and K_o^* , respectively. K_p , K_o and δt are the decision parameters of the proposed joint predictive policy which have to be optimized. For this purpose, a cost model is proposed to evaluate the performance of the joint policy based on the long-term mean cost rate criteria. It is presented in the next section.

5. PERFORMANCE EVALUATION OF PROPOSED JOINT POL-ICY

Accumulative total cost until time t of whole system includes costs of CR and PR (including set-up costs of maintenance), inspection costs, downtime costs, spare parts ordering costs (including set-up costs of the purchase, transportation costs), and inventory holding costs:

$$C_{T}(t) = \underbrace{C_{corr}(t) + C_{prev}(t) + C_{ins}(t)}_{C_{M}(t): \text{ costs related to maintenance}}$$
(11)
$$+ \underbrace{C_{downtime}(t) + C_{o}(t) + C_{hold}(t)}_{C_{I}(t): \text{ costs related to inventory}}$$

To assess the performance of the proposed joint policy, the long-term expected average costs of maintenance and inventory per unit time is considered. It is defined as:

$$C_T^{\infty}(K_p, K_o, \delta t) = \lim_{t \to \infty} \frac{E[C_M(t)] + E[C_I(t)]}{t}$$
(12)

If t is large enough, Eq. (12) can be rewritten as follows:

$$C_T^{\infty}(K_p, K_o, \delta t) \simeq \frac{E[C_M(N_m \,\delta t)] + E[C_I(N_m \,\delta t)]}{\# Operating \ time \ of \ system}, \quad (13)$$

where: #Operating time of system = $N_m \delta t$ - #Total downtime of system, N_m is the number of inspection times in [0, t] of whole system.

To develop a cost model for evaluating the policy performance, the additional following notations will be used in this section:

indicates whether component i is failed at time t $\mathbb{I}_{\{x_t^i \ge D^i\}}$ before any decision is made. If $x_t^i \ge D^i$, $\mathbb{I}_{\{x_t^i \ge D^i\}} = 1$: failed; if $x_t^i < D^i$, $\mathbb{I}_{\{x_t^i \ge D^i\}} = 0$: functioning; $\mathbb{I}_{PS}^{i}(t)$ indicates whether component i satisfies PR condition $(0 < R^i(t + \delta t | x_t^i) \le R_n^i)$ at time t. $\mathbb{I}_{PS}^{i}(t) = 1$: satisfying; $\mathbb{I}_{PS}^{i}(t) = 0$: otherwise; indicates whether component i is correctively $\mathbb{I}_{CR}^{i}(t)$ replaced at time t. $\mathbb{I}_{CR}^{i}(t) = 1$: replaced; $\mathbb{I}_{CR}^{i}(t) = 0$: otherwise; $\mathbb{I}_{ER}(t)$ indicates whether there is a component that must be made emergency CR at time t. $\mathbb{I}_{ER}(t) = 1$: emergency CR;

$$\mathbb{I}_{ER}(t) = 0$$
: no emergency CR

$$\begin{split} \mathbb{I}_{stock}^{i}(t) & \text{ indicates whether spare part of } i \text{ is available} \\ & \text{ in stock at time } t. \ \mathbb{I}_{stock}^{i}(t) = 1 \text{: available;} \\ & \mathbb{I}_{stock}^{i}(t) = 0 \text{: unavailable;} \end{split}$$

$$\begin{split} \mathbb{I}_{outstd}^{i}(t) & \text{ indicates whether spare part of } i \text{ is present on} \\ & \text{ an outstanding order at time } t. \ \mathbb{I}_{outstd}^{i}(t) = 1: \\ & \text{ present; } \ \mathbb{I}_{outstd}^{i}(t) = 0: \text{ not present;} \end{split}$$

$$\begin{split} \mathbb{I}_{OD1,k}^{i} & \text{ indicates whether, in } k\text{-th cycle, a purchase} \\ & \text{ decision for spare part of } i \text{ with date1 is placed.} \\ & \mathbb{I}_{OD1,k}^{i} = 1\text{: ordered; } \mathbb{I}_{OD1,k}^{i} = 0\text{: not ordered;} \\ & \text{ indicates whether, in } k\text{-th cycle, a purchase} \\ & \text{ decision for spare part of } i \text{ with date2 is placed.} \\ & \mathbb{I}_{OD2,k}^{i} = 1\text{: ordered; } \mathbb{I}_{OT1,k}^{i} = 0\text{: not ordered.} \end{split}$$

Inspection cost $C_{ins}(t)$

At each time t_k , the inspection is made on all functioning components of the system except for components satisfying PR condition at latest inspection time but for which any replacement action has been carried out until the current inspection time. The total inspection cost over the time span t is formulated:

$$C_{ins} = c_{ins} \sum_{i=1}^{N} \sum_{k=1}^{N_m} \mathbb{I}^i_{ins}(t_k),$$
(14)

where, $\mathbb{I}_{ins}^{i}(t_k)$ indicates whether an inspection action on the component *i* should be implemented at time t_k . $\mathbb{I}_{ins}^{i}(t_k) = 1$ means that an inspection is needed and $\mathbb{I}_{ins}^{i}(t_k) = 0$ otherwise. $\mathbb{I}_{ins}^{i}(t_k)$ is defined as follows:

$$\mathbb{I}_{ins}^{i}(t_{k}) = \begin{cases} 0 & \text{either } \mathbb{I}_{\{x_{t_{k}}^{i} \ge D^{i}\}} = 1 \text{ or } \left(\mathbb{I}_{PS}^{i}(t_{k-1}) = 1 \right) \\ & \text{but any replacement action (PR or CR)} \\ & \text{has been carried out until the current} \\ & \text{inspection time } t_{k} \right); \\ & 1 & \text{otherwise.} \end{cases}$$

Corrective and preventive replacement costs

 $C_{corr}(t) + C_{prev}(t)$

Between two inter-inspection times (the inspection time is not including), an intervention to restore the system if and only if the system has been failed. Therefore, total replacement cost can be separated into a replacement cost at inspection times and a replacement cost outside of inspection times (opportunistic maintenance times). Let $M \in \mathbb{N}$ denote the total number of intervention times in order to restore the system from failed state without inspection times. And let t_m represent the *m*-th intervention time on the system ($t_m \neq t_k$). If $M \neq 0$, the total replacement cost of the system during its mission is formulated as follows:

$$\sum_{m=1}^{M} \left(\sum_{i=1, i \neq j}^{N} c_{p}^{i} \mathbb{I}_{PR}^{i}(t_{m}) + \sum_{j=1, j \neq i}^{N} c_{c}^{j} \mathbb{I}_{CR}^{j}(t_{m}) + c_{ms} + c_{e} \mathbb{I}_{ER}(t_{m}) \right) \\ + \sum_{k=1}^{N_{m}} \left(\sum_{i=1, i \neq j}^{N} c_{p}^{i} \mathbb{I}_{PR}^{i}(t_{k}) + \sum_{j=1, j \neq i}^{N} c_{c}^{j} \mathbb{I}_{CR}^{j}(t_{k}) + c_{ms} \right)$$
(15)

where:

• At inspection time t_k , $\mathbb{I}_{PR}^i(t_k)$ and $\mathbb{I}_{CR}^j(t_k)$ are defined as follows:

$$\mathbb{I}_{PR}^{i}(t_{k}) = \begin{cases} 1 & \text{if } \left(\mathbb{I}_{\{x_{t_{k}}^{i} \geq D^{i}\}} = 0 \text{ and } \mathbb{I}_{ins}^{i}(t_{k}) = 1 \\ & \text{and } \mathbb{I}_{PS}^{i}(t_{k}) = 1 \text{ and } \mathbb{I}_{stock}^{i}(t_{k}) = 1 \end{pmatrix}, \\ & \text{or } \left(\mathbb{I}_{\{x_{t_{k}}^{i} \geq D^{i}\}} = 0 \text{ and } \mathbb{I}_{ins}^{i}(t_{k}) = 0 \\ & \text{and } \mathbb{I}_{stock}^{i}(t_{k}) = 1 \end{pmatrix}, \\ & 0 & \text{otherwise;} \end{cases}$$
$$\mathbb{I}_{CR}^{j}(t_{k}) = \begin{cases} 1 & \text{if } \mathbb{I}_{\{x_{t_{k}}^{i} \geq D^{i}\}} = 1 \text{ and } \mathbb{I}_{stock}^{i}(t_{k}) = 1 \\ 0 & \text{otherwise.} \end{cases}$$

• At time $t_m \neq t_k$, if it is assumed that the failure occurrence of components of the system are not simultaneous, the failed system is restored if there is at least one necessary spare part for CR action (i.e. the spare part can be either available in stock or bought emergently or the ordered spare part has just been delivered). The system is failed due to:

(i) a critical component i. Then $\mathbb{I}_{ER}(t_m)$ is defined:

$$\mathbb{I}_{ER}(t_m) = \begin{cases} 1 & \text{if its spare part } i \text{ is not available} \\ & \text{and outstanding in any current order,} \\ 0 & \text{otherwise.} \end{cases}$$

(ii) a non-critical component i. Then $\mathbb{I}_{ER}(t_m)$ is defined:

$$\mathbb{I}_{ER}(t_m) = \begin{cases} 1 & \text{if there is neither any spare part of} \\ & \text{components in MCS that contains the} \\ & \text{component } i \text{ is available nor} \\ & \text{presenting on outstanding order,} \\ 0 & \text{otherwise.} \end{cases}$$

In addition, other failed components and functioning components that satisfied PR condition at latest inspection time but for which any replacement has been made until the current time (t_m) are also opportunistically replaced at this instant. Therefore, the indicators $\mathbb{I}_{PR}^i(t_m)$ and $\mathbb{I}_{CR}^j(t_m)$ are determined as follows:

$$\mathbb{I}_{PR}^{i}(t_{m}) = \begin{cases} 1 & \text{if} \left(\mathbb{I}_{\{x_{t_{m}}^{i} \ge D^{i}\}} = 0 \text{ and} \\ & \mathbb{I}_{PS}^{i}(t_{k} < t_{m}) = 1 \text{ and} \\ & \mathbb{I}_{PR}^{i}(t_{k} < t_{m}) = 0 \text{ and} \\ & \mathbb{I}_{stock}^{i}(t_{m}) = 1 \right), \\ 0 & \text{otherwise.} \end{cases}$$

$$\mathbb{I}_{CR}^{j}(t_{m}) = \begin{cases} 1 & \text{if} \ \mathbb{I}_{\{x_{t_{m}}^{j} \ge L^{j}\}} = 1 \text{ and} \ \mathbb{I}_{stock}^{j}(t_{m}) = 1, \\ 0 & \text{otherwise;} \end{cases}$$

Note that after each preventive replacement of the component *i* at $t = t_k$ or $t = t_m$, $\mathbb{I}_{PS}^i(t)$ should always be reset zero.

Downtime cost $C_{downtime}(t)$

It is assumed that lead-time for emergency orders is negligible. Thus, in the k-th inspection cycle, the downtime of system is equal zero during from $(t_{k-1} + L)^+$ to $(t_k - L)^-$. The downtime of system can only occur in the period from t_{k-1}^+ to $t_{k-1} + L$ and in the period from $t_k - L$ to t_k . Thus the downtime of the system in the k-th inspection cycle is determined as:

$$C_{downtime}(t) = c_{d,f} \sum_{k=1}^{N_m} (t_{ef1,k} + t_{ef2,k})$$
(16)

where $t_{ef1,k}$ is the time elapsed by the system in the failed state in the period from t_{k-1}^+ to $t_{k-1} + L$, and $t_{ef2,k}$ is the time elapsed by the system in the failed state in the period from $t_k - L$ to t_k in the k-th inspection cycle.

Ordering cost $C_o(t)$

$$\sum_{k=1}^{N_m} \left[\left(\sum_{i=1, i\neq j}^{n_1} c_o^i \mathbb{I}_{OD1,k}^i + c_{1,ship} \right) \mathbb{I}_{\{n_1 > 0,k\}} \right.$$

$$\left. + \left(\sum_{j=1, j\neq i}^{n_2} c_o^j \mathbb{I}_{OD2,k}^j + c_{2,ship} \right) \mathbb{I}_{\{n_2 > 0,k\}} + c_{os} \right] \mathbb{I}_{\{n_1 + n_2 > 0,k\}}$$

$$(17)$$

where, $\mathbb{I}_{OD1,k}^{i}$ and $\mathbb{I}_{OD2,k}^{j}$ can be defined as follows:

$$\begin{split} \mathbb{I}_{OD1,k}^{i} &= \begin{cases} 1 & \text{if} \left(\mathbb{I}_{\{x_{t_{k-1}}^{i} \ge D^{i}\}} = 1 \text{ or } \mathbb{I}_{PS}^{i}(t_{k-1}) = 1 \right) \\ & \text{and } \mathbb{I}_{stock}^{i}(t) = 0, \\ 0 & \text{for otherwise;} \end{cases} \\ \mathbb{I}_{OD2,k}^{j} &= \begin{cases} 1 & \text{if } R_{p}^{j} < R^{j}(t_{k}|x_{k-1}^{i}) \le R_{o}^{j} \text{ and } \mathbb{I}_{stock}^{j}(t) = 0, \\ 0 & \text{for otherwise;} \end{cases} \end{split}$$

 $c_{1,ship}$ and $c_{2,ship}$ are the transportation costs are calculated as Eq. (8).

Spare parts holding cost $C_{hold}(t)$

$$C_{hold}(t) = \sum_{i=1}^{N} c_0^i k_h \sum_{z_i=1}^{Z_i} t_{hold, z_i}^i$$
(18)

where:

- Z_i total number of spare parts of component i that are used to replace (preventively and correctively) during the system's mission;
- t_{hold,z_i}^i holding time interval of z_i -th spare part. It is determined by:

$$t^{i}_{hold,z_{i}} = t^{i}_{output,z_{i}} - t^{i}_{input,z_{i}}$$
(19)

where, t_{output,z_i}^i and t_{input,z_i}^i are instants when z_i -th spare part is stocked and taken away from the inventory, respectively.

Determining optimal solutions of proposed joint policy

The optimal solution of the joint policy $(K_p, K_o, \delta t)$ can be obtained by minimizing the expected global average cost per unit of time of whole system $C_T^{*,\infty}(K_p, K_o, \delta t)$ i.e.:

$$C_T^{\infty}(K_p^*, K_o^*, \delta t^*) = \min_{K_p, K_o, \delta t} C_T^{\infty}(K_p, K_o, \delta t)$$

subject to: $0 \le L < \delta t$, (20)
 $K_p \in \left(0, \frac{1}{\min_{i=1, \dots, N} \left(I_B^i\right)}\right],$
 $K_o \in \left(0, \frac{1}{\min_{i=1, \dots, N} \left(I_B^i\right)}\right],$

The numerical calculation can be done by Monte Carlo simulation. The optimal PR thresholds R_p^{i*} and the optimal ordering thresholds R_o^{i*} corresponding to each system component is directly derived from the optimal value K_p^* and K_o^* , respectively.

 $K_o > K_n$.

6. NUMERICAL EXAMPLE

The main aim of this section is to validate and to analyze the performance of the proposed joint policy of maintenance and spare parts provisioning. For this end, a study is performed on a 6-component system whose the degradation evolution of each component is assumed to be a gamma process. The system structure is shown in Figure 3.



Figure 3. Reliability block diagram of the system consist of six components.

The parameters related to all components such as deterioration parameters, prefixed failure thresholds, ordering costs, preventive and corrective replacement costs, and importance measures are listed in Table 1. The parameters related to the

Table 1. Parameters for each component.

Comp.	α_i	β_i	D^i	c_o^i	c_p^i	c_c^i	I_B^i
1	0.8	1.25	40	120	36	96	0.15625
2	1.3	1.8	38	120	36	96	0.15625
3	0.8	1.5	45	180	54	144	0.28125
4	0.6	0.9	42	150	45	120	0.09375
5	0.7	0.8	39	150	45	120	0.09375
6	0.5	1.3	50	250	75	200	0.46875

system are inspection $\cos c_{ins} = 3$, set-up $\cos t$ of maintenance operation $c_{ms} = 30$, downtime $\cos t$ rate $c_{d,f} = 30$, emergency ordering $\cos t c_e = 100$, set-up $\cos t$ for placing an order $c_{os} = 3$, minimal transportation $\cos t$ for a delivery time $c_{0,ship} = 30$, transportation $\cos t$ for one spare part $c_{d,ship} =$ 5, minimal number of spare parts of an order $n_0 = 2$, inventory holding rate per a spare part per time unit $k_h = 0.004$, and lead-time L = 10 time units. The components of the system are s-independent and their parameters have been arbitrarily chosen for the purpose of the numerical study.

6.1. Experimental results

The PR thresholds are used to determine components that should be preventively replaced and the ordering thresholds are to determine components that should be ordered to prepare available spare parts for next preventive replacements. In this proposed joint model, an order is placed just after inspection time t_k with the two possible delivery dates, where date2 is to prepare available spare parts for PRs at t_{k+1} while date1 (that is earlier than date2) is to replenish as soon as possible spare parts if PRs and/or CRs cannot be performed at t_k on corresponding components due to the unavailability of spare parts. The lack is partly due to the uncertainty in the RUL prediction. Clearly the spare parts are required at date1 to reduce the system's breakdown and the emergency ordering costs, but on the other hand they may make the inventory holding costs increase. Hence, it is necessary to choose carefully the appropriate decision parameters of K_p , K_o , and δt in order to balance these costs.

According to a set of all given parameters, in order to find the optimum decision parameters (i.e. K_p^* , K_o^* , and δt^*), the expected global average cost rate C_T^{∞} is evaluated with different values of K_p , K_o , and δt by using Eq. (11) and Eq. (13)-(20). The obtained minimum global average cost rate is 20.129 with three corresponding decision parameters: $K_p^* = 1.51$, $K_o^* = 3.63$, and $\delta t^* = 45$, i.e. $C_T^{*,\infty}(1.51, 3.63, 45) = 20.129$. The optimal PR thresholds corresponding to each component are inferred from the K_p^* by using Eq. (9), such that: $R_p^{1*} = R_p^{2*} = 0.24$, $R_p^{3*} = 0.42$, $R_p^{4*} = R_p^{5*} = 0.14$, and $R_p^{6*} = 0.71$. Similarly, the optimal ordering thresholds corresponding to each component are inferred from the K_o^* by using Eq. (10), such as: $R_o^{1*} = R_o^{2*} = 0.56$, $R_o^{3*} = 1$, $R_o^{4*} = R_o^{5*} = 0.34$, and $R_o^{6*} = 1$. The results show that the PR threshold of the critical component is much higher than that of the non-critical components. The same conclusion is drawn for the ordering thresholds. The ordering threshold of each component is much higher than its PR threshold. It is also noted in this case that the optimal ordering threshold of component 3 and component 6 are equal to one, this means that the spare part of the two components must be regularly replenished at each inspection date t_k .

Figure 4 shows the cost surface considering at the $\delta t^* = 45$ as a function of the PR coefficient K_p and the ordering coefficient K_o . The surface is clearly convex.



Figure 4. Cost surface of the proposed joint policy as a function of the K_p and the K_o considering at $\delta t^* = 45$.

6.2. Comparison of the joint and separate optimized approach

Considering the benefits form the proposed joint model under the jointly optimized approach, a comparison with a traditional maintenance model and a traditional provisioning model, which are separately optimized, is performed. Under the separately optimized approach, the expected mean cost rate of the maintenance model, C_M^{∞} , depends only on the inspection cost, the preventive and corrective replacement costs, and the

set-up cost; while the expected mean cost rate of the inventory model, C_I^{∞} , depends solely on the downtime cost, the costs related to spare parts ordering, and the inventory holding cost. Figure 5 shows the average cost rate as a function of the inter-inspection time interval for the joint and separate optimization with the same given parameters.



Figure 5. Relation of the total average cost rate between the joint and separate optimization.

The obtained results clearly show that the cost of jointly optimized policy, in most situations, is lower than that of their separately optimized counterparts (i.e. the sum of C_M^{∞} and C_I^{∞}). This is because all cost parameters associated to the maintenance and the inventory are simultaneously considered in the joint model, hence achieving more appropriate values for the decision variables.

The relative cost difference between the two approaches varies from 2% to 3.5%, and of course, this difference is dependent upon the input parameters of the system. In the next paragraph, the influences of some main parameters such as the lead-time, the holding cost, and the set-up cost on the proposed joint policy are studied.

6.3. Sensibility analysis

To investigate the influences of the lead-time on the total average cost of the proposed policy, the numerical experiments are carried out for the different values of the lead-time. Figure 6 exhibits the optimum values of $C_T^{*,\infty}$ increase when the lead-time increases from 1 to 21 time units (the other given parameters remains unchanged).

The results obtained from the sensibility analysis show that when the lead-time increases, it leads to decrease the optimal inter-inspection time interval and increase the optimal PR thresholds as well as the optimal ordering thresholds. This means that: the system should be inspected more frequently, the components need to be preventively maintained earlier



Figure 6. Influence of the lead-time on the proposed joint policy.

(compared to their lifetime), and the spare parts also need to be ordered earlier so as to prevent a failure of components which may lead to the system failure.

The effect of the inventory holding rate is shown in Table 2, where the total average cost increases significantly as the increase of the inventory holding rate.

Table 2. Optimal results with given inventory holding rates.

k_h	δt^*	K_p^*	K_o^*	$C_T^{*,\infty}$
0.0	46	1.69	3.81	19.39
0.004	45	1.51	3.63	20.12
0.008	45	1.51	3.45	21.46
0.012	44	1.33	3.45	22.53
0.016	44	1.33	3.10	23.52
0.020	43	1.33	3.10	24.62

Herein, when the inventory holding rate k_h is varying from 0 to 0.02 with increments of 0.004, the optimal ordering thresholds (as well as the optimal PR thresholds) decrease to reduce the inventory levels. Besides, δt^* also decreases. This shows the system should be inspected more frequently in order to reduce the risk due to the decrease of the inventory levels.

Table 3 shows the influence of the set-up cost of the maintenance c_{ms} on the total average cost when the c_{ms} varies from 0 to 100 cost units.

It is surprising that the higher the set-up cost is the higher the total average cost is. When the c_{ms} increases, the optimal PR thresholds as well as the optimal ordering thresholds increase, which indicates that the components of the system tends to be preventively maintained earlier. At the same time the optimal inspection cycle decreases slightly. Consequently, there are more selected components in a group for the PR activities in order to save set-up cost.

 Table 3. Optimal results with given maintenance set-up costs.

c_{ms}	δt^*	K_p^*	K_o^*	$C_T^{*,\infty}$
0	46	1.33	2.92	19.55
20	45	1.33	3.28	20.21
40	45	1.51	3.63	20.68
60	45	1.69	3.81	21.03
80	45	1.86	3.81	21.59
100	44	1.86	3.98	22.16

7. CONCLUSION

In this paper, a joint predictive maintenance and spare parts provisioning policy for multi-component systems with complex inter-connections is proposed. Predictive reliability/RUL of components and their structural importance measure are jointly used and integrated in maintenance and spare parts decision-makings. Moreover, both economic and structural dependencies are investigated and considered in the proposed policy. This allows a better modeling of multi-component system. In addition, to evaluate the performance of the proposed joint predictive policy, a cost model is used. Finally, Monte-Carlo simulation approach is implemented in order to final the optimal decision parameters. The numerical results show that the proposed joint policy is more appropriate than when considering maintenance policy and spare parts provisioning one separately. The joint combination of predictive reliability and structural importance measure can provides a powerful tool for decision-making on maintenance et spare parts provisioning.

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NOMENCLATURE

N	number of components of the system
i	index for components, with $i = 1, 2,, N$
$X_t^i = x_t^i$	deterioration level of component i measured at
	time t
$(X_t^i)_{t\geq 0}$	stochastic process describing the deterioration
_	of component i over time t
α_i, β_i	shape and scale parameters of Gamma distribu-
	tion for component <i>i</i>
c_p^i	specific preventive cost for component i
c_c^i	specific corrective cost at failure for component
	<i>i</i> (generally $c_c^i > c_p^i$)
c_{ins}	inspection cost for each component
c_{ms}	set-up cost for a maintenance operation
$c_{d,f}$	loss cost per time unit incurred by the system in
	the failed state due to shortage of spare parts
c_{os}	set-up cost for placing an order and independent
	of the ordered quantities of spare parts

c_o^i	spare part ordering cost for component <i>i</i>
c_e	emergency ordering cost for one spare part
$c_{0,ship}$	minimal transportation cost for a delivery
$c_{d,ship}$	transportation cost per a spare part
n_0	minimal number of spare parts of an order at
	which a cost $c_{0,ship}$ is incurred
k_h	inventory holding rate per a spare per time unit
δt	inter-inspection time interval (inspection cycle)
L	lead-time for a regular order, $L > 0$
t_k	k-th inspection time, $t_k = k \delta t$ and $k \in \mathbb{N}$
$R^i(t s)$	predictive reliability of component i at time t
	given that component i has survived for time s
I_B^i	structural importance measure of component i
K_p	preventive replacement coefficient
K_o	spare parts ordering coefficient
R_p^i	PR threshold defined for component i
R_o^i	ordering threshold defined for component i
$C_T(t)$	cumulative total cost at time t
$C_M(t)$	cumulative maintenance cost at time t
$C_I(t)$	cumulative inventory cost at time t
N_m	number of inspection times of the whole
	system within $[0, t]$
C_T^∞	long-term expected total average cost rate
C^{∞}_M	long-term expected maintenance average cost rate
$\alpha \infty$	1

 C_I^{∞} long-term expected inventory average cost rate

References

- Armstrong, M. J., & Atkins, D. R. (1996). Joint optimization of maintenance and inventory policies for a simple system. *IIE transactions*, 28(5), 415-424.
- Birnbaum, L. (1969). On the importance of different elements in a multielement system. multivariate analysis. *Academic Press*, 2.
- Boudhar, H., Dahane, M., & Rezg, N. (2013). Order/remanufacturing policy of spare part with recovery option for stochastic deteriorating system. In *Ieee* 18th conference on emerging technologies & factory automation (etfa) (pp. 1–7).
- Do Van, P., Levrat, E., Voisin, A., Iung, B., et al. (2012). Remaining useful life (rul) based maintenance decision making for deteriorating systems. In 2nd ifac workshop on advanced maintenance engineering, service and technology, a-mest'12.
- Elwany, A. H., & Gebraeel, N. Z. (2008). Sensor-driven prognostic models for equipment replacement and spare parts inventory. *IIE Transactions*, 40(7), 629–639.
- Grall, A., Dieulle, L., Bérenguer, C., & Roussignol, M. (2002). Continuous-time predictive-maintenance scheduling for a deteriorating system. *IEEE Transactions on Reliability*, 51(2), 141-150.
- Le Son, K., Fouladirad, M., Barros, A., Levrat, E., & Iung, B. (2013). Remaining useful life estimation based on stochastic deterioration models: A comparative study.

Reliability Engineering & System Safety, 112, 165–175.

- Moinzadeh, K., & Schmidt, C. P. (1991). An (s-1, s) inventory system with emergency orders. Operations Research, 39(2), 308-321.
- Nguyen, K.-A., Do Van, P., & Grall, A. (2013a). Predictive grouping maintenance strategy for complex structure systems using importance measure. In *Ieee 2013 international conference on quality, reliability, risk, maintenance, and safety engineering (qr2mse)* (pp. 582–588).
- Nguyen, K.-A., Do Van, P., & Grall, A. (2013b). A predictive maintenance strategy for multi-component systems using importance measure. In *Proc. of the european safety and reliability conference, esrel 2013* (pp. 967– 975).
- Rausand, M., & Høyland, A. (2004). System reliability theory: Models, statistical methods and applications (Second ed.). John Wiley & Sons.
- Van Horenbeek, A., Scarf, P. A., Cavalcante, C. A., & Pintelon, L. (n.d.). The effect of maintenance quality on spare parts inventory for a fleet of assets. *IEEE Transactions on Reliability*, 62(3), 596 - 607.
- Van Noortwijk, J. M. (2009). A survey of the application of gamma processes in maintenance. *Reliability Engineering & System Safety*, 94(1), 2-21.
- Wang, L., Chu, J., & Mao, W. (2008). An optimum conditionbased replacement and spare provisioning policy based on markov chains. *Journal of Quality in Maintenance Engineering*, 14(4), 387–401.
- Wang, L., Chu, J., & Mao, W. (2009). A condition-based replacement and spare provisioning policy for deteriorating systems with uncertain deterioration to failure. *European Journal of Operational Research*, 194(1), 184– 205.
- Wang, W., Pecht, M. G., & Liu, Y. (2012). Cost optimization for canary-equipped electronic systems in terms of inventory control and maintenance decisions. *Reliability*, *IEEE Transactions on*, 61(2), 466–478.
- Xie, J., & Wang, H. (2008). Joint optimization of conditionbased preventive maintenance and spare ordering policy. In Wireless communications, networking and mobile computing, 2008. wicom'08. 4th international conference on (pp. 1–5).

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Architectures and Key Points for Implementation of E-maintenance Based on Intelligent Sensor Networks

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ABSTRACT

During the past few years industrial predictive maintenance has benefited from new developments in hardware and software systems. A key conclusion is that to maximize results, these systems need to be smarter with learning capabilities. Moreover, wireless sensor networks have led to a new revolution in the field of e-maintenance, offering new possibilities in measurement collection, aiming to empower monitoring with more advanced features. In what way can wireless sensor networks be applied to industrial maintenance? How can novelty detection be implemented on these systems? How can such systems scale up to offer distributed intelligence? This paper presents the WelCOM research program's approach on the aforementioned matters answering many questions that relate to intelligent sensor systems in the field of e-maintenance and proposing flexible architectures for the implementation of these systems.

1. INTRODUCTION

e-Maintenance empowers maintenance engineering and management with ICT tools that streamline the delivery of maintenance services, from the field level of measurements collection all the way up to maintenance decision support (Holmberg, 2010). It contributes to the aim of sustainable development in society and the proper function of a whole range of engineering assets, ranging from factories and, power plants to transport and built infrastructure. Wellestablished maintenance practices can lead to improve the efficiency of resources and production management, while supporting the quality and safety procedures and minimize environmental impact, thus contributing to the sustainability of the enterprise. Maintenance activities, such as repairs and service actions, only take place when actually needed, which is the essence of Condition-Based Maintenance (CBM). The development of low-cost and micro-size integrated sensors for taking machinery measurements, the upgrade in hardware capabilities for managing the process of condition data collection and transmission and the development of advanced methods for condition data management, processing and analysis, including machine learning and decision support tools, compose the framework for the current state of the art in condition monitoring within e-Maintenance. Empowered by wireless communications and networking, maintenance tools are made available in the form of flexible web-services, delivered to multiple device types, including tablets and other portable computing devices, while e-collaboration methods enable greater information and knowledge sharing, facilitated by the infrastructure of an e-Maintenance network (Figure 1).



Figure 1: E-maintenance network

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This paper presents technological developments that support the integration of e-Maintenance components by distributing monitoring and detection tasks to an ad hoc network of wireless sensor nodes. It is argued that the delegation of computing tasks to a lower physical level of data generation and processing, coupled with elements of learning and intelligence can upgrade the efficiency of condition monitoring infrastructure, while maintaining great deployment flexibility. Our research builds on earlier development of wireless sensing solutions (Emmanouilidis, Katsikas and Giordamlis, 2008) and a structured approach for incremental learning that takes advantage of increasing availability of condition monitoring data to support event detection and diagnostics (Emmanouilidis, Jantunen and MacIntyre, 2006). Within an e-maintenance architecture (Pistofidis, Emmanouilidis, Koulamas, Karampatzakis, & Papathanassiou, 2012), our reported work focuses on upgrading the capability of hardware-integrated solutions to efficiently support wireless condition monitoring by embedding more advanced computational features at the level of sensor nodes.

In Section 2, we present an analysis and brief outline of our development work on distributed and wireless condition monitoring. Coupling the computational capabilities of sensor nodes with machine learning features compose a powerful framework for implementing distributed and intelligent wireless condition monitoring, which pose new challenges for integrated learning capabilities in sensor nodes. These challenges are discussed in section 3. The concluding remarks are summarized in section 4.

2. DISTRIBUTED WIRELESS CONDITION MONITORING

2.1. Condition Monitoring and Wireless Sensing

CBM seeks to perform an early detection of deterioration and potential malfunctions to guide maintenance activities decisions. The asset is maintained or repaired as soon as some machinery condition parameters are detected to exceed a normal or expected range of values. Acting upon the detection and diagnostic recommendations, prognostics seek to determine the most probable time of failure in order to properly schedule preventive actions (IAEA, 2007), reducing costs and increasing quality and profits. Condition monitoring functions by acquiring data that relate to parameters, which constitute indicators of machinery condition. Among the typically measured physical parameters are temperature, pressure, voltage/current/power, RPM, torque, acceleration/Velocity/displacement.

Our reported work deals with the development and integration of more advanced features that leverage on the capacity of wireless sensor networks to delegate computing at the sensor node level. We distinguish two categories of such advanced features, namely:

- Level 1: Data enrichment and pre-processing. In vibration monitoring, these include pre-processing of the original time series to produce transformed representations in new domains, typically in the Frequency (spectrum), quefrency (cepstrum), or even joint time-frequency representations (e.g. wavelets). Even before such transformations take place, preprocessing such as filtering and smoothing is needed, while the spectrum is best estimated after some windowing function is applied to reduce spectral noise. Event detection and diagnostics applied on the transformed signal is still a hard problem. Feature extraction is applied at the pre-processing level to yield specific parameters that when considered independently or most commonly jointly, are more likely to yield discriminatory information and this aid the detection and diagnosis tasks. A word of caution is applicable here, as even the most informative parameter, when considered in isolation, may not provide sufficient whereas a parameter not-directly information, associated with the expected detection outcome may still convey crucial information. It is the combination of individual features that often conveys adequate discriminatory information, rather than the individual features themselves (Emmanouilidis, Hunter, MacIntyre and Cox, 2001).
- Level 2: Event detection and diagnostics. Acting upon extracted feature set combinations, rather than either on the original time series or individual features is recognized as the key to performing efficient event detection and diagnostics. Although it is possible to set simple alarm levels on parameters (e.g. vibration amplitude at a certain frequency or the overall RMS vibration in a frequency band exceeding a certain level), these constitute primary but not sufficient indicators. One reason for that is the cautionary remark mentioned earlier. But another important one is that is that machinery malfunction manifests itself in different ways, even for the same equipment type, depending on the actual equipment size, the positioning of sensors on the monitored equipment and even variations in the way the vibration signal propagates through the body of the monitored machinery. It is therefore often important to calibrate any pattern recognition technique applied for detection and diagnostics on the basis of evidence of data and extracted parameters from readings taken from the specific monitored machinery. This is where machine learning becomes important, both for detection, as well as diagnostics tasks.

Wireless condition monitoring solutions typically do not include such processing features, although Level 1 features have long being available and Level 2 ones are have become increasingly available on wired counterparts. In our reported work, Level 1 features are integrated within the wireless sensor network, that is within the sensing node. Based on features now calculated within the sensor node, new computing and machine learning requirements are posed, so as to integrate Level-2 features within the wireless sensing solution. The main requirements for such features, when employed in a wireless sensing solution context is to balance the potentially discriminatory power they may convey (individually or jointly) with low computing requirements. The right trade-off can be achieved by studying the problem at hand, which therefore implies the need to customize solutions by taking actual representative measurements from the monitored machinery.

This is consistent with observations that condition monitoring techniques are more efficient when perfectly tailored for the particular problem and usually when safety, capital value and potential losses in service or production are of critical importance (Holmberg et al., 2010).

2.2. Intelligent Sensors and Distributed Monitoring

Compared to conventional sensors, intelligent sensors are capable of more advanced functions than plain data collection. By combining sensing and computing at the chip level through micro-electromechanical (MEMS) technology and overall advancement in microelectronics, intelligent sensors can perform self-calibration based on the data collected and adaptive threshold techniques may be deployed for a more accurate condition monitoring. An intelligent sensor is perfectly capable of performing advanced data processing and signal analysis in the time and frequency domains. Bringing a network of such sensing nodes together has the potential to greatly scale-up the level of information processing and the impact on the performance of the performed monitoring. The enabling factors for such an upgrade are already in place, as communication between different sensors can be achieved by existing networking protocols. Coupling the networking capabilities with the individual processing power and sensor-embedded learning capabilities bring a major leap in forward for condition monitoring, that of distributed intelligent condition monitoring.

Distributed condition monitoring relies on the individual node's ability to function as an agent. An agent can adjust its functionality depending on its environment variables. The agent perceives its environment via sensors and acts accordingly via actuators. An agent that aims at optimizing certain performance measures, taking the form of an objective function, is called rational (Montoya et al., 2010).

In a sensor network implementation, many intelligent sensors or nodes, work in parallel to perform condition monitoring and notify base stations via a communications infrastructure. The nodes consist of basic components with simple interfaces. However, connected together in a network, the processing performance increases exponentially. The nodes play the role of the agents in a Multi-Agent system and the Intelligence is distributed among them, thus giving rise to a case of Distributed Intelligence (Montoya et al., 2010).

Low cost peripheral / distributed processing capabilities have been already utilized in large industries for many years, following the evolution of microcontroller and specialized distributed control system (DCS) and wired fieldbus technologies. However, the installation costs of complete systems were high mainly due to the sensor and power/communication wiring costs. It is the introduction of low-power and low-cost wireless interfaces and embedded sensors (MEMS) that now widens the distributed intelligence pattern applicability and the architectural alternatives for a basically data collection / health monitoring system. Still, for the definition of a concrete system's distributed architecture, key tradeoffs have to be set among important extra-functional properties such as power, timeliness and communication/processing bandwidth budgets, as well as fault tolerance, availability and installation/maintenance cost characteristics [Giannoulis et al, 2012].

Knowing the non-linear cost increase for a certain improvement in the quality of sampling electronics, as well as the higher energy and performance costs of wireless transmission compared to processing, the principal pattern is to push towards the periphery, functionality blocks such as local signal processing for the improvement of signal characteristics, calculation of reduced size (compared to the raw signal) sets of important properties, information quality improvements by fusion of data from other related sensors or neighboring sensor nodes, and execution of knowledge extraction algorithms, as long as the overall system cost and chosen performance metrics for the required scalability range are better than just sending the output of a block to a centrally located collecting, storage and processing system. [Pistofidis et al, 2012].

2.3. Signal Processing

Any intelligence built-in a sensor network has to be based on a primitive set of digital signal processing capabilities of the node's microcontroller and its A/D converters. Although such processing may be trivial for wired solutions, only limited such work has been reported as integrated in wireless condition monitoring implementations. Next we present such features built in our wireless condition monitoring implementation.

2.3.1. A/D Converter's Characteristic Improvement

The A/D converter's precision and integral nonlinearity (INL) factor affect the effectiveness of the node. For 4-20 mA current loop measurements poor, linear behavior of the A/D converter can lead to inaccurate results. In our approach, before initialization of the node's main functionality, the first step of an intelligent sensor should be the linear improvement of the A/D converter's

characteristic. An external well-designed D/A converter can be used as the force of calibration by feeding the A/D converter with key values used for calculating the A/D converter's output differences from the expected values. The flow diagram in Figure 2 describes the calibrating procedure before the main functionality of the intelligent sensor (Texas Instruments, 1999).



Figure 2: Calibration with an External D/A Converter

2.3.2. Signal Smoothing

In many cases, in order to make decisions from observing or processing the measured data, or to capture important patterns, signal smoothing might be useful in order to cancel out spikes and noise in the data set and generally increase signal-to-noise-ratio. For this purpose four techniques are considered depending on the applications:

- Low-pass digital filter.
- Exponential moving average, with which the applied smoothing percentage (alpha parameter) can be controlled and no particularly large window is needed for smoothing.
- Moving median with a 3-sample window, with which a substantial smoothing is achieved with the profound elimination of undesired spikes.

Figure 3 shows the effect of applying an exponential moving average (alpha parameter = 0.15) and a moving median filter on raw data.



Figure 3: Exponential Moving Average

• The Savitzky–Golay filters are low- pass filters that smooth the signal with the use of local least-squares polynomial approximation. The main asset of this type of filters is that they smooth noisy data, while preserving the shape and height of the peaks and spikes (Schafer, 2011).

2.3.3. Vibration Analysis

In our approach, for the purpose of vibration analysis, the accelerometer's data is collected by the A/D converter and via the microcontroller's DMA controller, is saved in RAM at a sampling rate much greater than the Nyquist rate. Upon completion of the collection, the microcontroller's CPU is interrupted and a series of actions take place:

- 1. DC bias removal, by subtracting the mean value from each data sample.
- 2. Filtering the data with a window function, Hanning, Hamming, Blackman or Bartlett. The aforementioned window functions are quite effective and require less computational complexity that others, as shown in table 1 (LDS Inc., 2003).

Window	Best for these Signal Types	Frequency Resolution	Spectral Leakage	Amplitude Accuracy
Barlett	Random	Good	Fair	Fair
Blackman	Random or mixed	Poor	Best	Good
Flat top	Sinusoids	Poor	Good	Best
Hanning	Random	Good	Good	Fair
Hamming	Random	Good	Fair	Fair
Kaiser-Bessel	Random	Fair	Good	Good
None (boxcar)	Transient & Synchronous Sampling	Best	Poor	Poor
Tukey	Random	Good	Poor	Poor
Welch	Random	Good	Good	Fair

Table 1: Window comparison

3. Calculating the FFT of the filtered data, using a recursive radix -2, out-of-place algorithm or an in-place

algorithm with bit- reversal permutation, depending whether the goal is speed or memory efficiency.

4. Calculating the amplitude of the complex numbers that were the result of step 3, thus providing the amplitude response. Results are buffered and sent to the network coordinator or base station via a communication protocol implemented in the nodes' firmware. Figure 4 shows an 8-kHz, 128-sample sine wave from a waveform generator, filtered with a Hanning window and figure 5 its amplitude response.



Figure 4: 128-sample sine wave, 8 kHz, filtered with Hanning window



Figure 5: Amplitude response of a 8-kHz 128-sample sine wave

Calculating velocity by integrating acceleration (figure 6), using the cumulative trapezoidal rule, as shown in figure 7. The resulted outcome is buffered and sent via communication protocol to the network coordinator.



Figure 6: acceleration, raw data after DC bias removal



Figure 7: Velocity, output from cumulative trapezoidal rule

2.3.4. Periodicity Detection

Periodicity detection is a powerful mining tool in automotive, aviation and manufacturing industries for condition monitoring. All rotating parts of machines can be studied and a change in the periodic structure of the machine vibrations can be detected for the prevention of machine wear or potential failure (Vlachos et al., 2005).

Two basic tools combined together provide information on periodicity: FFT for potential periods or period hints and autocorrelation for the verification of these period hints (Vlachos et al., 2005).

FFT gives the amplitude frequency of the signal and by setting an amplitude threshold, any frequency exceeding that threshold, becomes a hint. Figure 8 shows a superposition of two sine wave signals, with frequencies of 40 kHz and 80 kHz respectively. Figure 9 shows the amplitude response and the two main signal frequencies. By applying a desired threshold, these two frequencies or periods are selected as hints. The threshold setting algorithm could begin with an initial high value for the threshold and gradually decreasing it with a certain step. More advanced adaptive threshold algorithms could be implemented. Finally, the period hints are compared to the values that represent the autocorrelation hills and if the hints and the hills are equal or if they differ at a maximum of 30%, then

the detected periods are the time values of the hills, thus refining the period hints (figure 10).



Figure 8:Signal for periodicity detection



Figure 10: Biased Autocorrelation, two dominant periods verified and refined

2.3.5. Novelty Detection

An algorithm has been designed and developed to detect absolute differences between consecutive samples, that exceed a specified threshold and that may be crucial. The algorithm classifies the detected novelties into spikes, if there is a sudden change and return to normal and stage changes, if a more permanent change occurs and the values thereafter belong to a different range. The algorithm also calculates the time of occurrence, duration of these novelties, starting and ending values for state changes, starting and maximum values for spikes. The threshold setting algorithm begins with an initial high value for the threshold and gradually decreases it with a certain step, as in the case of periodicity detection. The initial value or upper threshold limit (UTL), as well as the final value or lower threshold limit (LTL), are automatically set with the use of Eq. (1) and Eq. (2) (Bakar et al., 2006):

$$UTL = m + 3\sigma / \sqrt{N} + m - 3\sigma / \sqrt{N} = 2 m$$
(1)
$$LTL = m - 3\sigma / \sqrt{N}$$
(2)

where,

m = mean value of data samples

 σ = standard deviation of data samples

N = total number of data samples

Figure 11 shows engine turbo charger RPM raw data and figure 12 the novelties detected by the algorithm. Dashed - line novelties are classified as spikes and dotted - line novelties as state changes. Figure 13 shows the results of the algorithm when applied on draft force measurements. Because of the noisy nature of these measurements, Savitzky- Golay filtering is applied before the algorithm and the new results are shown in figure 14, where the most important novelties now stand out. The classification is parameterized and state changes can be considered as spikes, by altering a parameter that affects the time duration of a spike. Figure 15 shows this effect. Especially, the state change that appeared at the 500-700 time unit range of figure 14 is now classified as spike in figure 15.



Figure 11: Main engine turbo charger RPM measurements



Figure 12: Main engine turbo charger RPM Novelties detected



Figure 13: Draft force novelties detected



Figure 14: Draft force novelties detected after Savitzky-Golay smoothing



Figure 15: Resulted graph after increasing the spike width parameter

3. FURTHER WORK

The next and most intriguing element of an intelligent wireless sensor network is the ability of learning. Learning is the added value of an intelligent sensor that leads to higher levels of decision-making and guidance for the maintenance manager. This is an on-going activity and our considerations cover two categories of Machine Learning: Classification and Clustering, which are further described as supervised or predictive and unsupervised or descriptive learning respectively.

Supervised learning uses a known data set to make predictions and to classify an unknown data object based on a model derived from the training set. In other words, the training set consists of pre-classified patterns and the goal is to label a new and unlabeled pattern. The model is derived from the use of the pre-classified patterns as the basis for learning the class descriptions, which in turn are used for the classification of new data. (Jain et al., 1999). An effective method under consideration is the *Naive Bayes Classifier*, because of its over-simplified assumptions and, yet, very positive outcome (Katsouros et al. 2013). This classifier is based on Bayes' theorem -from statistics theory- and produces results regardless of the presence or absence of a particular feature of the class (Murphy, 2012).

On the other hand, unsupervised learning makes predictions about unknown data without any training set, whatsoever. Its purpose is to discover interesting patterns in the data, a concept called Knowledge Discovery (Murphy, 2012). This form of data analysis can be realized with Cluster Analysis or *Clustering*, where the decision is to allocate patterns in known clusters or even form new clusters when this assignment does not appear to be credible. This approach can be applied to event detection. When readings and consequently a set of features are assigned to known clusters, then the condition state of monitored machinery can be said to belong to a known condition (Emmanouilidis et al., 2006). Typically this belongs to a normal operating condition. Depending on the problem formulation it may also belong to an unknown condition. Using the terms 'known' and 'unknown' here imply the association of a known condition with a condition for which representative readings have already been recorded. An unknown condition for the monitoring system is one that representative readings have not been recorded yet. This is an essential level of processing for event detection.

A detected event may either correspond to a situation where an unknown condition has been detected, or to one that a measurement is assigned to an abnormal condition, on the basis of pre-existing evidence. Clustering therefore can offer this first level of processing, that is essential of any event detection mechanism. Once data is assigned to 'unknown' category, the next step is to perform data labeling, that is to label the newly formed cluster by assigning it to a certain condition. There is a wide range of clustering techniques that can be applied in such tasks. In all cases a critical issue to be addressed is to define an appropriate distance metric, such as the Minkowski metric. Nonetheless, in many cases the set of parameters upon which a decision has to be reached can be of very heterogeneous nature and in such cases other heterogeneous distance metrics, such as Hausdorff distance may be applicable (Jain et al., 1999).

4. CONCLUSION

This paper presented work that achieved to upgrade the capability of hardware-integrated solutions to efficiently support wireless condition monitoring by embedding more advanced computational features at the level of sensor nodes. We have presented the trends and progress in the intelligence of wireless sensor networks and have proposed some key points that contribute to this concept and to the evolution of e-maintenance. It is our belief that the integration of such potent hardware solutions in wireless

condition monitoring, with advanced signal processing and learning features has the potential to offer a significant upgrade in the ability to deliver distributed and intelligent wireless condition monitoring solutions. Such developments would constitute a powerful addition to the e-maintenance solutions and are being developed as part of an emaintenance platform that aims to provide technical or managerial staff with smart choices and solutions, as well as valuable information and services at any point in time, leading to higher confidence in decision-making processes and improved maintenance performance.

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REFERENCES

- Bakar, Z.A., Mohemad, R., Ahmad, A., & Mustafa, M. D. (2006), A Comparative Study for Outlier Detection Techniques in Data Mining. 2006 IEEE Conference on Cybernetics and Intelligent Systems. June 7-9, Bangkok. doi: 10.1109/ICCIS.2006.252287
- Emmanouilidis, C. Jantunen, E., & MacIntyre, J. (2006), Flexible Software for Condition Monitoring, incorporating Novelty Detection and Diagnostics. *Computers in Industry Journal*. Vol.57, pp. 516-527. (ELSEVIER)
- Emmanouilidis, C., Katsikas, S., & Giordamlis, C., (2008), Wireless Condition Monitoring and Maintenance Management: A Review and a Novel Application Development Platform. Proceedings of the 3rd World Congress on Engineering Asset Management and Intelligent Maintenance Systems Conference (WCEAM-IMS 2008) 27 – 30 October 2008, Beijing, China, pp. 2030-2041, (SPRINGER).
- Emmanouilidis, C., Hunter, A., MacIntyre, J., & Cox, C. (2001). A multi-objective genetic algorithm approach to feature selection in neural and fuzzy modeling. *Journal of Evolutionary Optimization*, v3(1), pp.1-26.
- Fernández, L., Blasco, J., Hernández, J., & Montón, E., (2009), *Technologies for Health and Well-being*, Book Wireless Sensor Networks in Ambient Intelligence, Univ. Politécnica de Valencia, Technologies for Health and Well-being, Institute ITACA (Ed.)
- Giannoulis, S., Koulamas, C., Emmanouilidis, C., Pistofidis, P., & Karampatzakis, D., Wireless Sensor Network Technologies for Condition Monitoring of Industrial Assets. Advances in Production Management Systems International Conference (APMS) 2012
- Holmberg, K., Adgar, A., Arnaiz, A., Jantunen, E., Mascolo, J., & Mekid, S. (Eds.). (2010). *Emaintenance*. London, UK:Springer – Verlag London Limited.

- IAEA. (2007). Implementation Strategies and Tools for Condition Based Maintenance at Nuclear Power Plants. Vienna, Austria.
- Jain, A.K., Murty, M.N., & Flynn, P.J. (1999). *Data Clustering: A Review*, ACM Computing Surveys, Vol. 31, (No. 3).
- Katsouros, V., Papavassiliou, V., & Emmanouilidis, C. (2013). A Bayesian Approach for Maintenance Action Recommendation, International Journal of Prognostics and Health Management, *International Journal of Prognostics and Health Management*, Vol 4 (2) 034, pages: 6, 2013.
- LDS Inc. (2003), *Understanding FFT windows*, ANO14 Application Note.
- Murphy, K.P. (2012). *Machine Learning: A Probabilistic Perspective*. Cambridge, Massachusetts: The MIT Press.
- Montoya, A., Restrepo, D. C., & Ovalle, D. A. (2010). Artificial Intelligence for Wireless Sensor Networks Enhancement, Smart Wireless Sensor Networks, Yen Kheng Tan (Ed.), ISBN: 978-953-307-261-6, Rijeka, Croatia, InTech.
- Pistofidis, P., Emmanouilidis, C., Koulamas, C., Karampatzakis, D., & Papathanassiou, N. A layered emaintenance architecture powered by smart wireless monitoring components. 2012 IEEE International Conference on Industrial Technology (p.390-395),

March 19-21, Athens, Greece. doi: 10.1109/ICIT.2012.6209969

- Schafer, R., (2011), What is a Savitzky–Golay Filter, *IEEE Signal Processing Magazine*, Vol. 28 (No. 4),152 pages, doi:10.1109/MSP.2010.939665.
- Texas Instruments (1999) Additive Improvement of the MSP430 14-bit ADC Characteristic, Application Report.
- Texas Instruments (1999) *Linear Improvement of the MSP430 14-bit ADC Characteristic,* Application Report.
- Vlachos, M., Yu, P., & Castelli, V., (2005), On Periodicity Detection and Structural Periodic Similarity, IBM T.J. Watson Research Center, NY.

A Model-Based Approach for an Optimal Maintenance Strategy

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ABSTRACT

In this paper we introduce a novel model-based reliability analysis methodology to guide the best maintenance practices for the different components in complex engineered systems. We have developed a tool that allows the system designer to explore the consequences of different design choices, and to assess the effects of faults and wear on critical components as a result of usage or age. The tool uses pre-computed simulations of usage scenarios for which performance metrics can be computed as functions of system configurations and faulty/worn components. These simulations make use of damage maps, which estimate component degradation as a function of usage or age. This allows the designer to determine the components and their respective fault modes that are critical w.r.t. the performance requirements of the design. Given a design configuration, the tool is capable of providing a ranked list of critical fault modes and their individual contributions to the likelihood of failing the different performance requirements. From this initial analysis it is possible to determine the components that have little to no effect on the probability of the system meeting its performance requirements. These components are likely candidates for reactive maintenance. Other component faults may affect the performance over the short or long run. Given a limit for allowable failure risk, it is possible to compute the Mean Time Between Failure (MTBF) for each of those fault modes. These time intervals, grouped by component or Line Replaceable Units (LRUs), are aggregated to develop a preventive maintenance schedule. The most critical faults may be candidates for Condition-Based Maintenance (CBM). For these cases, the specific fault modes considered for CBM also guide sensor selection and placement.

1. INTRODUCTION

Preventive maintenance has been the main stay of industry (civilian as well as military) for a long time (Barlow & Hunter, 1960). This was based on the assumption that because mechanical parts wear out, operational reliability was directly linked to duration of use or age. However, rigorous run-to-failure experiments have shown that there is significant variability in lifetimes even for the same components installed in similar set ups and tested under identical conditions. Reasons for this range from manufacturing variations, intrinsic defects to non-use or age related failure effects. This has naturally increased the focus on Condition-Based Maintenance (CBM) (Jardine, Lin, & Banjevic, 2006).

CBM, however, has its own disadvantages like high design cost, added sensors and data collection components, increased system complexity and sources of error. What is needed for complex engineered systems is an optimum mix of reactive, time- or interval-based, condition-based, and predictive maintenance practices. Because maintenance costs can be a significant factor in the overall cost of a system or product, even up to 60-80% in military systems (Dallosta & Simcik, 2012), it is essential that maintenance be considered early in the design when flexibility is high and design change costs are low (Ender, Browne, Yates, & O'Neal, 2012). Changes made in production may be several orders of magnitude higher than those made early in the design cycle (FitzGerald, 2001). Keeping these objectives in mind, we have developed a model-based reliability analysis tool for complex engineered systems (Honda et al., 2014). This approach is system focused, i.e., it is more concerned with

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maintaining system function than with individual component operation. The tool allows the system designer to explore the consequences of different design choices, and to assess the effects of faults and wear on critical components as a result of operational stress.

Recent years have seen developments in simulation and optimization methods for fleet-level system reliability. Once such method (Mourelatos et al., 2011) calculates system reliability by probabilistically combining component reliability distributions for non-repairable as well as repairable systems, while assigning repair and maintenance costs to component failures. This work is complementary to the approach presented here that allows a simulation-based way for computing the system reliability distribution from individual component reliability distributions. However the reliability calculus presented in (Mourelatos et al., 2011) works primarily for serially configured systems where the any component failure results in system failure. This contrasts with the approach here of using simulations to compute the effect of component failure on system performance. Researchers have also tried to leverage models within a broader application of systems engineering to link models for mobility or survivability to models for reliability, maintainability, and availability or procurement and lifecycle sustainment cost. A notable effort in this direction is the Framework for Assessing Cost and Technology (FACT) web service developed for the US Marine Corps (Ender et al., 2012). FACT allows near realtime analysis for exploring design parameter trade-offs that affect the overall performance, reliability, and cost of a system design. The model-based reliability analysis technology described here can be thought of as a scalable model-based reliability analysis capability that can be integrated with a system engineering decision support framework like FACT.

The tool presented here builds on the Fault-Augmented Model Extension (FAME) technology (de Kleer et al., 2013) described in the following section. The reliability analysis mechanism uses pre-computed simulations of mission segments for which performance metrics can be computed as functions of system configurations and faulty/worn components. These simulations make use of damage maps, which estimate component degradation as a function of mission stress. This allows the designer to determine the components and their respective fault modes that are critical w.r.t. the performance requirements of the design.

In fact, given a design configuration, the tool is capable of providing a ranked list of critical fault modes and their individual contributions to the likelihood of failing the different performance requirements. Finally, recommendations can be made for the ideal maintenance strategy for each of the components. For cases where preventive maintenance is appropriate the tool helps to compute the time or mission intervals for scheduling purposes. For cases where CBM or predictive maintenance is applicable, the tool provides prior distributions of component failure that may be used in a Bayesianlearning or similar filtering/machine learning frameworks. As of now this technology is applied to systems and components described in the Modelica modeling language.

Results are presented based on the reliability analysis work done for the DARPA Advanced Vehicle Make (AVM) program. The system model considered here is a simplified drivetrain corresponding to a tracked military vehicle comprising an engine, a power transfer module (PTM) with a torque converter, a cross-drive transmission, drive shafts, final drives, battery, and a fuel tank.

The internal combustion (IC) engine model contains a torque map and fuel consumption map, heat generation, a thermostat and a starter motor. This engine model can be instantiated with different parameters including fuel map, torque map, friction map, engine inertia, crank speed, fuel type and thermostat parameters. The transmission model includes a mechanical model that splits the energy between the left hand side and right hand side drive shafts (i.e. tracks) and models the gear changes (shifts). It also models steering, braking and coolant subsystems.

The system boundary of this drive train model is at the final drives. Track models, controllers, and high fidelity coolant systems are not part of this design. In order to perform a simulation, we added additional surrogate components such as stimulus, load conditions and environment components in a test bench. The key test components are the road load and the surrogate coolant models. Controllers are not part of the system therefore time based signals are provided for each mission to the engine and transmission control ports. A schematic of this drivetrain is shown in Figure 1. Each component in this system design can be instantiated with different parameters, which gives flexibility to evaluate the reliability of different discrete design points (i.e. design configurations).



Figure 1. Schematic of sample AVM drivetrain (courtesy DARPA).

A mission is defined as a sequence of terrain blocks made up of differing surfaces, like asphalt, concrete and soil, and variation in gradients. The terrain profile is derived by sampling from a set of terrain power spectral density functions, which concisely describe an infinite set of possible terrain profiles with smooth roads, sand, boulders, etc. The distributions ensure that low-impact cyclic loads as well as rare but high-impact loads are realistically represented for the class of vehicle under consideration. A typical terrain profile is presented in Table 1.

In order to explain the insights for maintenance or system health management (SHM) strategy that may be gained using reliability analysis methodology described above, the following two sections will provide some details of the FAME technology and the reliability analysis tool. More details are available in (de Kleer et al., 2013) and (Honda et al., 2014).

2. FAULT-AUGMENTED MODEL EXTENSION (FAME)

The DARPA AVM program aims at developing a design flow that lets system designers adapt their designs through a tightly integrated build-test-modify loop with multiple points of feedback in a model-based design and simulation environment. In order for this workflow to yield reliable system designs, it is essential for designers to have the ability to analyze faults, fault propagation, and system-level impact. The FAME-based reliability analysis tool provides this capability.

FAME is based on the insight that most faulty behaviors are based on a few underlying fault mechanisms. FAME takes nominal component behavior descriptions (from Modelica model libraries) and parameterizable fault mechanism models as input, and deploys a model transformation mechanism to automatically generate a comprehensive set of fault-inducible component models. This technique when applied to a system design comprising Modelica component models results in a fault-inducible design where the effects of component faults can be investigated at the system level. A rough estimate of the reduction in modeling effort may be had by analyzing faults at the component level. The FAME technology is capable of modeling more than 7000 unique faults spanning nearly 1200 leaf-level components. Leaf-level components, like the Modelica Standard Library clutch model (Modelica.Mechanics.Rotational.Components.Clutch), are those that are not assemblies of simpler components, i.e. the equation block in these Modelica models comprise dynamics equations rather than equations that denote connections between components. Component assemblies and other higherlevel components inherit the fault behaviors of the components they are comprised of.

For the FAME model transformation process we leveraged the JModelica Modelica parser framework, and the JastAdd technology on which it is built, to inject faults into the nominal component model library (de Kleer et al., 2013). A



Figure 2. Basic FAME (Fault-Augmented Model Extension) architecture.

Java program incorporating JastAdd and JModelica runs over the supplied library, recognizes fault-susceptible component models, re-writes them as needed to provide fault behavior, and outputs the modified library to a new location. These Modelica component fault models include a generic parameter named *damage_amount* or a component-specific parameter, e.g. coefficient of friction for a brake, that determines the severity of the fault. The value of this parameter is determined by stochastic physics-of-failure models that capture the degradation or catastrophic fault modes of the associated components. These stochastic models are pre-simulated in a Monte Carlo framework incorporating model uncertainties as well as the expected spectrum of usage over the lifetime of the component. The results are stored as damage-parameter maps that are indexed by model material and geometric parameters and level of usage. The system-level Modelica models and simulations are detailed enough such that the variations in the component damage for any given age or usage shows up as distributions over the performance metrics. Figure 2 shows the basic architecture of this approach.

3. RELIABILITY ANALYSIS

The FAME reliability analysis tool supports analyses of system reliability and performance under both continuous wear and catastrophic failure of critical system components. It also scores design configurations according to reliability metrics and provides feedback to the designer about preferable choices of components or design configurations. "Reliability" describes the ability of a system to operate while meeting all requirements for a specified period of time or number of missions. Reliability is often quantified in terms of likelihood of failure, e.g. Mean Time to Failure (MTTF), Mean Time between Failure (MTBF), and Failures in Time (FIT) which captures system unreliability. The tool captures reliability using the metric Overall Probability of Mission Failure. In particular, the tool helps the designer to discover answers to the following questions:

Terrain	Speed (mph)	%	Distance (miles)
High Quality Paved Roads (Concrete)	40	3	3.50
Secondary Pavement (Concrete)	40	3	3.50
Rough Pavement (Concrete)	40	4	4.50
Loose Surface (Concrete)	35	8	9.25
Loose Surface w/ Washboard (Concrete)	30	10	11.50
Belgian Block, Cobblestone (Concrete)	30	2	2.25
Trails (Hard Soil)	25	30	35.00
Cross-Country (Hard Soil)	15	40	46.50
TOTAL		100	116.00

Table 1. Typical mission terrain and speed profile

- What system configurations are most reliable?
- Which component failure modes causes critical performance loss?
- Why is a particular component failure mode critical?
- What performance metrics are most at risk?
- How do these factors vary with number of missions?

Figure 3 shows the main user interaction elements of the tool marked in red. The main actions to be taken by the user are:

- 1. Select system configuration
- 2. Pick fault mode
- 3. Set number of missions
- 4. Set required probability for meeting requirements
- 5. Select graphs to gain insight.

The tool lists the individual probabilities of meeting each requirement, as estimated from simulations of the faultaugmented Modelica system model, as well as a pass/fail flag for the likelihood of meeting all requirements. These feedback are denoted by the top two blue boxes in Figure 3. The designer can also press radio buttons to investigate insight graphs for performance metrics of interest. The selector panel is shown inside the red box marked 5 and the insight graphs are in the blue box at the bottom. A set of three insight graphs are shown per performance metric:

• Damage amount vs. Number of Missions

Damage incurred by wear is a probabilistic amount estimated by mission stress factors and system properties. The left graph shows percentiles for amount of degradation for the selected component as a function of number of missions. The operation of the drivetrain was simulated several million times over a mission defined as a sequence of terrain blocks. Statistical variations in component parameters result in component-specific damageparameter maps, which are used to estimate damage incurred after a given number of missions. • Performance metric vs. Damage Amount

The middle graph shows how damage to the selected component impacts the selected performance metric. Damage to a component ranges from 0 (perfect condition) to 1 (total failure). This range is sampled and the corresponding fault simulations are carried out to populate this graph. In the example shown in Figure 3, the middle graph shows that, due to increased frictional losses in the PTM torque coupler component, the acceleration time to reach 10 kph increases with the damage amount (coefficient of friction).

• Probability of meeting performance requirement vs. number of missions

The right graph shows the calculated probability of achieving the selected performance metric after the target number of missions. In the example shown in Figure 3, the curve shows that, due to increased frictional losses in the PTM torque coupler component, the probability of meeting the desired acceleration time of 3 secs to reach 10 kph decreases with the number of missions. The red vertical dashed line at the target of 150 missions intersects the curve at a probability of 0.76. This is less than the target probability of .9 shown by the cyan dashed horizontal line. The requirement probability of .9 intersects the curve at about 130 missions.

The designer can also investigate the Figure-of-Merit (FOM), listed beside each configuration in the red box 1 (Figure 3). The FOM is calculated as the probability of mission failure (failure to meet at least one requirement) under the likelihood of a single component failure, aggregated across all components. The probability of component failure, and hence the probability of mission failure, is a function of the number of missions. The designer can click on a probability of mission failure value to view a breakdown of the failure probability in terms of components subject to wear/faults, as shown in Figure 4. From this graph, the designer can determine the component(s) most likely to be responsible for potential mission failure.

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Figure 3. FAME reliability analysis user interface (tool available at http://fame-deploy.parc.com:2040/).

The FOM breakdown graph lists component reliability for the ten most serious component faults. Component reliability expresses the probability that the component's failure will cause an overall mission failure after the set number of missions, and is color-coded to show the impact of the component's failure on the various performance metrics. In the example shown in Figure 4, the Engine.Inertia.Bearing.Friction fault (high engine bearing friction) is certain (probability = 1) after the set number of missions to retard acceleration-time-to-15km/hr to more than the required value listed in the require-

ments table on the main user interface (as shown in Figure 3). Similarly, other component faults are catastrophic w.r.t the same or one of the other performance metrics. In the case of the two fatigue failure faults, three performance metrics are shown to fail simultaneously because the simulation model does not move under gear or shaft failure.



Top 10 Faults

Figure 4. Figure-of-Merit (FOM) probability breakdown in terms of component failures.

4. MAINTAINABILITY ANALYSIS

As a logical extension of the above analysis, the designer can outline an appropriate maintenance strategy using this tool. Each high-level component, subassembly, or line-replaceable unit (LRU), e.g. engine, PTM, cross-drive transmission, has multiple fault modes. Each mode has a critical damage amount defined as the minimal damage amount that results in failing any one of the performance requirements. The critical damage amount for a component fault mode is determined by the first performance metric that fails as a result of this damage. This can be represented as:

$$d_{i,j}^c = \min_k d_{i,j,k}^c \tag{1}$$

where,

- d^c : critical damage amount
- i: index for high-level component or LRU
- *j*: index for component fault mode
- k: index for performance requirement.

At the LRU level, the minimum of these critical damage amounts can be computed over all associated fault modes. This would provide the critical damage at the LRU level.

$$d_i^c = \min_j d_{i,j,j}^c \tag{2}$$

From the Damage amount vs. Number of Missions graph (left graph in Figure 3), the number of missions m_i^c corresponding to d_i^c can be interpolated. Essentially, m_i^c is the maintenance interval, conceptually similar to MTTF for the LRU, and can be used to determined a maintenance schedule. It is important to note that this number is dependent upon the desired probability of meeting the performance requirements.

Table 2 shows these numbers for the different configurations and different acceptable risk levels for mission failure. Acceptable risk of mission failure is defined as follows: in order to set the risk at 10%, set the desired probability of meeting requirement to 0.9 for all requirements. The drivetrain example considered here had six unique configurations. Configurations 4 and 6 are missing from the table since these configurations fail to meet at least one of the requirements from the start of their mission life. Overall, configuration 2 seems to be the best in terms of system uptime between necessary maintenance events (maintenance interval), and hence maintenance cost, followed closely by configuration 5.

5. MAINTENANCE STRATEGY

5.1. Change in Maintenance Interval with Allowable Risk

From Table 2 it can be seen that the engine maintenance interval is not changed much by changing the acceptable risk of mission failure. By comparison, the cross-drive transmission and the PTM correlate strongly with changing risk level.

Configuration No.	1	2	3	5	
	Caterpillar C9	Caterpillar C9	Caterpillar C9	Caterpillar C9	
Components/LRUs	Allison X200-4A	Allsion XTG411-A	Allison X200-4A	Allison X200-4A	
	Final Drive 3.0	Final Drive 3.0	Final Drive 3.3	Final Drive 2.7	
Acceptible risk of mission failure	10% (Desired probabilities of meeting requirements all set to 0.9)				
Cross-drive Transmission	56	56	12	56	
Engine	50	65	38	61	
Power Transfer Module (PTM)	96	82	86	96	
Left Final Drive	>8000	>8000	>8000	>8000	
Right Final Drive	>8000	>8000	>8000	>8000	
Road Wheel	>8000	>8000	6	>8000	
Acceptible risk of mission failure	5% (Desired probabilities of meeting requirements all set to 0.95)				
Cross-drive Transmission	42	42	11	42	
Engine	49	65	24	61	
Power Transfer Module (PTM)	63	63	63	63	
Left Final Drive	>8000	>8000	>8000	>8000	
Right Final Drive	>8000	>8000	>8000	>8000	
Road Wheel	>8000	>8000	6	>8000	
Acceptible risk of mission failure	1% (Desired probabilities of meeting requirements all set to 0.99)				
Cross-drive Transmission	25	25	10	25	
Engine	49	61	36	57	
Power Transfer Module (PTM)	28	28	101	28	
Left Final Drive	>8000	>8000	>8000	>8000	
Right Final Drive	>8000	>8000	>8000	>8000	
Road Wheel	>8000	>8000	4	>8000	

Table 2. Estimated maintenance intervals for drivetrain example (numbers represent missions)

This is shown more clearly in Figure 5. The final drives seem unaffected by the risk level, likely because of not being stressed significantly in the usage scenario selected. The road wheels have a similar story, except in the case of configuration 3 where it is overstressed. Some simple inferences can be drawn here about the appropriate maintenance strategies for different LRUs. The cross-drive transmission and the PTM seem good candidates for scheduled maintenance due to the correlation of their critical damage levels, d_i^c 's with number of missions. The engine does not show such a strong correlation and hence it is better managed using a conditionmonitoring or CBM approach.

In addition to the simple inferences above, there is some more key information that we can extract from the FAME simulations and use for maintenance strategy. We need to consider not only frequency of failure and consequence of failure, but also the predictability of failure (as measured by variance in failure time for the population,) and cost and ease of main-



Figure 5. Maintenance interval vs. acceptable risk of mission failure for configuration 2.

Engine fault	Maintenance interval	Requirement affected
Engine.Inertia.Bearing.Friction	49	acceleration to 10 kph
Engine.DriverPulley.Bearing.Friction	125	acceleration to 10 kph
Engine.DrivenPulley.Bearing.Friction	80	acceleration to 15 kph
Engine.Pump.Bearing.Friction	80	acceleration to 15 kph

Table 3. Estimated maintenance intervals (in missions) for engine faults under 1% risk of mission failure

tenance/repair/replacement. Note that ease of maintenance is related to design choice, so it is part of the methodology to improve maintainability.

5.2. Ordering Component Faults by Importance

The correlation of the maintenance interval with the acceptable risk of mission failure provides only a guide to the selection of maintenance strategy for any given LRU. What is needed is to order the importance of fault modes for each component. This will determine which fault mode needs to be monitored carefully, and which ones could be lower priority. As an example, consider the engine component, which has 4 important fault modes in the drivetrain system considered. Table 3 shows the maintenance interval of these 4 fault modes along with the performance requirement affected in each case. The acceptable risk for mission failure is 1% for this table.

From the fault-specific maintenance interval values it is clear that a good monitoring system for the engine crankshaft bearing (Engine.Inertia.Bearing) is needed to track frictional wear and tear. The pulleys are less critical and may be checked during scheduled maintenance. However, since they do affect performance requirements reactive maintenance is not advised. This is a good example that can be used to check the validity of the inferences that can be drawn from the reliability analysis tool. While the maintenance specifics of military Caterpillar C9 engines is not known, heavy duty engines often have oil debris sensors that measure the contamination of the oil due to wear and tear of moving metal parts. Commercial vehicle engines typically recommend manual inspection of timing belts that connect the driven pulleys to the driver pulley. Belt slip is the primary cause of frictional losses at the pulleys. It should be noted that the maintenance strategy inferred from the reliability estimates automatically generated by the tool corresponds with field-tested expertise.

5.3. Ease of Maintenance

Another key point to note from Table 2 is that the cross-drive transmission fails more frequently in configuration 3 as compared to the other design configurations. Ease of maintenance is a factor here. If this is the configuration chosen by the designer (reliability or maintainability are not the only considerations), then care should be taken in the design to make this LRU easily accessible for maintenance and repair. Most military vehicles have a requirement on the time duration for specific maintenance actions since harsh operational and environmental conditions can make the simplest of maintenance extremely difficult or impossible (DES JSC TLS POL REL, 2009).

5.4. Stochasticity of Fault Modes

Some component fault modes are more deterministic than others. In terms of maintenance, more deterministic fault modes are better candidates for scheduled maintenance. Consider the engine pump bearing example shown in Figure 6. The left plot shows that there is not much variance in the wear characteristics of a population of these bearings (all the percentile curves are close to each other). Consequently, the right plot shows that the probability of meeting the associated requirement dips sharply near the 170 missions mark. This fault is a good candidate for scheduled maintenance since there is not much variability in the number of missions before failure. A safe maintenance interval like 150 missions (probability of failure < 1%) may be chosen in this case.

By comparison brake slip due to friction wear tends to have a more gradual transition to failure as shown in Figure 7. This fault mode has more variation in how the particular component degrades with usage. It probably needs a CBM approach informed by a sensor to monitor brake pad wear. Indeed, brake pad wear sensors had been invented decades back (Wiley & Williams, 1980) with application in military land vehicles.

6. CONCLUSION

This paper introduces a novel stochastic model-based reliability and maintainability analysis framework with applications to a broad class of complex engineered systems. A few examples of suggested maintenance strategies were presented for individual component fault modes as well as for components at the LRU-level. Cases where additional sensors make sense were identified. Some validation of these suggested maintenance strategies was provided based on real world maintenance practices. However, it is important to note that no comprehensive maintenance strategy was presented. This pa-



Figure 6. Reliability analysis of engine pump bearing friction wear.



Figure 7. Reliability analysis of brake friction wear.

per represents an initial step towards facilitating design-forreliability and design-for-maintainability in the model-based design paradigm. Although no comprehensive maintenance strategy was presented, such a strategy is the subject of current research, where higher fidelity models that include manufacturing and material variability are planned to be used.

The FAME reliability analysis tool is available online at http://fame-deploy.parc.com:2040/. Interested readers are encouraged to try out the tool and send comments to the authors.

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REFERENCES

- Barlow, R., & Hunter, L. (1960). Optimum Preventive Maintenance Policies. *Operations Research*, 8(1), 90–100.
- Dallosta, P. M., & Simcik, T. A. (2012, March-April). Designing for Supportability: Driving Reliability, Availability, and Maintainability In... Defense AT&L: Product Support Issue, 34-38.
- de Kleer, J., Janssen, B., Bobrow, D., Kurtoglu, T., Saha, B.,

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Moore, N., & Sutharshana, S. (2013). Fault augmented modelica models. In 24th International Workshop on Principles of Diagnosis.

- DES JSC TLS POL REL. (2009). Applied Reliability and Maintainability Manual for Defence Systems. Ministry of Defence, Abbey Wood (South), Bristol, UK.
- Ender, T., Browne, D., Yates, W., & O'Neal, M. (2012). Fact: An m&s framework for systems engineering. In *The interservice/industry training, simulation & education conference (i/itsec)* (Vol. 2012).
- FitzGerald, A. (2001). Design for Maintainability (DFM). http://www.theriac.org/ DeskReference/viewDocument.php?id= 222#section6.
- Honda, T., Saund, E., Matei, I., Janssen, W., Saha, B., Bobrow, D., de Kleer, J., & Kurtoglu, T. (2014). A simulation and modeling based reliability requirements assessment methodology. In 26th International Conference on Design Theory and Methodology (iDETC/DTM).
- Jardine, A. K., Lin, D., & Banjevic, D. (2006). A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance. *Mechanical Systems* and Signal Processing, 20(7), 1483–1510.
- Mourelatos, Z., Li, J., Pandey, V., Singh, A., Castanier, M., & Lamb, D. (2011). *A simulation and optimization methodology for reliability of vehicle fleets* (Tech. Rep.). DTIC Document.
- Wiley, D., & Williams, D. G. (1980, May 20). Brake pad wear detection system. (US Patent 4,204,190)

BIOGRAPHIES



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Modeling the Semantics of Failure Context as a means to offer Context-Adaptive Maintenance Support

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ABSTRACT

Acting upon the data involved in typical diagnostics and prognostics tasks is often confounded by the complexity of the corresponding situation and needs to take into account domain-specific or even installation-specific knowledge considerations. While domain knowledge is often captured in various forms, such as is typically done in Fault Modes, Effects and Criticality Analysis (FMECA), the contextualisation of the captured data and related knowledge to a corresponding situation, in other words a situated-aware modeling of data and knowledge, is often missing. Our research leverages the efficiency of maintenance support for mobile actors. Investing in modern service provision technologies, this work targets the effectiveness of capturing and sharing field expertise. An analysis of both the modeling specification and the functional requirements for such an approach. is provided. The semantics of "Failure Context", a context that guides user's navigation towards relevant diagnostics and maintenance-related knowledge, are mapped into an appropriate data schema. Based on this, a system capable of managing the core information of the Failure Context, while offering adequate tools that support experts to build on, browse through, and reach contextuallyrelevant decisions is implemented. The development follows a reference-annotation design pattern to deliver on spot capture and enrichment of maintenance-related knowledge. Thus, the developed system provides the means for the effective management and exploitation of 'micro-knowledge fragments', associated with FMECA-related entities and knowledge. This is a significant enabler for the effective elicitation and management of field-captured expertise, enabling the enrichment and validation of maintenancerelated knowledge.

1. INTRODUCTION

E-Maintenance has emerged from the fusion of maintenance practice with information and communication (Liyanage, Lee, Emmanouilidis, & Ni, 2009).Currently, a wide range of systems, from shop-floor sensing platforms to executive decision support tools have established their role and added value in scaling maintenance performance and tuning the optimization of its background economy (Mouzoune & Taibi, 2013, 2014).

E-Maintenance initially focused on technology integration efforts. The design scale of embedded systems and the versatility of SoC (System on a Chip) architectures enabled the integration of more powerful sensing infrastructure. Through time and advancements, sensor grids effectively evolved into self-aware WSNs (Wireless Sensor Networks) and e-Maintenance systems managed to align with the benefits of IoT (Internet of Things) trends (Emmanouilidis & Pistofidis, 2010a). Smart wireless sensors with embedded intelligence continue to be one of the main pillars of e-Maintenance and the reference implementation of Wireless Condition Monitoring (Emmanouilidis & Pistofidis, 2010b).

Aiming to produce schemas that provide optimal descriptive performance, data modeling has progressed at a different pace than software and hardware integration. Early on, standards, such as MIMOSA¹, achieved a solid coverage for a valid base of related concepts. Upon these standards research efforts targeted focused industrial testbeds, bringing insight into how to fuse data in order to compose maintenance knowledge (Savino, Brun, & Riccio, 2011).

Following the state of web 2.0 and mobile technologies, e-Maintenance reaches now to support users that exhibit a continuously context-changing access profile. Service-

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¹ MIMOSA Standard - <u>http://www.mimosa.org/</u>

oriented maintenance has allowed the compilation of tools into mutli-user web portals, where access is provided through flexible dashboard interfaces (Mouzoune & Taibi, 2014). Accommodating the needs of a mobile user and furthermore the needs of a shop-floor maintenance actor, modern e-Maintenance systems facilitate context-adaptive engines to compile portable views that support management over detailed and structured maintenance knowledge (Pistofidis & Emmanouilidis, 2012).

Filtered visualizations of maintenance data and knowledge navigation assistance have significant value, especially when personnel is expected to act/decide/perform on-spot and at a highly responsive and reliable level. Decision upon maintenance actions, at any level, should be driven by facts and evolving field expertise. Such knowledge is tacitly shared among maintenance experts but its elicitation, management and exploitation is not well-addressed by established maintenance and asset management solutions. To effectively manage shared knowledge, a process should be tuned to assist in its recording, management and evolution. This process needs to balance the synergy between two tasks: (i) proper provision of previously established knowledge entities as a reference and (ii) means for its effective review, evaluation and enrichment by fusion agents. On an industrial shop-floor, maintenance engineers and technicians can act as knowledge fusion agents, while an evolving FMECA-related information structure as reference for diagnostics-support.

Many e-Maintenance solutions focus on the efficiency of handling maintenance data and rigid knowledge. In practice knowledge is indirectly produced when a semantic map is placed upon solid data, commonly termed as metadata. Maintenance metadata management is less than adequately addressed in most software systems supporting maintenance and asset management. The majority of e-Maintenance systems opt to expand the descriptive scope of their models rather than introduce an extra layer of semantics. This decision eventually leads to an impressive support for standards, schemas and data formats, along with a huge volume of flat data, which are nonetheless too complex for human actors to process at any significant level. Data analytics emerge to serve with domain agnostic engines, aimed at porting and tuning mathematical models to test their ability in inferring maintenance knowledge from silos of maintenance history data. When working directly on flat data, this pattern may produce semi-functional mechanisms of maintenance intelligence that offer limited efficiency, while introducing overwhelming computational costs. Furthermore, it is a pattern that leaves experts largely unexploited, with limited contribution to shared knowledge and expertise. The engineers are called to study the findings extracted from monitored parameters of a past event. The context for such an event is often poorly recorded and the engineer lacks the necessary insight that was present when dealing with the problem in the first instance.

This paper presents research that addresses the mentioned requirements by employing modern technologies and delivering a metadata-oriented approach on managing maintenance knowledge. Maintenance insight can be collected on the shop-floor, prior to any back-office computation and act as the foreground of maintenance intelligence. As a data preparation stage, it benefits from the experts' fully contextualized cross-examination of approved maintenance profiles. To fulfill this task, the expert is provided with appropriate tools to review and annotate related data. An annotation schema of maintenance tags enables the user-labeling of events. The way this is achieved is explained by presenting the system behavior of an emaintenance user that utilizes metadata and fuses shop-floor generated expertise with a constantly evolving unit of maintenance intelligence.

The remainder of the paper is structured as follows. The next section presents related work and emphases the need for more efficient on the field knowledge recording and management. Section 3 analyses the modeling principles for the refined semantics of a Failure Context, while section 4 outlines the design features for a portable implementation of a maintenance-support tool. Section 5 presents the developed Intelligent Maintenance Advisor (IMA), focusing on the way it is tuned to handle the underlying knowledge in an industrial lifts manufacturing application case. A summary of the main conclusions and future work targets is provided in section 6.

2. CONTEXT-AWARE MAINTENANCE SERVICES

Service-Oriented Architectures have evolved into software patterns that adapt service-provision and serviceconsumption to the specific needs of application domains. E-Maintenance has progressed through various solution designs, where different environments were employed as hosts of software agents and services. Identifying which SOA-ready devices are currently available and how they can functionally participate (functional roles: client, server etc.) in a modern SOA solution, is a key step when researching new SOA approaches for e-Maintenance (Cannata, Karnouskos, & Taisch, 2010).

Wireless connectivity has become a feature for the majority of e-Maintenance solutions. Apart from sensors and SOA architectures, e-Maintenance is currently investing on extensive utilization of portable devices. Portable data visualization, analysis and remote management has greatly surpassed the expectations of many problem spaces and is being studied as one of the main pillars for mobility in e-Maintenance (Emmanouilidis, Liyanage, & Jantunen, 2009). Migrating software logic away from servers and PC stations, both in terms of background analysis and client access, has allowed maintenance to port its functions in high trending technologies such as mobile (native and web) applications (Campos, Jantunen, & Prakash, 2009).
The management of physical asset management data has matured from digital repositories of periodic reports to massive distributed silos of monitoring parameters and domain knowledge. During the last years, while embedded interoperability followed a slow maturity pace, backend analytics of Big Data are making leaps of evolution. Many enterprise solutions rushed to benefit from the domain insights that could be offered by the constantly growing toolset of cloud analytics. The cloud can now be used for orchestrating complex tasks such as predictive maintenance planning and prognostics (Lee, Lapira, Bagheri, & Kao, 2013). The volume of aggregated data is transforming what was formerly perceived as a costly burden into a valuable corporate asset with significant exploitation prospects.

Apart from volume size and physical distribution, e-Maintenance data have undergone an important semantic transformation. Widely accepted schemas, such as MIMOSA (www.mimosa.org), follow strict cycles of recomposition, where extensibility and conformance to specifications is assessed and validated. One of the core concepts in simplifying the provision of complex services is the development of Context models. Context-awareness is a feature that requires the capturing, clustering and interpretation of refined semantics. These must include parameters that compile meaningful context snapshots, which in turn can drive desired adaptations of the system's functionality. Deciding the synthesis of useful contexts for the maintenance domain and extracting the rules and correlations that can effectively boost the performance of maintenance tasks is an intensive modeling process (Nadoveza & Kiritsis, 2013; Pistofidis & Emmanouilidis, 2013). Expanding context modeling further than location awareness and commonly accepted semantics, means producing domain-specific knowledge patterns that can act as triggering mechanisms of service adaptations. The end result is highly enriched information that can drive the provision of context-adaptive maintenance services.

A good example of such a context study is the field knowledge that populates an FMECA (Failure Modes, Effects and Criticality Analysis) data model. Managing FMECA knowledge with software tools has been a part of many modern commercial e-Maintenance systems (PTC Windchil FMECA², ReliaSoft Xfmeca³). The majority of them emphasize in supporting a constantly updated list of FMECA standards (i.e. MIL-STD 1629⁴, IEC 60812⁵, BS 5760-5⁶, SAE ARP 5580⁷, SAE J1739⁸), offering

excessively complex desktop clients to access, enter and update the appropriate data. For many e-Maintenance suites, update and evaluation of the FMECA model, are tasks where only maintenance engineers and technical managers are authorized to contribute to. This pattern usually results in FMECA updates that primarily focus on how executive engineers perceive failures and not on how shop-floor technician experience and address failure. Furthermore, the maintained FMECA model is usually designed and utilized in a manner similar to its hardcopy counterpart: as a static digital report/table that records causality of failure events. This access model is lacking interactivity and feedback from the field practice it is designed to assist.

The majority of the above e-Maintenance systems disconnect the model of knowledge management from the one of reporting components. Usually, the intention to capitalize in capturing field expertise is translated into long non-contextualized forms for every different maintenance task. System's interaction with maintenance personnel is largely depended on exhaustive reports that require more time and information than currently available to the user. This approach suffers from the following drawbacks:

- **Repeated Knowledge** Indirect reference to relevant assets, tasks or personnel in entities already associated with a direct link – commonly known as referencing loops. Many modern systems overload the referencing volume of their schemas to compensate for complexity and to achieve faster response. Such an approach can create consistency issues, in terms of valid maintenance correlations and information loops. Reliability issues can prove to be a deal-breaker for a diagnostics system.
- **Rigid Encapsulation** Maintenance feedback, is often stored into records of a ticketing/reporting component. The schema holds their semantics tightly grouped in report-instances, limiting flexibility and blocking the scaling and reuse of knowledge, unless additional data services are built to manage them. Browsing a history of long non-validated reports, populated with unrelated data to the task at hand, is not an efficient way to handle knowledge reuse and provide decision support. The ability to pick modules of expert feedback and on-thefly compile a targeted report history can be vastly superior.
- Underpowered Fusion When conducting an FMECA analysis, history of maintenance assessments constitutes a primary source of background reference knowledge. Former model versions can be fused with insight extracted from validated events and shop floor facts. Modern systems employ off-line data analytics to cluster and classify reported observations and remarks. Models that do not employ solid connections between reported and approved knowledge are often in greater need of such analytics to drive the inference or creation of such correlations. Instead of introducing demanding

² PTC Windchil FMECA - <u>http://www.ptc.com/product/windchill/fmea</u>

³ ReliaSoft Xfmeca - <u>http://www.reliasoft.com/xfmea/</u>

⁴ https://src.alionscience.com/pdf/MIL-STD-1629RevA.pdf

⁵ http://webstore.iec.ch/preview/info_iec60812%7Bed2.0%7Den_d.pdf

⁶ <u>http://www.techstreet.com/products/1087481</u>

⁷ <u>http://standards.sae.org/arp5580/</u>

⁸ http://standards.sae.org/j1739_200208/

prerequisites for data analytics, fusion can be designed to occur transparently and on-line, in parallel to model population and feedback provision. Semantic tags constitute a state-of-the-art web methodology for clustering and classification of knowledge. Their adoption for maintenance knowledge can prove to bring many benefits to both its management and analysis.

Nonetheless, the above potential is still left largely unexploited by e-Maintenance solutions. Effective collection of expertise relies heavily on parameters such as expert's context, concise input and connection with a valid knowledge base. These were core targets for our research.

3. REQUIREMENTS FOR DIAGNOSTIC MODELING

Building the model of an application-focused context is essentially a process of classification for semantics associated with a decided core entity set. The selected semantics must compile a meaningful framework that can provide insight into the state of both the entities and their relationships. Our research evaluates the semantics that compose a new context of maintenance diagnostics. This context serves as knowledge map for information linked to assets' failures. Next, the design specifications and data modeling for capturing such a context are described.

Conducting a successful FMECA analysis, produces a data table that constitutes a highly enriched unit of field knowledge. This reference unit is the result of an engineering study that involves many steps of documenting existing knowledge. FMECA quality is bound by the validity and the timely nature of the processed data. Aging repositories of outdated information can severely impact the performance of the supported diagnostics. Considering that both the functional behavior and condition state of a single machine can significantly change between different production profiles or life-cycle periods, implies that reference information, which can decisively influence a critical maintenance assessment, must be constantly reevaluated based on qualitative feedback.

Compact Diagnostics Reference and Feedback – Whenever a user is prompt for an assessment, it is always helpful to provide a starting reference point. This reference information must be well connected and compact, facilitating the navigation on its semantics and browsing of its content. Modeling the user feedback must be similarly concise and well-framed. To effectively support the full scope of maintenance inspection and practice, reporting from current software tools tend to become excessively complex, often resulting in partially and incorrectly filled reports. Modeling the user feedback with semantics that simplify entry and leverage its value is crucial for balancing the users predisposition to the process, especially when a mobile maintenance actor needs ready-to-use and highly descriptive semantics to support a swift and valid entry. **Feedback to Approved Diagnostics** – FMECA modeling semantics should be differentiated from the users' feedback. Most systems provide distinct entity sets to model the core diagnostics and the reported feedback. Creating a modeled intermediate, acting as the bridge between them, is a very useful feature for data maintenance and one that can be effectively incorporated in the form of Approved Data. Approved Data include user entries, identified as information of higher value and thus handled as reference points. Labeling mechanics for such a process can be supported by models enabling sharing and cross evaluations of assessments. Approved Data function as the pool of candidate knowledge that will be inserted to the Reference Diagnostics, during the scheduled FMECA re-evaluation.

Diagnostics Data Provenance - User diagnostics are tightly connected with time locality. Being a core dimension of all context interpretations, time can reveal patterns that impact maintenance diagnostics decisively. Every data entered in a maintenance system, or any modern software system for that matter, is time-stamped and the action is logged. Apart from system administration reasons and the obvious significance of knowing the time of an event, the meta-interpretation of a timeline from legacy data has proven to offer many new insights. Data Provenance refers to the ability to trace and verify the creation of data. It documents the inputs, entities and processes that influence data of interest, in effect providing a historical record of the data and its origins. Data Provenance of maintenance assessments can identify patterns that can constitute valuable evolving knowledge. The proper modeling of entity correlations can empower the fusion of such timelines, allowing highly informative overviews of events, thus providing to the maintenance actor the right context.

4. THE SEMANTICS OF FAILURE CONTEXT

Modeling FMECA has been addressed by various standards that approach the process through different design perspectives. The proposed model builds a framework of diagnostics utilizing MIMOSA as a starting point for the modeling of core related semantics. Extending upon these semantics, our model brings more depth in specific aspects of failure causality and proposes a new schema for structuring the user's reported feedback. MIMOSA is a solid schema with an extended range of supported maintenance sub-domains. While the depth of its entity-tree provides descriptive accuracy, it can also overload systems with unexploited dimensions of maintenance details. These may introduce a significant overhead. Our goal is to produce a model effectively tailored for a service-oriented backend logic that handles requests of mobile maintenance actors. Such architectures and content provision patterns require modular semantics, appropriate for fast composition and processing of enriched mashups. In order to achieve data management efficiency, the proposed context schema adopts a subset of MIMOSA semantics, customized to offer a

balanced and lightweight handling of its depth. The concepts that participate in the core entity-set of the proposed failure context include (Figure 1):

- Assets: The entity whose properties describes the attributes of an industrial asset. These included essential registry data, classification attributes, criticality scales and components hierarchy pointers.
- Agents: This entity corresponds to system actors that communicate data for both FEMCA knowledge and annotation semantics. Though initially populated by human actors, it's modeled to support integrated system actuators, such as sensors and external systems.
- Actions: The entity that focuses in the description of maintenance actions. These are modeled as appropriate solution steps/packages that address prevention or correction of the recorded failure modes.
- Events: The most essential component of the failure context. It addresses the modeling of both failure modes and the associated failure mechanisms. Failure mechanisms lead to failure modes and feature as their causes or effects. Extending the MIMOSA hypothetical event entity, we propose a schema that supports scaled effects semantics, assessing the quality of their impact.

Following the MIMOSA taxonomy of events, both Failure Modes and Failure Mechanisms are modeled by the same entity; the *Hypothetical Event*. While MIMOSA chooses to omit them, the proposed Hypothetical Event schema includes occurrence and detection scale to assess frequency and detection potentials. Along with severity, this set of attributes can drive an RPN-based (Risk Priority Number) evaluation of Failure progress. MIMOSA offers a generic and flexible approach for causality relationships, pairing Hypothetical Events through unclassified links. The proposed version provides direct and fixed semantics with attributes that map causes and effects upon a basis of scaled impact. While Causes are associated with Failure Modes, through one attribute, Effects are separated in three classes:

- Symptoms They constitute effects of low significance for the related Asset and its environment. They provide the means to model "observations" as part of formally captured Failure Mode knowledge. Symptoms events constitute whose description can be characterized as vague, abstract and not easily quantifiable. Nevertheless they facilitate the integration of uncharted insight inside the reference model of Failure Modes.
- Functional Failures These events model effects directly connected with specific functions of the related asset. Their role is to distinguish between events that manifest the dynamic change of functional behavior, from events that describe a static status or condition. They can be particularly useful in the analysis of propagating failures, where functional participation of

assets in process workflows can produce chains of effects. The timeline of such effects can reveal the parallel progression and connection of failure modes.

• **Final Results** - These effects include the Failure Mode's most critical results. They are descriptions of events, that significantly impact the condition of the asset and its parent/child components. They record a final and usually irreversible failure status, and should invoke attention for the state of interfacing assets. These events must be well documented, since they constitute the most decisive evidence for the identification of a Failure Mode.



Figure 1. The knowledge dimensions of the Failure Context

Our research offers a new method for capturing the feedback of maintenance staff. The model invests on a data preparation process that can greatly enhance analytics. By building maintenance reports with multiple references to an approved FMECA table, we capitalize in the creation of predefined correlations. Supporting further modularity, we break these reports to smaller referencing units. Context fusion increasingly advertises the need to scale down exhaustive schemas and port semantics to refined knowledge units with metadata profiles. This is exactly our goal in modeling the Failure Context. The diagnostics annotation system is modeling user feedback by combining:

1. <u>Maintenance Tags:</u> Tags are keywords that can be applied to maintenance data objects as descriptive annotations (

- 2. Figure 2). Their descriptive goal may vary and can be classified in categories of keywords. The semantic scope of tags in generic domains is usually unframed and their use can facilitate the creation of a tag cloud. A maintenance tag cloud is a simple and effective way to cluster semantics and infer their likely adoption.
- 3. <u>Maintenance Remarks:</u> Maintenance personnel are asked to input their evaluation in qualitative and quantitative manners. For an assessment, the importance of a tag can be augmented by a small note that provides more analysis, or a numeric value that quantifies belief. More automated response patterns, such as checkboxes and selection options are also favored to assure interfacing simplicity and fast input. This form of micro-knowledge fragments, if effectively managed and mined can become extremely valuable.



Figure 2. Managing the context of maintenance reference and annotations.

One of our aims is to offer a versatile schema that supports capturing and use of **maintenance micro-knowledge** by means of tags, with support for optional remarks. The model allows the creation of tag templates configured to map tacit knowledge embedded in maintenance practice. Tag instances are provided by staff in the form of annotations or metadata for approved diagnostics (FMECA core entities). Their title, category and compatibility can be configured and updated by maintenance engineers. Each tag template can be profiled to support the optional addition of: (i) textual notes, (ii) numeric values and (iii) a status lock. These optional fields are used to leverage the tags knowledge value and provide engineers with better insight on how they can expand and adjust the semantics of available tag templates.

Essentially this tagging process enables the instant sharing of assessments between maintenance professionals. The timeline of such maintenance tags creates a layer of metadata upon the validated knowledge of recorded failures modes and mechanisms. This collection of metadata and their direct connection to approved diagnostics compose an extended and validated FMECA. Furthermore, access and navigation in such layered maintenance information can provide the appropriate context for the successful completion of challenging maintenance tasks.

5. INTELLIGENT MAINTENANCE ADVISOR

Next we analyse the functional requirements of the WelCOM-IMA tool, the adopted design and implementation technologies, as well as its final implementation. As a first step, the provided e-Maintenance services are described and their focus is explained. The competitive advantages of a software tool that can manage the Failure Context are mapped onto industrial needs, using case-scenarios.

5.1. E-Maintenance Mobility

Mobile e-Maintenance involves potent smart portable devices, offering wide displays and powerful multi-core processors. The rapid evolution of mobile Operating Systems and their development frameworks, offer a fluid experience even for the most demanding web applications and enterprise portals. Our goal is to exploit such potentials and address the needs of mobile maintenance personnel:

Greater control over richer information - Early versions of e-Maintenance mobility used the 3-inch displays of industrial PDAs to provide sample history and brief reports. Instrumentation PDAs could also visualize spectrum harmonics and graphs. In most cases, the ability to store, handle and (rarely) process a greater volume of data introduced vendor-locked hardware/software specs with high cost. Recent medium-range tablets are able to hold GBs of local cached data, thus are capable of hosting a maintenance model, within a single native application. The performance of high speed memory affects the solutions' efficiency, as it defines the complexity of data that can be instantly accessed and processed by the mobile actor. Diagnostics can handle structured data with multiple requirements for handling similarly complex metadata. Therefore, mobile e-Maintenance should move much further than the provision of sample history.

Better connection patterns – Wireless communication is the main link between mobile components and e-Maintenance servers. A good example of how easily can a modern device facilitate mobility, is the fact that many industries and application domains have utilized tablets for remote desktop administration of suites and software tools that are physically installed on back-office stations. Mobile personnel can receive a fully compiled environment of a maintenance dashboard that is actually run and executed on a remote machine. Modern E-Maintenance portals offer total control over the workflow, configuration and invocation of e-Maintenance backend processing (i.e. diagnostics), physically distributed (hosted) in optimally integrated services. The developed system brings this kind of control to mobile users, through wide-screen tablets.

Intuitive Interaction and Multi-Access Environments -The majority of enterprise systems that participate in SOA architectures, currently invest in providing flexible interfaces for each employed access profile. This essentially means that their client environment is upgraded, both in terms of content visualization and navigation, to accommodate the needs of a mobile user too. Web technologies currently capitalize in the design of touchfriendly, personalized and context adapted interfaces for portable devices. Modern 10-inch tablets, while thinner and lighter than any industrial PDA, offer solid build and a generous layout for intuitive web environments. The proposed system aims to couple the versatile access context of a 10 inch tablet with Web 2.0 technologies to produce a well-balanced tool for managing maintenance knowledge. Though native applications exhibit a slightly better interaction experience, the mobile web version was favored because (Pistofidis & Emmanouilidis, 2012):

- Mobile web apps can **run on every tablet irrespective to its operating system** (android, iOS, wp8). Native applications constitute OS-locked implementations and require extensive re-engineering for cross-platform compatibility. Web applications can be upgraded to hybrid applications, enjoying the benefits of both. Accessing web applications from different devices requires no additional porting, as services and interfaces support uniform access from any available browser.
- Mobile web apps **do not require installation and do not ask for any kind of access** to personal account information. Recent mobile browsers can boost their performance in compiling even the most demanding and visually loaded interfaces.
- Mobile web apps offer more options for efficient scaling. Since they do not invest on local (portable device) logic, web applications tip the balance of complexity to the backend servers. This design feature is aligned with current trends in Cloud and Big-Data. Scaling and load balancing of backend logic is a much easier and streamlined process in web application SOA designs. Furthermore, web apps offer extensive scaling potential for the frontend e-maintenance interfaces too. Web applications can employ many versatile patterns and rich frameworks, to integrate different clients and service outputs into the same user environment. Such technologies allow for less coding and a more robust implementation when, for example, integrating CMMS functionality to an E-Maintenance platform.

Faster Input and Sharing - Social networks are dominating the digital extension of many personal and professional communication spaces. Users, whether at home or at work, require the provision of tools that allow them to provide input at a real-time manner and with many sharing

options. Social network portals and their multi-user virtual environments are the most valid testbeds where analysts identify the interaction patterns that users adopt and favor. Some very interesting and useful points can be identified, from the popularity of certain actions by their mobile users:

- Users are most likely to complete fields that require short and concise feedback, than long detailed text.
- Users want to engage the process of feedback with the shortest possible navigation path.
- Users want to indicate approval and positive feedback with direct annotations.
- Users want to organize social assets into virtual collections, using annotations and tags.
- Users want to share in such environments and expect validation, acceptance or feedback from other users.
- Users prefer to view and manage a timeline/feed of events that summarize the status of the social context they have configured to participate in.

Indifferent to the above, most e-Maintenance systems have attempted to collect and map field expertise with exhaustive forms. Especially when addressing mobile maintenance, long forms and inefficient navigation lead to user rejection. Very often the usage of such mobile tools by technicians is done much later than it is supposed to and often after a maintenance task is completed, thus out of context input is likely. Our research uses the mentioned points and specifications to create a web tool designed and developed to encourage mobile use of FMECA-oriented knowledge.

5.2. Implementation Technologies for IMA

This work presents the development and functionality of a web application that benefits from mobile web and mobile cloud technologies, the WelCOM Intelligent Maintenance Advisor. Implementation details follow next.

Back-end logic – These components execute the background management of maintenance diagnostics. To implement WelCOM-IMA's web services we employed the flexibility of a Node.js platform, a runtime environment that can execute Javascript at the backend. At the core of Node.js, the V8 Chrome engine that allows support and integration of libraries/modules that can address a vast range of application requirements. Express is such a library and it facilitates the development of web applications on top of Node.js. Node.js can very efficiently virtualize both application and server instances. Thus, load balancing for the maintenance services of IMA can be easily incorporated with no re-engineering. All the services that address the creation, browsing and annotation of the system's Failure Context, are implemented with the flexibility offered by Javascript. This is aligned with a design decision to benefit from the synergy between Javascript components and JSON models, across frontend and backend logic.

Front-end interfaces – The interfaces of a system denote its support for various access patterns. WelCOM-IMA targets mobile actors and thus utilizes technologies that excel in producing mobile optimized web views. Tweaking and customizing the components of a rich web template, our frontend client employs HTML5, CSS and Javascript to build a fluid and touch friendly client interface. WelCOM-IMA facilitates jQuery along with a rich set of other Javascript frameworks, to provide adequate control over maintenance data and offer intuitive user experience. The template scripting language JADE powers a backend engine that dynamically compiles WelCOM IMA's interfaces. This engine makes the WelCOM IMA a fully modular and customizable client, able to comply with various needs in terms of maintenance data visualization and entry.

Physical Data Model - Modeling maintenance semantics is an essential process for the design of any e-Maintenance solution. Many implementations still use relational databases for the physical instantiation of data their models. XML maintenance schemas have dominated the formats of exchanged knowledge for many years, due to their lightweight, human-readable and easily parsed structure. MIMOSA publishes and maintains a very thorough and descriptive XSD schema for all the entities it supports. SOA architectures, especially ones with enterprise web components, are rapidly shifting from XML data to JSON data. JSON syntax is even more lightweight than XML and can be optimally parsed and processed by any programming technology. JSON is a technology coupled with the concept of mashups. A mashup implies the easy and fast integration of multiple data sources to produce enriched information units that can be transferred and consumed uniformly and in a multipurpose manner. JSON mashups are flexible modules of refined information, and thus currently drive the models of many knowledge management systems. WelCOM-IMA uses JSON to enable capturing FMECA-related information inside JSON data. The handling efficiency of JSON with frontend and backend Javascript components, is supported by the use of a noSQL database, namely MongoDB. The consumption of MongoDB's virtual collections, by WelCOM-IMA components, offers the transaction efficiency required by mobile templates and Node.js.

Extending upon a subset of MIMOSA's entities, we have produced a Schema (Figure 3) that elaborates the attributes and the correlations of FMECA related maintenance data and tags. Hypothetical Event is the entity that maps all type of events participating in the Failure Context. While Failure Mechanisms and Failure Modes are both types of this entity, the instances of the former act as an initial stage for the instances of the later. While Failure Modes are events with a with causes, effects and solutions associated with them, Failure Mechanisms are events that lack such information but may be linked to a Failure Mode. If at some point the significance and the profile of a Failure Mechanisms are upgraded to include causality and proposed solutions, then the appropriate attributes are populated. In such a scenario, while the event's place in the FMECA structure remains the same, its diagnostic value is upgraded. This is a process that gradually builds an Asset Fault Tree. New Failure Events are better perceived and profiled with causes, effects and solutions, when employing the versatility of a Tag Instance entity. Users are able to evaluate and tag all event data and assets. Sorting and fusing this tag-cloud, can effectively point the FMECA review process to the right direction.



Figure 3. WelCOM IMA core entities schema

5.3. Instantiation in an Application Case

WelCOM-IMA is a part of an e-maintenance platform and comprises part of the platform's knowledge management functionality. It aims to serve the management and delivery of diagnostics knowledge to shop-floor staff. The WelCOM architecture is designed to integrate software components that operate on different systems contexts, such as sensors, servers and portable devices (Pistofidis, Emmanouilidis, Koulamas, Karampatzakis, & Papathanassiou, 2012). Starting from the sensor-embedded pre-processing of monitoring parameters, WelCOM middleware manages, processes and enriches a maintenance model to deliver higher level services for maintenance support and planning.

The WelCOM piloting takes place at KLEEMANN Lifts, a manufacturing industry the delivers complete lifts solutions and an international presence in the lifts industry, holding more than 2% of the global market. The industrial unit that holds key production and business value is the company's latest Electric Elevator. The testing tower at Kleemann's industrial facilities in Kilkis provides one of the test cases that are populating the system with FMECA-related information, whereas other primary and secondary production machinery are currently being studied in the tool.

WelCOM			U pistofid 🗸	
	Welcom -IMA			
EE PMECA Table V	WelCOM Intelligent Maintenance Advisor			
Core Entitles	W DitalFMECA > FMECA Table > Core Entries			
 I nttry Types I shell Menanement 				
Account Management	Core Entities of FMECA Knowledge		~	
	10 * records per page		Search:	
in big meer cause	Code Litle	Actions		
	Field 🔚 Asset Type	🔁 Into 🕂 Add		
	Ent13 🗮 Accet	● Info + Add		
	±nc14 i≣ Agent	⊕ Info + ∧dd		
	Enrit 🔚 Asset Puntion	⊕ Info + Add		
	Enc17 I Asset Type Function	⊕ Info + ∧dd		
	Encls III Maintenance Action	⊕ Info + Add		
	Enc21	😝 Info 🕇 Add		
	Lot22 🚍 Accet Type Hypothetical Event	😝 Info 🔶 Add		
	Showing 1 to 8 or 8 entries		Previous 1 Next	

Figure 4. WelCOM-IMA Core Entities Directory

The WelCOM-IMA instantiation in this industrial case study employed use case scenarios to document how the user can browse and enrich maintenance knowledge, while also extending the available options for entity types and tags. The tool offers a core entity set that holds the reference maintenance knowledge. After inserting credentials for authentication the user is presented with a directory of FMECA core entities. A brief description of entity semantics and a button link to the appropriate instantiation form are seen in this first screen (Figure 4).

5.3.1. Navigation through Diagnostics Context

The modeled knowledge is provided as a fully connected map of diagnostics. The user is able to list the instances of every entity and navigate through them following patterns of maintenance relationships (causality, supervision, solution, taxonomy etc.). Moving from agent to asset, from asset to event and from event to event (Failure Mechanism to Failure Mode), a user can browse details of the documented failure profiles of assets. At every step the navigation of the produced view is supported by profiled and highlighted buttons, drop down option lists and fully configurable data-tables with paging and search tools. Using the maintenance map, the shop-floor technician can traverse the details of events that match current evaluation and/or observations. Through them the search will lead to identifying a Failure Mode associated with most of related acknowledged events (as effects or causes). A Failure Mode screen presents a rich set of FMECA-oriented semantics. Causality attributes support the root-cause analysis of the on-going failure and the suggested maintenance action aids the decision on how to address it (Figure 5).

5.3.2. Maintenance Knowledge Enrichment

The developed system addresses the needs of both mobile technicians and office engineers, thus it was important to close the distance between them, offering a sharing space for collaborative exchange of maintenance insight. It supports their ability to offer fast and efficient feedback by prompting them to simply acknowledge and flag pre-defined semantics. Feedback is summarized by descriptive tags to assets, agents, events and solutions. Each tag can signify a state, an action, an observation or an alarm, in short anything that matters in the context of diagnostics. A basic set of offered tags, includes "Confirm" (tagging the detection of a failure event), "Working here" (on-going maintenance action and proximity to an asset), "Observation" (logging of an observation).

≡ Entity Attributes - Asset Hypothetical Event ✓				
Event Title:	Final failure of the Deflector Sheave's bearings			
Event Type:	Failure Mode 🕘			
Associated Asset:	Testing Lift \ominus			
Severity Level:	Criticaly High 🛞			
Occurrence Level:	Very Rare Θ			
Detection Level:	Very High ⊖			
Associated Asset Funtion(s):	Lift cabin motion transmission $\ \Theta$			
Effects (Functional Failures):	Lift function failure ③			
Effects (Final Results):	Catastrophic failure of Deflector Sheave's bearing ③			
	Rope deflection at Deflector Sheave $ \ominus $			
Effects (Symptoms):	Noise at Deflector Sheave \ominus			
	Vibration at Deflector Sheave 🛞			
Causes (Directly Associated):	Natural wear without properly scheduled replacement - Deflector Sheave bearing $\ \odot$			
	Defective bearing - Deflector Sheave 🥥			
	Installation/assemply error of Deflector Sheave light			
	Poor maintenance of Deflector Sheave $\ \odot$			
Suggested Maintenance	Deflector Sheave replacement 🛞			
Action(s):	Deflector Sheave bearing replacement $ \ominus $			
	🗞 Labels 🗸			

Figure 5. Information screen for an Asset Failure Mode.

Additionally, a "Confirm" tag may carry a certainty numeric value. All tags support input of textual notes, offering assessment details (Figure 6). Analysis of the collected textual notes can reveal semantics for different applications, maintenance departments, policies, or even work teams. WelCOM-IMA offers the means to create new tag templates where engineers and maintenance directors can configure the semantics and the (optional) input profile of new tags (Figure 6). Configuration fields include taxonomy with tag categories, a description, a set of compatible entities and the support for numeric value, textual note and a status lock. These templates, upon creation, are instantly available for shop-floor and managerial personnel to use them and best capture/translate their assessments. The annotation task has to be swift and easy. WelCOM-IMA provides a "Label" drop list, in every interface that presents instances that can be tagged. This drop list offers the ability to annotate the instance with a new tag, or view the annotation history of this specific instance. Choosing to add a new tag, the user is presented with a touch-friendly interface listing all available tags that support the entity of the assessed instance. While the brief description and the category informative of the underlying semantics, a side-form facilitates the direct input of additional feedback, for each supported tag (Figure 7). The simple touch of the tag's button concludes the tagging process and records the new assessment as a timestamped entry in the instance's annotation history. Maintenance engineers can now view the annotation history of each asset and failure event. WelCOM-IMA provides three forms of annotation timelines: (i) instance-oriented, (ii) user-oriented and (iii) global. Each one enables a different view over assessments that can drive different sets of conclusions.

≡ Update Form Lal	oel Types			~
Label Title:	Contirm (*required)			
Label Category:	Disgnostics v			Ψ
Label Description:	(required) A lag that confirms the occurence of an even	l. Il ma	y also be supported by a certaintly percentage.	
Supported Entities:	Asser lype Inhel Types Inhel Types Inhel Annotation Asset Agent Asset Undon Asset lype Lunction Maintenance Action Entities that can be annotased by the label. No e	<i>⇔</i>	Asset Hypothetical Event Asset Type Hypothetical Event	
Support Numeric Value:	~			
Support Text Note:	×			
Support Boolean Toggle:	×			
	✓ Update 🛛 🗙 Cancel			

Figure 6. Configuring a new tag template.

■ Asset Hypothetical Event - Available Labels v				
⑦ Entities Table ⓒ Return/Cancel ↑ Create New Label ♥ Annotations List				
10 records per page Search:				
Label Additional Info				
Seconfirm	Numeric Assessment :	Numeric value to quantify th		
A Category : Diagnostics Descrip	User Remark : tion 1	Textual note for further description		
Brief Description: A tag that confirms the occurrence of an event. It may also be supported by a certainily percentage.				
Observation	User Remark :	Lextual note for further description		
📥 Category : Basic Descrip	tion 0			
Showing 1 to 2 of 2 entries		← Previous 1 Next →		



Subservation	×	Deflector Sheave Asset	chrisem	Thu Mar 27 2014 01:29:44 Standard Time)
User Remark:	Back to	o normal operation status!		
🗣 Working here 🔳	×	Deflector Sheave bearing replacement Maintenance Action	npapatha	Thu Mar 27 2014 01:28:48 Standard Time)
User Remark:	Compl	eted by engineer! Supported pistofid!		
💊 Working here 🔳	×	Testing Lift Asset	pistofid	Thu Mar 27 2014 01:27:03 Standard Time)
User Kemark:	Correc	tive maintenance. Bearing replacement.		
🗣 Confirm 🔳	×	Advanced fault on the Deflector Sheave's bearings Asset Hypothetical Event	chrisem	Thu Mar 27 2014 01:25:46 Standard Time)
Numeric Assessment:	100			
User Remark:	This is	going on for sure. Let's schedule bearing replacemen		
Source Observation	×	Deflector Sheave Asset	npapatha	Thu Mar 27 2014 01:23:28 Standard Time)
User Remark: Something is wrong with the Deflector sheave. Maybe a bearing issue.				
Confirm	×	Vibration at Deflector Sheave Asset Hypothetical Event	chrisem	Thu Mar 27 2014 01:21:51 Standard Time)
Numeric Assessment:	90			
User Remark:	Really	intense! I am sure something is wrong.		
S Confirm	×	Noise at Deflector Sheave Asset Hypothetical Event	pistofid	Thu Mar 27 2014 01:17:10 Standard Time)
Numeric Assessment:	80			
User Remark:	Probat	oly nothing		

Figure 8. Annotations global timeline: a Failure's Context.

The interpretation of these timelines can have a big impact in the performance of on-spot diagnostics. Having access to a timeline of annotations correlating assets and events is a tool that "connects-the-dots" of a Failure's Context (Figure 8). The time locality of events, the focused tag semantics and the annotated knowledge, offer a perception boost to the context-switching mindset of mobile personnel.

6. CONCLUSION

Studying the annotation history of a failure event or an asset empowers maintenance professionals to extract valuable patterns of machinery behavior. The ability to manage the underlying structured knowledge and perform analytics over the collective micro-knowledge of staff operating on the shop floor, constitute a powerful enabler that upgrades the level of knowledge management, by incorporating into the loop maintenance mobile actors. WelCOM-IMA offers an effective method to facilitate the contribution and participation of all maintenance staff in managing the evolution of maintenance events and knowledge. WelCOM-IMA enables the organization and collaborative evaluation of maintenance assessments based on semantic tags. Following a bottom up approach in knowledge composition, it delivers a tool that profiles, instantiates and shares the building blocks of failure diagnostics. Therefore, it can adapt the maintenance meta-model to semantics tuned for a specific application. This constitutes a significant enabler for the elicitation and management of field-captured knowledge, a feature often missing in many tools.

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REFERENCES

- Campos, J., Jantunen, E., & Prakash, O. (2009). A web and mobile device architecture for mobile e-maintenance. *The International Journal of Advanced Manufacturing Technology*, 45(1-2), 71-80.
- Cannata, A., Karnouskos, S., & Taisch, M. (2010). Dynamic e-maintenance in the era of SOA-ready device dominated industrial environments *Engineering Asset Lifecycle Management* (pp. 411-419): Springer.
- Emmanouilidis, C., Liyanage, J. P., & Jantunen, E. (2009). Mobile solutions for engineering asset and maintenance management. *Journal of Quality in Maintenance Engineering*, 15(1), 92-105.
- Emmanouilidis, C., & Pistofidis, P. (2010a). *Machinery self-awareness with wireless sensor networks: a means to sustainable operation*. Proceedings of the 2nd workshop on maintenance for sustainable manufacturing, 12 May 2010, Verona, Italy.
- Emmanouilidis, C., & Pistofidis, P. (2010b). Wireless condition monitoring and embedded novelty detection *Definitions, Concepts and Scope of Engineering Asset Management* (pp. 195-238): Springer.
- Lee, J., Lapira, E., Bagheri, B., & Kao, H.-a. (2013). Recent advances and trends in predictive manufacturing systems in big data environment. *Manufacturing Letters*, 1(1), 38-41.
- Liyanage, J. P., Lee, J., Emmanouilidis, C., & Ni, J. (2009). Integrated e-Maintenance and intelligent maintenance systems *Handbook of maintenance management and engineering* (pp. 499-544): Springer.
- Mouzoune, A., & Taibi, S. (2013). Towards an intelligence based conceptual framework for e-maintenance.
 Proceeding of 8th International Conference on Intelligent Systems: Theories and Applications (SITA), 8-9 May 2013, Rabat, Morocco.
- Mouzoune, A., & Taibi, S. (2014). Introducing Emaintenance 2.0. *International Journal of Computer Science and Business Informatics*, 9(1).
- Nadoveza, D., & Kiritsis, D. (2013). Concept for Context-Aware Manufacturing Dashboard Applications. 7th IFAC Conference on Manufacturing Modelling,Management, and Control, 19-21 June 2013, Saint Petersburg, Russia.
- Pistofidis, P., & Emmanouilidis, C. (2012). Developing Advanced Context Aware Tools for Mobile Maintenance. Proc. of the 2nd IFAC workshop on Advanced Maintenance Engineering, Services and Technology, 22-23 November 2012, Seville, Spain.
- Pistofidis, P., & Emmanouilidis, C. (2013). Profiling context awareness in mobile and cloud based engineering asset

management Advances in Production Management Systems. Competitive Manufacturing for Innovative Products and Services (pp. 17-24): Springer.

- Pistofidis, P., Emmanouilidis, C., Koulamas, C., Karampatzakis, D., & Papathanassiou, N. (2012). A layered e-maintenance architecture powered by smart wireless monitoring components. Proc. of the IEEE International Conference on Industrial Technology (ICIT), 19-21 March 2011, Athens, Greece.
- Savino, M. M., Brun, A., & Riccio, C. (2011). Integrated system for maintenance and safety management through FMECA principles and fuzzy inference engine. *European Journal of Industrial Engineering*, 5(2), 132-169.

BIOGRAPHIES



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Performance and Condition Monitoring of Tidal Stream Turbines

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ABSTRACT

Research within the Cardiff Marine Energy Research Group (CMERG) has considered the integrated mathematical modelling of Tidal Stream Turbines (TST). The modelling studies are briefly reviewed. This paper concentrates on the experimental validation testing of small TST models in a water flume facility. The dataset of results, and in particular the measured axial thrust signals are analysed via time-frequency methods. For the 0.5 m diameter TST the recorded angular velocity typically varies by $\pm 2.5\%$ during the 90 second test durations. Modelling results confirm the expectations for the thrust signal spectrums, for both optimum and deliberately offset blade results. A discussion of the need to consider operating conditions, condition monitoring sub-system refinements and the direction of prognostic methods development, is provided.

1. INTRODUCTION

Research within the Cardiff Marine Energy Research Group (CMERG) has established a series of generic design guidelines for the developing commercial deployment of Tidal Stream Turbines (TST). Design considerations were reported by O'Doherty, Mason-Jones, O'Doherty, Evans, Woolridge and Fryett (2009). The mathematical models combine Computational Fluid Dynamics (CFD), structural Finite Element Analysis (FEA) to provide Fluid-Structure-Interaction (FSI) results. Non-dimensionalised power and thrust curves, along with flow visualisations, are produced for a variety of configurations and flow conditions. The non-dimensionalised research was reported by Mason-Jones, O'Doherty, Morris, O'Doherty, Byrne, Prickett, Grosvenor, Owen, Tedds and Poole (2012). The progress and outputs of the modelling studies are briefly reviewed in section 1.1.

The mathematical models are validated via the testing of scale model (0.5 m diameter) turbines in a water flume facility at Liverpool University. A dataset of results was available for a particular set of performance and monitoring evaluation tests. For these a three blade turbine was used, with a constant plug flow of 0.94 m.s-1 and at a range of controlled conditions within the power curve profiles. Previous studies and testing had compared results for designs with varying numbers of blades and had confirmed the optimum blade angle setting for the 3 blade option. Recent studies have used profiled flow conditions and with the addition of surface waves.

For the dataset considered in this paper, the recorded signals were angular velocity, servo motor current (used to oppose flow generated motion and hence to estimate generated power) and the overall axial thrust. Tests were split between an 'optimum' setup (three identical blade angles) and an 'offset' setup. For the latter, one of the three blades was deliberately set at other than its optimum pitch angle. This condition was deemed to represent potential blade faults, whereby one damaged or deteriorated blade would contribute less than usual to the generated power output. From a condition monitoring viewpoint such deviations in performance were expected to also be detectable in the more accessible axial thrust signals.

The experimental signals are described in detail in section 3, along with the limitations of the signals, with respect to time-frequency analysis (section 4).

In section 4, traditional frequency spectrum plots are initially presented. The frequency spectrums obtained included components, for any given set of test conditions, observed at the rotational frequency (ω_r) and at either or both $2.\omega_r$ and $3.\omega_r$. Thrust measurements, from the turbine supporting structure, are more easily made in comparison at rotating elements and their potential to form a constituent part of an integrated TST monitoring system is explored.

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With the aim of more robust detection of individual blade problems, methods of improving the frequency spectrum resolutions were required. In particular synchrosqueezing time-frequency methods were assessed and are presented in section 4.4.

1.1. Review

Tidal energy can provide a highly predictable and sustainable level of energy. One of the emerging technologies is the use of submerged tidal stream turbines (TST), which for example, may be seabed mounted. UK tidal stream technologies are increasingly being installed and tested as full-scale devices. The first example was the Marine Current Turbines (MCT) 11m diameter, 2 blade horizontal axis Seaflow device. The 300 kW capability from a tidal flow of approximately 2.8 ms⁻¹has increased to 1.2 MW for the subsequent SeaGen project. TST technologies are rapidly developing, different designs are being proposed, and experimental performance testing is also carried out at small scale, with support from sophisticated mathematical modelling. A review of research progress is provided by Ng, Lam and Ng (2013).

1.2. Modelling

For horizontal axis tidal turbines (HATT) the computational fluid dynamics (CFD) models have been considered in a non-dimensionalised manner and have led to generic power and thrust performance curves for use by designers. The non-dimensional performance curves were validated via experimental testing at the water flume facility in Liverpool University.

Figure 1 [Myers and Bahaj (2012)] shows the general arrangement for a HATT installation and summarises the main parameters and effects of interest.



Figure 1. Horizontal Axis Tidal Turbine (HATT) [Myers & Bahaj (2012)]

The CFD models have been extended to include Fluid-Structure Interactions (FSI). Accordingly the 2 way coupling between fluid flows and structural deflections are used to improve the simulation results for realistic flow and installation conditions. The experimental testing has also been developed to allow profiled flow testing, in addition to the original plug flow testing. The addition of surface waves has also been developed for the water flume facility at Liverpool University.

The experimental testing to validate the range of mathematical modelling activities has provided an opportunity to assess potential condition monitoring and prognostics methods. Of particular relevance, to such aspects reported in this paper, are models used to investigate the interactions between the turbine blades and the supporting structures. There are observable shadow effects as the blades pass in front of the supporting structure. As will be reported in section 4.1, cyclic variations in the axial thrusts are produced as a consequence of such effects. It is the cyclic variations that are investigated, with frequency domain and time-frequency domain methods, as an potential contributing sub-system to a TST condition monitoring system. The modelled effects have been reported by Mason-Jones, O'Doherty, Morris and O'Doherty (2013). The contributions of such models are reported in section 4.

1.3. Condition Monitoring & Prognostics

Condition monitoring and fault diagnosis is considered to be elemental in developing marine current turbine energy extraction. Tidal energy technology has yet to be proven with regard to long term operational availability and reliability. It is accepted that the harsh marine environments and problems with accessibility for maintenance may exasperate availability and reliability problems. Bahaj (2011) noted that minimising uncertainty surrounding the operation and maintenance of such devices will be crucial in improving investor confidence and economically viable achieving power extraction. Experience within the wind energy sector, for example as reported by Hameed, Ahn and Cho (2010), Yang, Tavner, Crabtree and Wilkinson (2010) and Tian and Jin (2011), has suggested that online condition monitoring and fault detection could minimise maintenance costs and improve availability of the energy extraction technology. As such condition monitoring and fault diagnosis hardware and software architectures should at this stage seek to be general and adaptable

Figure 2 [Grosvenor and Prickett (2011)] outlines constituent components for such a generalised TST monitoring system. The investigations reported in this paper focus on the use of supporting structure based sensors. In particular, the potential of time-frequency analysis methods applied to the background cyclic variations in the supporting structure are considered.

2. EXPERIMENTAL TESTING

A series of scale model turbines have been developed by the CMERG group for water flume testing. For the tests reported and analysed in this paper a 0.5 m diameter, 3

blade turbine was used. Each blade pitch angle was adjustable and from previous testing, not reported here, the optimum blade pitch angle had been determined to be 6° for the configuration in use. This prior testing information was also utilized to simulate a blade fault. In this case one of the blades was deliberately offset, to a pitch angle of 15° .



Figure 2. Constituents of a Generalised TST Monitoring System.

The water flume was configured and operated to provide plug flow conditions (constant flow with water depth) and an average axial flow velocity of 0.94 m.s^{-1} .

A direct drive servo motor was used to generate controllable torques in opposition to those from the flow and turbine blades. Accordingly tests were achievable for a range of conditions from within the turbine performance curve. These ranged from the peak power conditions down to the free-wheeling condition with negligible power output. These were classified by a percentage of maximum torque measure, with 19 settings ranging from 45% downwards in 2.5% steps to 0% of maximum torque. The servo motor was capable of delivering a maximum torque of approximately 4.92 Nm. As stated, the tests were performed for both optimum blade settings ($6^{\circ}-6^{\circ}-6^{\circ}$) and with one blade deliberately offset ($6^{\circ}-15^{\circ}-6^{\circ}$).

For each individual test data was recorded for between 90 and 150 s. The recorded signals consisted of the servo motor current (used to calculate power outputs), the angular velocity of the turbine and the total axial thrust.

Figure 3 show the general setup for the water flume tests. The junction between the vertical turbine support tube and the horizontal supporting frame was fitted with a force block. The strain gauge arrangement of the force block enabled the measurement of the total axial thrust.

3. EXISTING DATASETS

Accordingly the analysed dataset consisted of a total of 38 test cases, equally split between optimum blade and offset blade setups. Figure 4 summarises the test configurations for the turbine power curves.



Figure 3. Liverpool University Water Flume and Experimental Setup.

These are plotted as power coefficient, C_p , vs tip speed ratio, TSR. The former is the ratio of actual power compared to theoretical power. TSR is a normalized measure, for a given turbine, of the angular velocity. The performance reducing effect of the one offset blade is evident.



Figure 4. Power Curves for Experimental Datasets

Example results are shown in Figure 5. The upper plot shows the thrust signal variations during a 90 s test for optimum and offset blade cases, for 30% and 32.5% torque settings. The lower plots shows the angular velocity fluctuations for the same cases.



Figure 5. Example Experimental Results: Axial Thrust and Angular Velocity Signals for Optimum and Offset Cases.

Figure 6 shows an extract of the datasets of Figure 5. The zoomed time axis is equivalent to approximately 5 turbine rotations for the conditions considered..



Figure 6. Zoomed Axial Thrust and Angular Velocity Signals

There are some cyclic variations apparent in the signals and these observations were the basis for the time-frequency analyses.

The datasets were not ideal for such analysis methods. The axial thrust was sampled at approximately 47.6 Hz. The angular velocity was sampled at only 1.75 Hz. For any particular test case there was also evidence of quantisation effects in the digitized thrust signals.

For the range of conditions in the 38 datasets the 90 s recordings represented between 192 and 359 turbine rotations, for angular velocities between 128 and 239 rev.min⁻¹. When the analysis is aimed to provide information per blade per revolution these characteristics potentially pose considerable limitations.

In commercial installations the TST power generation will be controlled to produce the maximum power within the prevailing flow conditions and constraints. For the condition monitoring approaches to be applicable they need to be insensitive and/or adapt to the prevailing flow conditions. The datasets spanning a range of angular velocities, and hence TSRs, for in this case a fixed flow velocity were utilised to assess this aspect.

4. ANALYSIS

4.1. Axial Thrust Modelling

Figure 7 shows the steady-state output from a CFD model used to predict the constituent and total thrust for a HATT. The CFD results shown are for a 3 bladed full size (10 m diameter) turbine, with the blades set at optimum pitch angles. Plug flow with a velocity of 3.086 ms⁻¹ was used with operating conditions pertaining to a TSR of 3.61.



Figure 7. CFD Modelling of Thrusts

For the full size turbine the latter equates to an angular velocity of 21.3 rev.min⁻¹.

The thrust models were developed for the ANSYS fluid flow (CFX) platform. The fluid domain box was 50 m square and 150 m long and was established with appropriate plug flow boundary conditions. The mesh, for the multiform reference form (MRF) cylinder, of 12 m diameter and 4.5 m length, (surrounding the 3 bladed turbine model), consisted of 4.6 M cells.

The models are computationally intensive and settle to give steady state results. Figure 7 shows the thrust components for 1 turbine revolution. As expected the blade effects, passing and shadowing the support tube, are offset by 120° from each other. The small contribution, from the flow impinging on the hub, is not included in the time-frequency analysis. The total axial thrust displays relatively small cyclic variations, when compared to the mean axial thrust. Figure 8 shows the thrust profile for 3 blades for 2 turbine revolutions.



Figure 8. CFM Model of Blade Thrusts and Individual Blade Frequency Spectrum.

Figure 8 also shows the frequency spectrum for an individual blade, for 8 constituent terms all of which are at multiples of the fundamental frequency. The average thrust value is not plotted.

4.2. Frequency Analysis

The 38 experimental datasets were initially analysed by using standard Fast Fourier Transform (FFT) functions with the Matlab environment. The obtained spectrums were investigated to determine whether differences between the optimum blade and offset blade subsets were reliably detectable. Figure 9 shows a composite waterfall spectrum plot, for the 19 optimum blade tests. The percentage of maximum servo motor torques ranged from 0% (freewheeling) to 45% (close to peak power generation). The frequency spectrums are shown as amplitude² plots.



Figure 9. Waterfall Thrust Amplitude² Frequency Spectrum for 19 Optimum Blades Tests.

The rotational frequency (ω_r) was readily detectable, from the total axial thrust signals, and strongly correlated with the recorded angular velocities. For the optimum blade results shown the ω_r values ranged from 2.50 to 3.98 Hz. These are in accordance with the mean angular velocities, that ranged from 150 to 239 rev.min⁻¹. The harmonics, $2.\omega_r$ and $3.\omega_r$ were generally detectable. The $3.\omega_r$ components were expected (discussed in section 5.1) and are in agreement with the thrust modelling exercise. There were some potential differences in the patterns observed for $2.\omega_r$ components when comparing optimum blade and offset blade results. The discussed data limitations and the time varying turbine rotational velocities during testing were deemed to reduce the clarity of such observations. Accordingly the angular velocity fluctuations were analysed and time-frequency methods were utilised.

4.3. Angular Velocity Fluctuations

The 38 datasets were subjected to simple statistical analysis. Figure 5 (section 3) is an example of typical time domain angular velocity data. For the optimum blade tests the typical fluctuations were found to be $\pm 2\%$ of mean values. For the offset blade test the fluctuations were generally larger and a typical value was $\pm 2.5\%$ of mean values.

4.4. Time-Frequency Analysis

In light of the angular velocity analysis the spectrogram function within Matlab was used to obtain time-frequency plots. By optimizing the spectrogram parameters, including the number of FFT points, the overlap extent and windowing, the plots typically provided observable ω_r , $2.\omega_r$ and $3.\omega_r$ components. Due to the dataset limitations the spectrogram plots were not obtainable with sufficient resolution in either the time or frequency axes, and are not presented here.

Other approaches, including order analysis and time series analysis are also currently being investigated, and are not reported. Rather, the application of an emerging timefrequency method known as synchrosqueezing is assessed for the turbine data.

A small number of research groups have developed and reported on the synchrosqueezing, and have made available toolkits for use within Matlab. Iatsenko, McClintock and Stefanovska (2013) reported on one such toolkit. Reported applications include the condition monitoring and fault diagnosis of gearboxes. The latter was reported by Li and Liang (2012).

Iatsenko et al (2013) described synchrosqueezing as a nonlinear transformation of windowed Fourier transforms and wavelet transforms. Synchrosqueezing is used to increase the data concentration and allows for extraction and reconstruction of the analysed signals components. They made detailed comparisons with other methods, for a variety of test signal cases/types.

In the analysis reported here the Matlab toolkit developed at Lancaster University, and reported by Iatsenko et al (2013), was used. The algorithm may be applied to time domain signals, for which the sample rate is specified as an input parameter. Other parameters provide choices for the type and combinations of plots that are produced. To reduce the computational overheads either or both minimum and maximum frequencies of interest can be specified.

A parameter 'f0' has a unity default value. However by varying the value of 'f0' resolution of the overall frequency spectrum results can be improved. Alternatively 'f0' may be used to improve the time resolution, at the expense of the spectrum resolution. The latter was found to provide determination of the time-varying rotational frequency due to velocity fluctuations.

Iatsenko et al. (2013) reported that 'f0' is a critical value in time-frequency analysis and confirm that it determines a tradeoff between time and frequency resolutions. The optimal 'f0' setting depends of the signal analysed, however determining the time-frequency area of interest enables an automatic procedure for the selection of parameters within the algorithm.

The two plots that were utilized in analyzing the turbine data were (i) a coloured-coded time-frequency spectrogram plot and (ii) a time-averaged Synchronised Windowed Fourier Transform (SWFT) plot.

Figure 10 shows an example result for (i), for optimum blades at 30% torque. The sample rate was 47.6 Hz, the frequency range was set to 2.6 - 3.4 Hz and the 'f0' value was 0.75. For the 4286 samples in the 90 s thrust signals these settings produced 41 time distributed spectrums. The lower plot of Figure 10 shows a composite plot for the 41 spectrums obtained and the variations due to angular

velocity changes.. The algorithm is shown to determine the variations in the rotational frequency, which is inversely proportional to the angular velocity fluctuations, during the test duration.



Figure 10. Synchrosqueezing Results for Optimum Blades at 30% of Maximum Torque.

The synchrosqueezing algorithm was also applied with different parameters in order to produce type (ii) plots, i.e. time averaged SWFT plots. In such cases the frequency range was set to 0 - 10 Hz and the 'f0' parameter was set as 2. Figure 11 shows comparative results obtained for 4 of the datasets. These examples are for the cases shown previously in Figure 5, i.e optimum and offset blades at 30% and 32.5% of maximum torque settings.

Figure 12 shows the spectrum results, for torque settings between 20 and 45%. For both the optimum blade and offset blade cases the rotational frequency, ω_r , was consistently detected. The variation in the amplitude of this component with the operating conditions, determined via the percentage torque settings, was consistent with the FFT results of Figure 9. However there is no consistent pattern for the $2.\omega_r$ and $3.\omega_r$ components. Neither is there any distinct difference for the optimum and offset datasets considered.

It is, for example, merely a coincidence that the spectrums of Figure 11 shows 3 main components for the optimum blade results used as examples and that only 2 main components are apparent for the offset blade examples.



Figure 11. Comparison of Thrust Amplitude Frequency Spectrum Results.



Figure 12. Comparison of Frequency Components for Optimum and Offset Blades.

There are benefits in using the synchrosqueezing toolbox; the time average spectrums produced show the harmonic components more distinctly. Conversely, with the settings used to produce Figure 10, the time varying angular velocities can be evaluated directly from the thrust signal.

Further insights into the spectrum results obtained with respect to the $2.\omega_r$ and $3.\omega_r$ components are provided in section 5. These emanate from an extension of the thrust

modelling. Such results are being produced by CMERG from further simulations using the blade thrust CFD models. These are not yet available, and an estimated approach is used in this paper to support the discussions.

5. DISCUSSION

5.1. Cyclic Axial Thrusts

Figure 8 (section 4.1) showed the CFD model blade thrusts for a full-scale 3 bladed TST, for 2 turbine rotations and with a zoomed thrust axis. The CFD model assumes that the blades are identical and that all geometries are appropriately symmetrical. This is reflected in the total axial thrust variations (now for 1 turbine rotation) shown in Figure 7 (section 4.1). Included in Figure 8, were the FFT computed frequency spectrum plots for an individual blade. In this discussion the FFT spectrum for the total thrust cyclic variations are now considered.

The upper plot of Figure 13 shows the thrust amplitude spectrum for the combined axial thrust values. As stated, perfect symmetries and setups pertain to the CFD simulations and the 3 blades are offset from each other by exactly 120° . Accordingly the frequency vectors from the 3 blades cancel each other out, except for those at $3.\omega_r$ and multiples thereof. This provides an immediate inconsistency with the spectrums for the experimental results.

The tolerances pertaining to the experimental scale-size model were thus considered. The manufacture of the turbine was to a high standard, however small eccentricity and other non-symmetries are likely. More particularly, the turbine was designed to have adjustable blade pitch angles. These were adjusted, and set as appropriate between tests, using a surface table and standard angle templates. There was some reliance on the skill and judgment of the experimenter.

To simulate this relatively small adjustment was made for one of the blades to create some asymmetry compared to the ideal case shown in Figure 8. For the results discussed here the adjustment consisted of a 10% reduction in the mean thrust level combined with a 10% reduction in the range of thrusts for blade 2. The FFT amplitude spectrum results then obtained for the total thrust are shown in the lower plot of Figure 13.

The difference is then that all ω_r , $2.\omega_r$ and $3.\omega_r$ components can be seen in the spectrum, and are in closer agreement with the experimental results.

The simulated adjustment in this example is small compared to the difference in thrust values that would apply for the deliberately offset blade. For the offset blade the change to a 15° pitch angle is far more substantial, if judged by the reduced power performance at such a setting, as was seen in Figure 4 (section 3).





Figure 13. Comparison of Thrust Amplitude Frequency Spectrum for Symmetrical Blades and with Simulated Effects due to Tolerances.

5.2. Prognostics

The analysis of the potential use of one constituent of developing TST condition monitoring systems has been presented and discussed. The total thrusts acting on a TST support structure are more accessible than measurements from rotating elements. The latter will be vital for the monitoring systems and some developments towards this are discussed in section 5.3.

For the experimental datasets, with their far from ideal characteristics, there are results of interest from the time-frequency analyses. The synchrosqueezing methods improved the extraction of useful spectrum information from those datasets. In particular the angular velocity fluctuations were obtainable directly from the thrust signals.

The full-scale deployment of TSTs will inevitably mean that the operation and monitoring of each individual TST will be heavily site specific. The logging of operational conditions is a vital element of prognostic systems and the recording and analysis of structural thrust signals is believed to have a role to play in such systems.

5.3. Future Developments

The next generation of 0.5 m diameter scale-model TST is about to be deployed for water flume testing. The number of signals to be captured is to be extended, and the sample rates and resolution of the existing signals will be greatly improved. The additions include sensing of rotating components. A strain gauge based blade torque sensor has been developed. A 3-axis MEMS accelerometer has been included and the servo motor drive will provide an encoder output. The latter will improve the synchronization of recorded signals to turbine rotations. Researchers such as Bechhoefer, Wadham-Gagnon and Boucher (2012) have reported experiences with 3-axis MEMS accelerometers for wind turbine monitoring. Wider scale wind turbine performance monitoring has also been reported, for example by Uloyol and Parthasarathy (2012).

6. CONCLUSIONS

The use of support structure thrust signals as a constituent part of a TST monitoring system has been investigated. The limitations of the existing experimental datasets have been quantified and assessed. CFD models have been used to justify the cyclical patterns observed in the thrust signals. The models have been adapted to allow for manufacturing tolerances and small misalignments. These adaptations have enabled a closer correlation between the observed and modelled frequency components. The next generation of scale TSTs to be tested will provide more appropriate data characteristics. The longer term, site specific, monitoring of such signals will provide operating profile information for subsequent prognostics models.

REFERENCES

- Bahaj, A.S., (2011), Development of marine current turbines for electricity production. *IEEE Power and Energy Society General Meeting*, July 2011 Detroit, pp. 1–4.
- Bechhoefer, E., Wadham-Gagnon, M. & Boucher, B. (2012). Initial condition monitoring experience on a wind turbine. Annual Conference of Prognostics and Health Management Society (pp 1 8), September 23-27, Minneapolis.
- Grosvenor, R.I. & Prickett, P.W. (2011). A discussion of the prognostics and health management aspects of embedded condition monitoring systems. Annual Conference of Prognostics and Health Management Society ($pp \ 1-8$), September 25-25, Montreal.

- Hameed, Z., Ahn, S.H. & Cho, Y. M. (2010). Practical aspects of a condition monitoring system for a wind turbine with emphasis on its design, system architecture, testing and installation, *Renewable Energy*, vol. 35, no. 5, pp. 879–894.
- Iatsenko, D., McClintock, P.V.E. & Stefanovska, A. (2013). Linear and synchrosqueezed time-frequency representations revisited. *Digital Signal Processing*, arXiv:1310.7215v2 [math.NA] pp1-45.
- Li, C. & Liang, M. (2012). Time-frequency signal analysis for gearbox fault diagnosis using a generalized synchrosqueezing transform. *Mechanical Systems and Signal Processing*, vol 26, pp. 205 – 217. Doi:10.1016/j.ymssp2011.07.001.
- Mason-Jones, A., O'Doherty, D.M., Morris, C.E., O'Doherty, T., Byrne, C.B., Prickett, P.W., Grosvenor, R.I., Owen, I., Tedds, S. & Poole, R.J. (2012). Nondimensional scaling of tidal stream turbines. *Energy*, vol 44 pp. 820 – 829. doi: 10.1016/ j.energy.2012.05.010.
- Mason-Jones, A., O'Doherty, D.M., Morris, C.E., & O'Doherty, T. (2013). Influence of a velocity profile and support structure on tidal stream turbine performance. *Renewable Energy*. Vol 52, pp. 23 30. Doi:10.1016/j.renene.2012.10.022.
- Myers, L.E. & Bahaj, A.S. (2012). An experimental investigation simulating flow effects in first generation marine current energy converter arrays. *Renewable Energy*. Vol 37, pp. 28 36. Doi:10.1016/j.renene.2011.03.043.
- Ng, K-W., Lam, W-H. & Ng, K-C. (2013). 2002-2013: 10 years of research progress in horizontal-axis marine current turbines. *Energies.* Vol 6, pp. 1497 1526. Doi:10.3390/en6031497.
- O'Doherty, T., Mason-Jones, A., O'Doherty, D.M., Evans, P.S., Woolridge, C.F. & Fryett, I. (2009), Considerations of a horizontal axis tidal turbine. *Energy*, vol 163 (issue EN3), pp. 119 – 130.
- Tian, Z. & Jin, T. (2011). Maintenance of wind turbine systems under continuous monitoring, *Reliability and Maintainability Symposium (RAMS)*, pp. 1–6.
- Uluyol, O. & Parthasarathy, G. (2012). Multi-turbine associative model for wind tunnel performance monitoring. *Annual Conference of Prognostics and Health Management Society (pp 1 – 8),* September 23-27, Minneapolis.
- Yang, W., Tavner, P. J., Crabtree, C. J. & Wilkinson, M. (2010). Cost-effective condition monitoring for wind turbines, *Industrial Electronics, IEEE Transactions on*, vol. 57, no. 1, pp. 263–271.

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Educated at Cardiff University obtaining a BEng Mechanical Engineering degree (1978), a MEng via fluid dynamics research (1981) and a PhD on the topic of inprocess measurement of machined components (1994). He is currently a reader in systems engineering at Cardiff University and has been employed as a lecturer there since 1984. He has published 90 journal and conference papers, mainly on the topic of machine and process condition monitoring. He is co-director of the Intelligent Process monitoring & management (IPMM) centre. He is a chartered engineer and a member of the Institute of Measurement and Control.

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Lessons Learned in Fleetwide Asset Monitoring of Gas Turbines and Supporting Equipment in Power Generation Applications

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ABSTRACT

Condition monitoring remains an important technology for equipment life cycle management. Historically, online condition monitoring systems are installed only on the most critical assets within a power plant, process plant, or manufacturing facility. Less critical equipment, while vital to operation of the plant, are only monitored or tested periodically using manual route based technologies. This historical practice leaves equipment specialists with a small amount of time for analysis of collected sensory data (vibration, temperature, oil, power, etc.) as they spend the vast majority of working hours collecting equipment sensory data. Fortunately, data acquisition technology has evolved, making it possible to transform standard and advanced machinery measurements from manual collections to online collections, increasing time for specialists to analyze, and yielding opportunities for automated diagnostics and prognostics. By taking advantage of automation, the ability of equipment owners and operators to lower life cycle costs and increase reliability of plant equipment is greatly improved.

The transition from manual route based measurements to a fleetwide surveillance program touches many elements from sensors to networked data acquisition nodes to servers to historians and predictive technologies. Within power generation plants, installation costs, information technology strategies, and long term vision come together to create higher machine reliability at lower operational cost and new automation in performance monitoring, diagnostics, and advisory generation. With automation, comes increased sensory data from pumps and turbines that require new tools for data management, data mining, and data transformation into actionable information. A case study reviews the open and extensible data architecture of a fleetwide monitoring system deployed, the ongoing efforts, and current benefits delivered to the power generation industry participants.

1. MOTIVATION FOR FLEETWIDE MONITORING

Fleetwide Monitoring (FWM) is the implementation of applications for monitoring, maintaining and optimizing generation (and other) assets from a centralized location (Hussey, 2010). Fundamentally, FWM involves monitoring assets within a fleet of assets to detect operational and equipment problems earlier enough to mitigate damage, manage risk, identify performance problems, and manage business and market conditions or risks. A key part of FWM involves the use of advanced online monitoring technologies developed in the 1990s and 2000s and first applied in aerospace, transportation, and petrochemical applications. The goal of FWM is intelligent top-down approach to plant maintenance and scheduling. The goal is accomplished by the move toward centralized monitoring and diagnostic centers, the integration of advanced monitoring applications, and continued use of existing monitoring and maintenance technologies. The efforts supporting the goal will be facilitated by emerging standards supporting interoperability of equipment and technologies from multiple vendors.

1.1. Aging and New Power Plants

The power generation industry is undergoing a transition from traditional power using Nuclear and Coal to more efficient gas turbine combined cycle technologies (EIA, 2011). The United States Power Industry has relied on Nuclear and Coal based power generation for the majority of base load demand for many years, Figure 1. As of March 2011, 51% of all generating capacity is over 30 years old (Cook, 2013).



Figure 1. Age and capacity of electric generators.

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To keep these older generation assets producing power, additional maintenance is required. Adding to the maintenance challenges in power generation, the majority of new assets brought online in the last 20 years are natural gas based, Figure 2. Combustion turbine and combined cycle power generation plants are more economical to operate, given the lower price in natural gas. However, natural gas plants incorporate newer technology that is more complex and often more costly to repair. As a result of older power plants aging, and newer plants being more complex, a growing need for FWM coupled with automated diagnostics and prognostics is needed.



Figure 2. Newer power plants are natural gas plants.

1.2. Change in Operational Patterns Underscore Reliability Needs

Base load demand is now predominately provided by combined cycle gas turbine and steam turbine operations. Larger coal plants are now used to meet peak demand and smaller coal plants are being decommissioned. The result of this operational change is the combined cycle plants have higher reliability and availability demands. Further, the operating coal plants are experiencing reliability challenges as they operate differently than their design, that is they cycle on and off as compared to continuous operation.

As a result of these increasing reliability demands, the executive teams at power generation plants are challenged to leverage new technologies to address increasing reliability demands and workforce optimization. These power generation companies are collaborating with the Electrical Power Research Institute (EPRI) to address reliability needs from an industry perspective.

1.3. The Change from Manual Data Collection to Automatic Surveillance

A core objective of FWM is to greatly reduce the time equipment specialists spend collecting condition indicating sensory data, and as a result to increase the amount of time specialists spend analyzing sensor data and results from automated analysis, Figure 3. This change from manual sensory data collection is intended to result in improved consistency in diagnostics thru automation and standardization. Other improvements include better fusion of technology exam sensory data with process data. The end result is expected to be a more integrated monitoring and diagnostics center with improved visualization, enabling engineering and specialist workforces to perform higher value tasks.



Figure 3. Workforce optimization thru online monitoring.

In comparison to manual route based data collection, Figure 4, online monitoring systems overcome several disadvantages. The first overcome disadvantage of manual route based sensory data collection is sparse data collection schedules. With manual route based exams, specialists visit the machines on schedules perhaps just once per month or once per quarter. These schedules may be interrupted by unplanned higher priority needs of the plant. In a large power generation enterprise, for example, staff and time is needed for nearly 60,000 manual exams per month. A second overcome disadvantage is equipment availability for an exam. The equipment may not be in operation during the specialist physical visit.



Figure 4. Manual technology exam measurements.

Third, there is a high probability of missing an event, as the symptom of degradation may not adequately show itself during the periodic visit. Fourth, when the technical exam sensor data is collected, it often remains on the specialist's computer, until such time as the specialist determines it is important to report during a face to face meeting. In other words, an individual's limited view of the overall equipment may prevent data from being reported at a face to face meeting. And perhaps most importantly, over 60% of specialist manpower is used to collect sensory data, with limited time left for analyzing and reporting equipment health.

The goal of intelligent top-down approach to plant maintenance and scheduling is met by the implementation of centralized monitoring and diagnostics centers. These centers require continuous updates of equipment performance and condition. To reach the goal then, the technology exams that are now performed manually will become automatic and online.

2. FLEETWIDE ASSET MONITORING SYSTEMS ARCHITECTURE

There are several aspects to the implementation of an online fleetwide asset monitoring systems. These include field communications, measurement coverage, data management, interoperability. installation costs. and Field communications is imperative to FWM as it allows data acquisition systems to report equipment conditions in realtime. The data acquisition systems also must cover all of the traditional condition and performance monitoring technologies, as well as allow for new advanced monitoring technologies. With the addition of FWM, terabytes of sensory data become available. Tools to manage the data, extract information, and guide diagnostics and prognostics applications are paramount. With careful planning, selection of sensors and server technology, the installation costs of FWM applications can be mitigated. Since a FWM system has many components, interoperability of components from different vendors brings flexibility to integrate existing systems with new technologies.

2.1. Field Communications

Many plants are deploying wireless communications networks within the physical plant. These networks allow plant personnel to access documentation, email, and task related applications using portable computing technology such as tablet computers. This business communications network is convenient for implementation of an online monitoring system.

To implement a FWM system, automatic data collection nodes, capable of measuring sensors from multiple technologies, are added to the business computer communications network, whether this is wired or wireless, Figure 5. By placing the data acquisition systems on the business computer network, the data acquisition systems avoid interfering with control systems, and face less interference evaluation. Figure 6 shows a sample data acquisition system including data acquisition hardware, power supplies, fuses, and communication equipment.



Figure 5. Data acquisition system on the business network.



Figure 6. Sample data acquisition hardware cabinet.

2.2. Flexibility of Measurements

Measurement technologies for condition monitoring are prescribed in standards including the ISO 17359 condition monitoring standard (ISO, 2003). Measurements mentioned in the standard include temperature, pressure, flow, current, voltage, vibration, acoustic emissions, oil, and speed. Data acquisition systems must be able to digitize these physical phenomenons from a variety of sensors both those making dynamic and static measurements. Dynamic measurements are of physical phenomenon that changes rapidly such as vibration, motor currents, and pressure. Static measurements include oil, temperature, flow, and loads. Dynamic measurements may utilize analog to digital sampling rates in the 10's of thousands of measurements per These systems are designed to continuously second. monitor sensors, in order to overcome the problem of missing an equipment degradation indication.

2.3. Data Management at the Data Acquisition Level

A challenge in FWM, is managing the large amount of data being acquired. For example, just monitoring two critical feed water pump shafts with two bearings can produce over one terabyte of data per week with continuous sampling. To overcome this sensory data deluge, the continuous monitoring data acquisition systems must be designed to record and transfer sensory data on an event bases, Figure 7.



Figure 7. Data acquisition system software diagram.

To determine when a sensory data recording event has occurred, these networked systems must be both data acquisition and analysis network nodes (DAAN). Several FWM hardware vendors now offer an embedded architecture that implements embedded analysis for data reduction, Figure 7. This evolution has occurred as more online hardware has deployed, and end user and information technology (IT) feedback has been gathered. With this architecture, data is filtered at the DAAN, producing only sensory data with new information.

Both dynamic and static measurements are made with their time stamps synchronized. Some sensory values may come from communications to local control systems. As the sensory values arrive in memory, the DAAN analyzes the time stamps and values of sensory measurements to determine an event based trigger. With a trigger identified, sensory time waveform data is recorded to local on-board storage and placed in an out box directory for later transfer onto the network. The format of the time waveform recording is an open format such as the National Instruments TDMS format, UFF58 binary, or some other format that is documented and facilitates interoperability between vendors.

It should be noted that the DAAN, when recording data to its local disk, has provided metadata including equipment hierarchy, sensor calibration information, sensor location, time stamps, and other pertinent information to facilitate data search, off-line analysis, and peer to peer comparisons. The equipment and sensor location hierarchy should follow an information model commonly used in industry. This allows for interoperability of Data Acquisition systems and for downstream prognostics applications (Monnin et all, 2011) For condition monitoring there is not a formal standard, yet some good examples to build from. These include OSA-CBM, the IEC 61970 Common Information Model (CIM), and ISA-95 equipment model.

In a FWM application, 100's of DAANs may be added to the business or maintenance network. These DAANs themselves then need to be managed. A server class computer, also residing on the business network, is responsible for managing the DAANs, noting the health of sensors and data acquisition hardware as well as retrieving sensory data recordings from them, Figure 8.



The server tasks include discovery of monitoring devices, insuring correct configuration of the monitoring devices, managing network and communications security, and monitoring the health of the DAAN as well as the attached sensors. These tasks are performed using both standard and proprietary vendor specific communications protocols to detect, configure, manage, and retrieve data from the DAANs.

2.4. Data Management at the Maintenance Server

The maintenance server has the responsibility of hosting specialist visualization and analysis software. With these tools, vibration analysts in particular can retrieve vibration time waveforms to perform comprehensive visual and comparative analytics within a single rotating machine and components or across machine peers. The maintenance server also has the responsibility of transferring condition indications to the plant historian where DAAN collected condition indicators are later correlated with process and operations data, Figure 9.



Figure 9. High level architecture of monitoring system.

Analysis of sensory data from the DAANs, and supporting control systems occurs in multiple locations, and ranges from threshold alarms, to advanced signal processing of time waveforms, to automated diagnostics, and health prediction, Figure 10. To optimize the overall process of tracking equipment health, reliability, and availability; a distributed analytical architecture provides both advanced calculations capabilities and data fusion opportunities. By distributing analytics amongst the DAAN, Maintenance Server, and Enterprise Historians; the amount of raw sensory data is reduced by conversion to key condition indicators, and threshold alarms



Figure 10. Data management and analytics architecture.

With sensory data and condition indicators available from multiple assets, automation of diagnostics and prognostics becomes possible. Since the entire event driven sensory data is labeled with equipment hierarchy metadata, similarity analysis with similar equipment, is now possible. When comparisons to fault signatures, operational states, and peer equipment are made; the sensory data is managed and reduced to actionable information.

2.5. Managing Installation Costs

By comparison to traditional condition monitoring technology, the costs of data acquisition equipment, sensors, networking equipment and server computers can add up quickly. However, with the advent of multi-mode sensors, proliferation of sensory data acquisition technologies, the industrial adoption of wireless networks, and the lowering cost of computer technologies; the industry has an opportunity to install FWM systems at lower costs than previously available.

Vibration sensors for example are now available from industrial suppliers with both temperature and vibration in a single sensor. These same vendors also offer tri-axial sensors (three directional vibration sensors in one) in industrial grade packaging. These multi-mode sensors reduce cabling and conduit equipment and labor costs.

Data acquisition systems are available from a number of vendors, and the market these vendors participate in is growing as a result of global drive to automate sensory data collection in a broad base of fields. This market trend is driving down the costs of data acquisition equipment. Further, many data acquisition systems offer the ability to monitor multiple sensing technologies from multiple assets or machines in a single device. These data acquisition systems also include the ability to filter data, only recording sensory data periodically and on event, thereby reducing the cost of data analytics and storage.

Wireless technologies are quickly being adopted in many fields. These include industrial networking supporting business network applications in the field, as well as wireless data acquisition and sensory technologies. This adoption is expanding the offerings from a larger number of vendors, as well as best practices and services for installing and managing wireless networks. With a larger field of wireless technology suppliers and practitioners, the cost of the wireless infrastructure is lowering while the reliability is improving.

Finally, the cost of computer server technology needed to host maintenance server applications is quickly reducing, while improving information technology management tools. These trends lower both the cost of hardware, and also the installation and maintenance costs of the computing infrastructure.

Coupling with the lower cost of components, careful planning to sequence installation activities will also help lower installation costs. For example, have multiple machines of a similar type instrumented at the same time will breed economies of scale. If possible, specifying the FWM technologies be installed at the initial construction of the plant or unit can have nearly a seven times reduction in installation costs.

2.6. Interoperability

The power generation community, with the support of EPRI continues to strive to open interoperable systems. EPRI promotes evolution of equipment models, data storage formats, and hardware data acquisition technology that strive towards interoperability between vendors. This effort is illustrated in the EPRI Fleetwide Monitoring for Condition Assessment publication (Shankar, 2006)

2.7. Systems Architecture Summary

In summary, the networked automatic sensory data collection system performs many tasks. The system resides on a business network, to reduce interference with operations. The DAANs have built in analytics and intelligence to determine when to record sensory data and to determine its own operational status and health. The server computer managing the network aggregates sensory data from all DAANs, publishes condition indicators to a plant historian, and provides search, retrieval, and analytics of collected data recordings.

Technology costs from the sensor, to the DAAN, to the server computing technology are advancing with cost benefits, ease of installation and operation improvements, and greater computer power to automate diagnostics and health prediction functions. These technology trends, coupled with proven online monitoring systems architectures, yield a new opportunity for online fleetwide monitoring.

3. AUTOMATING ALERTS, DIAGNOSTICS, AND PROGNOSTICS

Once the DAAN's are installed on selected equipment, it is possible to aggregate sensory data (at the maintenance server) and to implement exception reporting, also known as anomaly detection. When any asset is instrumented with degradation indicating sensors, it is possible to build threshholding alarms (warning, alert, and danger level alarms) based on either industry standards per equipment class, or based on statistical deviation from established norms. For example, it is recommended practice to monitor all sensors, and results of calculations from sensor values (condition indicators) to create a baseline of normal operation. By using the baseline, it is possible to set threshold alarms on individual sensor values or condition indicators at intervals of standard deviation from expected normal values (ISO 2003).

This practice of using standard deviation alarms or equipment class standards can be referred to as threshholding predictive maintenance. With thresh-holding and trending alarms, the trended rate of change becomes an indication of future performance or health of a machine and also a prediction of maintenance needs.

A more advanced approach is to utilize a combination of trends, a combination of sensory values and condition indicators, which together form a pattern of normal or abnormal operation. These patterns can then be used to track actual pattern movement with expected patterns allowing the difference or residual to indicate the "error" or health degradation (CCJ, 2014). The patterns can be defined with one piece of equipment, and then used as a fault signature for other pieces of equipment with similar components and function. What is learned from one pump can be applied to similar pumps in similar operating conditions. There are several such anomaly detection, or advanced pattern recognition products on the market which accomplish this specific task. Examples include Instep PRiSM[™] and General Electric's SmartSignal[™] trend analysis applications. These products are popular in the power generation and petrochemical industries.

4. CASE STUDIES

4.1. Attributes of a Successful Fleetwide Monitoring Program

There are many case studies in the field of condition monitoring; some are fleetwide monitoring case studies. In successful cases, the selection of assets, monitoring technology, repeatable test conditions, and defined exception reporting are key aspects of a successful condition monitoring program. In fact, the most successful programs implement best practices such as those described in the ISO 17359 standard (ISO, 2003). In addition, there must be organizational buy-in to the condition monitoring program. This buy-in is best undertaken at the management level, where reporting of activities and program impact are expressed in economic terms.

In its Fleetwide Monitoring for Equipment Condition Assessment report (Shankar, 2006), the Electrical Power Research Institute (EPRI) calls out five primary challenges to fleetwide monitoring (FWM). The first challenge is standardization: in equipment evaluation technologies, terminology of equipment and sensing types, and company maintenance procedures. The second is identifying a cost justification that can be used to obtain management "buyin", or formal acceptance to invest in fleetwide monitoring. Thirdly, there exists a challenge to build visibility across the organization and to promote best practices, centralization of management and monitoring. Centralization fosters collaborative efforts across company organizations and identification of best practices and technologies. A fourth, and perhaps most important challenge, is alarm management. In particular, a mechanism to validate alarms prior to planning a response is critical in building confidence in the program. The fifth challenge is the integration of multiple monitoring technologies, to obtain the benefits of each and to create a holistic view of monitored equipment.

To address these challenges, EPRI is working with its member power generation companies to document best practices and specific cases. As an example, there is a specific EPRI project focused on cost benefit analysis. Within the project cost benefits are categorized as direct benefits and indirect benefits. Direct benefits include the reduction in time and expense necessary to maintain equipment. This benefit arises by using improved knowledge and understanding of equipment health. Indirect benefits result from avoiding a reduced power event or unscheduled downtime. The indirect benefits include the cost avoidance of significant equipment damage.

4.2. Southern Company's First Plant

Southern Company embarked on their fleetwide monitoring program in the late 2000's with the adoption of several EPRI recommendations and products (Hussey, 2010). Southern Company operates over 280 power generation units at 73 power plants including gas turbine, combined cycle, steam (coal), hydro and solar, Figure 11. While meeting the specific business model and company culture, Southern Company implemented the first phase of their fleetwide monitoring and diagnostics (M&D) center, beginning in 2007.



Figure 11: Southern Company power generation map.

There are five core goals of the Southern Company M&D center. First, is to establish a higher frequency monitoring program with sensory and condition indicating data arriving in minutes as opposed to once per week or longer. This first goal required the addition of continuous monitoring equipment as described earlier in this paper. The second goal is for the selected equipment to be monitored around the clock. The third goal is to mitigate the loss (through retirement) of experienced resources. By centralizing the M&D center, knowledge from experienced resources can be captured in various "best practices" documentation. A fourth component of the M&D center is a multidisciplinary focus including operations, maintenance, instrumentation and engineering. Fifth, and finally, a core goal is to establish a partnership with operations in order to eliminate any animosity that may arise from the new oversight the M&D center would have with the equipment under operations control.

Initially, just one plant was monitored for 1.5 years to document results and to provide guidance for future condition monitoring programs. Online condition monitoring hardware and FWM applications were added to critical steam turbine and gas turbine generators. The benefit to cost ratio was estimated to be a 4:1 and three additional plants were added to the centralized M&D center pilot. In 2010, management authorized expansion of the fleetwide monitoring program to 17 plants or about 1/3 of Subsequent to this roll-out of turbine the entire fleet. generator FWM applications, Southern company has begun to take advantage of lower cost sensing and data acquisition hardware, following developing recommended EPRI requirements. This allows Southern company to extend its FWM program to balance of plant equipment.

Several lessons are taken from Southern Company's experiences. The first is to start slowly. There are a number of complexities in change and management aspects of a fleetwide program. It is recommended to start small, perhaps at a single plant and even specific issues of a

specific equipment type. Goals should be set with respect to the issues and equipment reliability measures. From these goals, the appropriate applications technology can be selected with the best promise of meeting the goals.

The second lesson from Southern Company is to get executive "buy-in". Executive support is very important in both the establishment and on-going improvements to the M&D center.

A third lesson is to select participating staff with multidisciplinary skills. These skills include operations, instrumentation, controls, engineering and maintenance experience and training. With multi-disciplinary skills, team members are more easily able to engage and interact with other business and functional units within the enterprise.

The fourth lesson arising from Southern Company's M&D efforts is to invest in a proven information technology (IT) infrastructure to manage both data and knowledge obtained during the growth of Southern's FWM program. This infrastructure includes intelligent data acquisition, networking, and server hardware and software. According to Southern Company, the level of sophistication of smart trending (pattern recognition software) and data acquisition equipment maps to the success of an online condition and performance monitoring program.

4.3. Luminant Energy Mining Operations

Luminant is the largest power generation company in Texas. It operates eight natural gas driven plants (combustion turbines), five coal plants, and one nuclear power plant. Supporting its steam generation coal plants, it operates nine surface coal mines, Figure 12. While Luminant sports a state of the art M&D center in Dallas, Texas, many of its condition monitoring programs are rooted in its mining operations (Lawson, 2010).



Figure 12: Luminant power generation map.

Luminant's Mine Maintenance Support Services (MMS) is the core group behind its condition monitoring program. Over the past several decades, the MMS group has utilized a range of technologies including vibration, oil, ultrasonic, infrared, and strain to monitor condition and degradation of mining equipment used in support of steam power generation plants. The MMS team is made of personnel with a broad range of skills including electrical, mechanical, maintenance, and computer systems, and project management.

In the four years leading up to the article, MMS efforts have produced an 18% savings in maintenance spend. These efforts produce a condition of maintenance (COM) report that feeds into allocation of maintenance funding, allowing Luminant to do the right maintenance at the right time.

The Luminant team produces a series of reports indicating the health or "maintenance need grade" of core equipment assets. These reports are both tabular in nature sharing multiple metrics as well as graphical, including equipment mimics and trends. Further, Luminant has collected a significant amount of sensory and condition indicating data that helps evolve the internal procedures and processes for condition monitoring. Luminant even shares its sensory data with OEMs to help evolve the design of equipment it uses.

Luminant's lessons are similar to those of Southern Company. One similar approach is getting the "buy-in" from management to support funding and growth of the program. Another similarity is the multi-disciplinary skills represented within the monitoring and maintenance team. Luminant adds both visual and numerical reporting to its elements of success.

Luminant finally leverages its IT infrastructure to house, manage, and mine the many years of sensory and condition indicating data it has collected. This accumulation of sensory and condition indicating data is a prime example of a Fleetwide application.

4.4. Duke Energy Fleetwide Implementation

Duke Energy has deployed DAANs, condition indicating analytics, as well as anomaly detection and visualization tools within several of their power generation plants in North America, Figure 13. Each of these plants has deployed 20 or more DAAN nodes per power generation block (Cook, 2013). Each plant has a computer server managing the DAANs, calculating condition indicators and reporting these condition indicators to the OSIsoft PITM Historian. Instep Software's PRiSMTM software is at work building data driven models of normal behavior for anomaly detection.



Figure 13: Duke Energy power generation M&D map.

There are a series of steps Duke Energy has followed to implement SmartGen (a monitoring and diagnostics program) at each of its plants, Figure 14. The core steps include Planning, Enclosure Drawings, Site Design, Site Install, Software Integration, and Plant Turnover. The components of each major step are shown here as a suggested guide.



Figure 14: Steps to implementation of a fleetwide monitoring program.

There are several lessons learned from the work at Duke Energy's gas turbine power generation plants. Deployment of automated sensory data collection on the fleetwide scale requires significant resources for planning and implementation. Implementation managers are needed at each facility to manage the sequence, personnel resources, and equipment resources that come together to roll out the DAANs, server software, and enterprise connectivity.

Hardware installations can proceed ahead of software installation, especially identification of sensor types and locations and the subsequent installation. Server installations should be timed to coincide with DAAN installation. Once sensors and DAANs are installed, a validation process is needed to validate sensory measurements and calculated condition indicators match traditional manual based activities.

As the anomaly detection occurs on the OSIsoft PITM Historian, validation on both condition indicators and PI representation of the condition indicators must occur prior to building data driven models. This is similar to any data science or predictive analytics application, data integrity is of high importance.

Personnel at all sites are excited and bought into the prospect of automated data collection, assisted/automated diagnostics and predictive techniques. Site persons continue to ask for more automation, more sensory types, and greater equipment coverage. Regular implementation process meetings focused on streamlining the implementation process, and on streamlining feedback are recommended.

The biggest lesson learned is that the system is working as expected. Already, visibility of equipment reliability has greatly improved, and plans are now being made to track maintenance savings and availability improvements. With a track record of plant installations, the roadmap for addressing additional plants is established, and can be built upon. Duke Energy is well on its way to complete its fleetwide monitoring and diagnostics center. Duke's efforts promise to result in maintenance savings and availability improvements, while increasing equipment health visibility and optimizing logistics of maintenance.

5. CONCLUSION

There are many factors which impact the success of an online fleetwide condition monitoring program. Starting small and leveraging common condition monitoring technologies simplifies initial FWM applications and reduces risk. With initial success, it is then possible to include the sophistication of the data acquisition and analysis node, the sophistication of automated diagnostics and prognostics (the analytics), and to articulated expected return on investment. Buy-in from senior management, along with multi-disciplinary M&D staffing, and thought out project plans are also important to the success of the FWM efforts. The case studies of Southern Company, Luminant, and Duke Energy each articulate these lessons. Given the continued evolution of monitoring technologies, including the embedded analytics of DAANs, and the in-line technology used for automated diagnostics and prognostics; there exists great promise for those organizations considering fleetwide asset monitoring.

REFERENCES

- Combined Cycle Journal (CCJ) (2014). M&D part 2, whats behind the dashboard – diagnostics and prognostics, January 2014
- Cook, B. (2013). Duke Energy SmartM&D project, National Instruments Week 2013, August 2013.
- Hussey, A. (2010), Understanding the potential of fleetwide monitoring, *Energy-Tech Magazine*, Woodward

Communications, tech.com/article.cfm?id=28887

http://www.energy-

- International Standards Organization (ISO) (2003), *Condition Monitoring and Diagnostics of Machines – General Guidelines*, First Edition, reference number ISO 17359:2003(E), Switzerland (2003).
- Lawson, K. (2010) Luminant's condition monitoring program achieves notable successes, Reliability Web.com, online article, <u>http://reliabilityweb.com/index.php/articles/luminants_c</u> <u>ondition monitoring program achieves notable succe</u> <u>sses/</u>
- Monnin, M., Voisin, A., Leger, J., Iung, B. (2011), Fleetwide health management architecture, *Proceedings* of the annual conference of the prognostics and health management society, September 2011
- Shankar, R. (2006), Fleetwide Monitoring for Equipment Condition Assessment, Electrical Power Research Institute (EPRI), reference number 1010266, March 2006
- US Energy Information Administration (EIA) (2011), *Electric Generator Report*, Form EIA 860 and form 860M, Electric Power Monthly, March 2011.

BIOGRAPHIES

Preston Johnson is the Principal Sales Engineer for Condition Monitoring Systems at National Instruments (NI) in Austin, Texas. NI creates innovative computer-based products that aid engineers in the design, prototyping, and deployment of instrumentation systems for test, control, and embedded applications. He has worked for National Instruments for over 25 years in roles of Field Sales, Sales Management, Automation Business Development, Sound and Vibration Segment Manager, and Platform Manager for Condition Monitoring Systems. In his current role as Principal Sales Engineer for Condition Monitoring Systems, his interest lies in embedded signal processing, data acquisition systems and architectures, and prognostics. Preston works with NI OEM and End User customers to deploy fleetwide asset monitoring systems that lower operation costs, improve machinery reliability, and ultimately increase revenue. He earned his BSEE in Electrical Engineering and Computer Science from Vanderbilt University in 1985 and his MBA in Information Technologies from the University of Texas in 1987.

Definition of parametric methods for fault analysis applied to an electromechanical servomechanism affected by multiple failures

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ABSTRACT

In order to detect incipient failures due to a progressive wear of a primary flight command electromechanical actuator, prognostics could employ several approaches; the choice of the best ones is driven by the efficacy shown in failure detection, since not all the algorithms might be useful for the proposed purpose. In other words, some of them could be suitable only for certain applications while they could not give useful results for others.

Developing a fault detection algorithm able to identify the precursors of the above mentioned electromechanical actuator (EMA) failure and its degradation pattern is thus beneficial for anticipating the incoming failure and alerting the maintenance crew such to properly schedule the servomechanism replacement.

The research presented in the paper was focused to develop a prognostic technique, able to identify symptoms alerting that an EMA component is degrading and will eventually exhibit an anomalous behavior; in particular four kinds of failure are considered: friction, backlash, coil short circuit, rotor static eccentricity. To this purpose, an innovative model based fault detection technique has been developed merging together several information achieved by means of FFT analysis and proper "failure precursors" (calculated by comparing the actual EMA responses with the expected ones). To assess the robustness of the proposed technique, an appropriate simulation test environment was developed.

The results showed an adequate robustness and confidence was gained in the ability to early identify an eventual EMA malfunctioning with low risk of false alarms or missed failures.

1. INTRODUCTION

Prognostics is a discipline whose purpose is to predict the moment in which a certain component loses its functionality and is not further able to meet desired performances. It is based on analysis and knowledge of its possible failure modalities and on the capability to individuate the first signs of aging or wear and, then, evaluate the magnitude of such damage (fault detection / evaluation). The above mentioned data will be then used as input of a proper failure propagation model.

The use of this discipline in aeronautics, as in many other technological fields, could be very useful if applied to maintenance, since it lowers both costs and inspection time. In order to optimize these advantages, the discipline known as Prognostics and Health Management (PHM) has born: its purpose is to provide real-time data on the current status of the system and to calculate the Remaining Useful Life (RUL) before a fault occurs or a component becomes unable to perform its functionalities at a desired level. The advantages gained by means of PHM strategies are evident comparing the features of a system conceived according to this discipline with the ones of a classical design.

The primary flight controls are a critical feature of the aircraft system and are therefore designed with a conservative safe-life approach which imposes to replace the related components subsequently to a certain number of flight hours (or operating cycles): obviously, this approach is not able to evaluate the effective status of the items (and estimate the ability to operate still correctly) but merely requires the aforesaid maintenance operations.

In particular, the aforesaid design criterion is not able to evaluate possible initial flaws (occurred during manufacturing) that could generate a sudden fault which could compromise the safety of the aircraft and don't allow to replace only the really failed components (with the related inefficiencies and additional costs).

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Instead, in a system suitably conceived taking into account the PHM strategies, failures could be managed in a more proper way, obtaining the following advantages:

- 1. lower operating costs;
- 2. less maintenance interventions are required;
- 3. lower number of redundancies installed on board aircraft;
- 4. aircraft safety and reliability are improved;
- 5. any maintenance work can be planned appropriately optimizing the necessary actions (limiting downtime and related costs and allowing a more effective organization of the maintenance and management of spare parts warehouses) and limiting the logistical difficulties resulting from the manifestation of the fault.

The research presented in the paper was focused to develop a fault detection/evaluation technique able to identify failure precursors (alerting that the system is degrading) and to evaluate the corresponding damage entity; in fact, a progressive degradation of a system component, which does not initially create an unacceptable behavior, often leads to a condition in which the efficiency of such component is impaired and hence the whole actuation system operation could be compromised. In order to develop the above mentioned research, a typical aircraft primary command EMA has been modeled in the MATLAB Simulink® simulation environment and several sets of simulations (in nominal conditions or with various failures) have been performed.

2. AIM OF WORK

The aims of this work are:

- 1. the proposal of a numerical algorithm able to perform the simulations of the dynamic behavior of a typical electromechanical servomechanism taking into account the effects due to four different types of progressive failures (dry friction, backlash, coil short circuit and rotor static eccentricity);
- 2. the proposal of an innovative fault detection/evaluation method able to detect the EMA failure precursors and evaluate the corresponding failures entity.

To assess the robustness of the proposed techniques, an appropriate simulation test environment was developed; in particular, in order to evaluate the effects due to the abovementioned failures on the EMA behavior, several simulations (related to different combinations of damages) have been performed. The results obtained from each simulation have been compared with the ones provided by a monitoring model in order to evaluate the related differences and, consequently, define a correlation with the corresponding failures. By means of proper algorithms, the above mentioned results are used to timely identify the failures and evaluate their magnitudes. To this purpose, an innovative model based prognostic technique has been developed merging together several information achieved by means of FFT analysis and proper "failure precursors" (calculated by comparing the actual EMA responses with the expected ones). The so obtained results showed an adequate robustness and confidence was gained in the ability to early identify the malfunctioning with low risk of false alarms or missed failures.

PROPOSED ACTUATION SYSTEM NUMERICAL MODEL



Figure 1. EMA scheme.

As shown in figure 1, a typical electromechanical actuator used in a primary flight control system is composed by:

- 1. an actuator control electronics (ACE) that closes the feedback loop comparing the commanded position (FBW) with the actual one, elaborates the corrective actions and generates the reference current (I_ref) ;
- 2. a Power Drive Electronics (PDE) that regulates the three-phase electrical power;
- 3. an electrical motor, often BLDC type;
- 4. a gear reducer having the function to decrease the motor (angular) velocity (called RPM) and increase its torque at values suitable for the user¹;
- 5. a system that transforms rotary motion into linear motion: ball screws or roller screws are usually preferred to acme screws since they, having a higher efficiency, perform the conversion with lower friction;
- 6. a network of sensors used to close the feedback rings (current, angular speed and position) that control the whole actuation system (reported in Fig. 1 as RVDT).

As previously established, the primary goal of the research is the proposal of a technique able to identify symptoms alerting that an EMA is degrading: therefore, in order to assess the robustness of the aforesaid technique, a suitable simulation test environment has been developed. The proposed numerical model, reported in figure 2, is consistent with the EMA architecture shown in figure 1 and has been implemented in the MATLAB/Simulink® environment.

¹ The RPM or torque variations are obviously related to the gear ratio of the mechanical reducer. The output torque (downstream the reducer) is also affected by efficiency of the mechanical transmission.



Figure 2. Proposed EMA block diagram developed in MATLAB/Simulink® environment.

It is composed by six different subsystems:

- 1. an input block that generates the different position commands (Com);
- 2. a subsystem simulating the actuator control electronics, that close the feedback loops and generates as output the reference current *I_ref* (ACE);
- 3. a subsystem simulating the power drive electronics and the trapezoidal BLDC electromagnetic model, that evaluates the torque developed by the electrical motor as a function of the voltages generated by the threephase electrical power regulator (BLDC EM Model);
- 4. a subsystem simulating the EMA mechanical behavior by means of a 2 degrees of freedom dynamical system (EMA Dynamic Model);
- another input block simulating the aerodynamic torques acting on the moving surface controlled by the actuator (external forcing TR);
- 6. a block simulating the EMA monitoring system (Monitor).

The proposed numerical model is also able to simulate the effects due to conversion from analogic to digital of the feedback signals (ADC), electrical noise acting on the signal lines and position transducers affected by electrical offset.



Figure 3. BLDC EM Model block diagram.

Figure 3 shows the numerical simulation algorithm that implements the brushless DC motor electromagnetic model: it is composed by three blocks representing the reference current generator, the three-phase PWM inverter system and the BLDC motor electromagnetic model.

The BLDC EM Model block diagram has been developed according to the mathematical models and the assumption proposed by Çunkas and Aydoğdu (2010) and Halvaei Niasar, Moghbelli and Vahedi (2009). The trapezoidal back-EMF and the electrical current waveforms of the three-phase BLDC motor, evolving as a function of rotor position (*theta_r*), are shown in figure 4.



three-phase BLDC motor.

The motor driving is performed by means of the PWM current control block (figure 5) that compares the reference phase currents (I_ref_a , I_ref_b , I_ref_c) with the motor's actual phase currents (Ia, Ib, Ic); indeed, the considered block diagram does not implement the structure and the real operation of the three-phase PWM inverter: its behavior is simulated by means of a relay block, having proper thresholds (that user might select), for each phase.



Figure 5. PWM block diagram.

The output of this subsystem, as shown in figure 6, is a three components rotating voltage vector representing the corresponding phase voltages *Va0*, *Vb0* and *Vc0*.



Figure 6. Example of dynamic evolution of the three-phase voltages regulated by PWM block.

As happens for the I_ref calculation, at a same instant a phase has a positive value, another has a negative value having the same modulus of the positive one and the remaining one must be null (the proposed model realizes this last statement only on a mean value). The three components show the typical 120 degrees displacement. The EM model (shown in figure 7) calculates the threephase currents (Ia, Ib, Ic) and the developed mechanical torque TM as a function of the PWM three phase voltages (Va0, Vb0, Vc0) and the effective rotor velocity DThM. The considered BLDC motor has a three-phase winding topology with star connection: it has three resistive (R) – inductive (L) branches on which a counter-electromotive force² (back-EMF) acts. As reported in [2], the back-EMF phase voltages are implemented by using Simulink look-up table functions. It must be noted that the three back-EMF constants ke_i (one for each of the three branches) may also take into account some possible electrical failures (like partial coil short circuit or rotor static eccentricity) by modifying the parameters of the functions f(u) (figure 9): these values, multiplied by the effective rotor velocity DThM, provide the corresponding real back-EMF values.



Figure 7. EM Model block diagram.

Since phase currents are known, total motor torque can be computed; this calculation is carried out by the subsystem TM (shown in figure 7): the sum of the three phase currents, multiplied by their respective back-EMF constants ke and by the number of polar couples, gives the corresponding value of the total motor torque TM.³

It must be noted that, in order to validate the just illustrated numerical model, the dynamic response developed by the aforesaid system under certain operating conditions (control input, boundary conditions and entities of different faiths) was compared with data obtained from the literature. In particular, the back-EMF and phase current waveforms, related to different values of the rotor angular velocity, and the dynamic responses of the BLDC caused by various command inputs have been compared with corresponding cases reported in literature by Lee and Ehsani (2003), highlighting a satisfactory compliance between simulations and literature data.



Figure 8. EMA Dynamic Model block diagram.

Figure 8 shows the subsystem simulating the EMA mechanical behavior: it is composed of two non-linear second order dynamic models linked together by means of an instantaneous model simulating the elastic reaction (Treaz) dues to shaft stiffness⁴: the first dynamic system is related to the group including motor and gears, while the second one represents the final user. The BLDC Motor and User subsystems implement the second order dynamic models simulating respectively the behaviors of BLDC motor/gear reducer and final user (i.e. the aircraft command surface controlled by the EMA). This type of simulation algorithm, widely explained by Borello, and Dalla Vedova (2012), is also able to simulate the effects of the dry friction forces developed in rotor bearings, gear reducer, hinges and screw actuators; in particular, the frictional torque is calculated by means of the numerical model proposed by Borello, Maggiore, Dalla Vedova and Alimhillaj (2009).



Figure 9. Mechanical Transmission block diagram.

The Mechanical Transmission subsystem shown in figure 9 simulates the behavior of the transmission shaft linking together gear-motor assembly and final user, calculating the corresponding reaction torque (*Treaz*) as a function of *ThM* and *ThU* (respectively motor and user position) and *Ktr* (transmission shaft stiffness) taking into account the effects of the mechanical backlashes.

² In nominal conditions (no failure considered) the back-EMF acting e.g. on the phase "a" is a function of the rotor position *ThM* having the amplitude of $ea = ke \cdot DThM$, that ke is back-EMF constant of the considered phase. In case of electrical failure (such as coil short-circuits or static eccentricity) the back-EMF constants may be suitably modified by means of three functions f(u) (one for each motor phase) properly conceived in order to simulate the effects of these failures.

³ The so obtained mechanical motor torque TM is limited by means of a Simulink Saturation block in order to take in account the actual performance of the real system.

⁴ It must be noted that the description of the general architecture of the two d.o.f mechanical system employed in the present work and its mathematical model are reported in references [8] and [13].



Figure 10. Monitoring Model block diagram.

3. RELATED MONITORING MODEL

The above Simulink model, as explained in the previous section, is able to simulate the dynamic behavior of an actual electromechanical servomechanism taking into account the effects due to command inputs, environmental boundary conditions and several failures. So, even with proper limitations, this model allows simulating the dynamic response of the real system in order to evaluate the effects of different faults and designs, analyses and tests different diagnostic and prognostic monitoring strategies. In order to conceive a smart system able to identify and evaluate the progressive failures, it is necessary to compare its dynamic behaviors with the ones provided by an ideal system operating in nominal conditions (in order to neglect the effects due to the aforesaid failures). To this purpose, a new numerical model (more simplified and compact than the previous one), dedicated to monitoring operations, has been developed. As shown in figure 10, the Monitoring Model controller represents a simplified version of the proposed EMA numerical model having the same logical and functional structure; such a model, with respect to the detailed one, is able to give similar performance, although less detailed, requiring less computational effort and reduced computational time.

The Controller calculates the output reference current *I_ref* as a function of the motor angular position ThM, the motor angular velocity DThM and the commanded position Com. In order to simplify the electromagnetic numerical model, the three-phase BLDC motor has been modelled as an equivalent single-phase electromagnetic motor and the driving torque TM is directly obtained multiplying the current Cor by a torque constant GM. The difference between reference (I_ref) and actual currents (Cor) enters a SIGN block that returns the corresponding phase supply voltage +/-Vdcm (respectively, when reference current is higher than actual current or vice versa); these values, decreased of back-EMF, calculates (by means of a transfer function modelling the resistive-inductive circuit) the actual phase current Cor used in feedback for motor torque computation TM. A saturation block is provided to take into account the corresponding torque limits.

In the aim to simplify the actuator mechanical model, the gearmotor-user assembly has been degraded to a simpler 1 d.o.f. non-linear second order dynamic system (neglecting the effects due to system inertias, transmission shaft stiffness and backlashes and reducing the inertial and viscous terms to the same shaft) and all the friction torques acting on the actual system are ignored.

4. EMA FAILURES AND DEGRADATIONS

Since EMA have been only recently employed in aeronautics, their cumulated flight hours or on-board installations are not so much to permit to obtain reliable statistics about more recurring failures. However, it is possible to discern between four main categories of failures:

- 1. mechanical or structural failures;
- 2. BLDC motor failures;
- 3. electronics failures;
- 4. sensor failures.

The present work has been mainly focused on the effects of mechanical failures due to progressive wear, that causes an increase of backlash and friction, and on two typical BLDC motor failures: the coil short-circuits ad the bearing wear generating rotor static eccentricity. Electrical and sensor failures are not less important than the other ones, but their evolutions are usually very fast (if not instantaneous) and the corresponding failure precursors are often difficult to identify and evaluate; nevertheless, it is the intention of the authors to study these types of failure in a next work. As known, dry friction phenomena always occur when two surfaces are in relative motion: when friction coefficients increase due to wear, reaction torque becomes higher and the motor must provide higher torques to actuate the control surface. As shown by Borello, Maggiore, Villero and Dalla Vedova (2010), increased dry friction, while still not causing the seizure of the entire system, reduces the servomechanism accuracy and, sometimes, influences the system dynamic response generating unexpected behavior (stick-slip or limit cycles). The mechanical wear could also generate backlash in EMA moving parts such as gears, hinges, bearings and especially screw actuators.

These backlashes, acting on the elements of the mechanical transmission, reduce the EMA accuracy and can lead to problems of stiffness and controllability of the whole actuator, as shown by Borello and Dalla Vedova (2006). BLDC motor failures are mainly seen as progressive coil short-circuits or bearing wear generating rotor static eccentricity. Short-circuits usually start between a few coils belonging to the same phase (coil-coil failure). Since into short-circuited coils the voltage remains the same and the resistance decreases, a high circulating current arises, generating a localized heating in conductor: this heating favors the extension of the failure to adjacent coils. If this kind of failure is not promptly detected it could propagate and generate phase-phase or phase-neutral damages. The static eccentricity of a rotating body consists in a misalignment between the rotor rotation axis and the stator axis of symmetry; this misalignment is mainly due to tolerances and imperfections during motor construction or to a gradual increase of wear of the rotor shaft bearings. When this failure occurs, the motor having more than one polar couple generates a periodically variable magnetic flux, since the air gap varies during its 360° degrees turn.



Figure 11. Reference system for the definition of air gap.

In case of static eccentricity, the air gap changes during a spin of the rotor (figure 11) and its behavior can be represented by the function:

$$g'(\vartheta) = g_0 + x_0 \cos(\vartheta) \tag{1}$$

where g_0 , is the clearance between stator and rotor (without considering misalignment) and the second term represents the variation of the air gap with ϑ related to the misalignment x_0 ; in terms of motor performances, provided torque is lower than in nominal conditions; instead, spectral analysis reveals sub-harmonics increasing for higher eccentricities. The rotor static eccentricity and the partial stator coil short circuit effects have been modeled by means of a simplified numerical algorithm. Since the both failures change the magnetic coupling between stator and rotor, the algorithm simulates the aforesaid failures modifying values and angular modulations of the back-EMF coefficients⁵.

$$ke_a = Ke_i \cdot Ce_i \cdot (1 + \zeta \cdot \cos(\vartheta_r)) \tag{2}$$

The so obtained constants (ke_a , ke_b , ke_c) are then used to calculate the corresponding counter-electromotive forces (ea, eb, ec) and to evaluate the mechanical couples (Cea, Ceb, Cec) generated by the three motor phases (figure 7).

5. FAULT DETECTION/EVALUATION ALGORITHMS

As already said, prognostics is an engineering discipline whose purpose is to predict an incipient failure of a certain component, allowing possible interventions before the initial flaw propagates. The failure detection/evaluation could be achieved by means of a proper algorithm (typically applied to a numerical model) able to detect the failures and predict their evolution. This fact underlines a limit of prognostics: it could predict only failures which presents a gradual growth and it is not able to detect sudden faults. Prognostics algorithms can have several complexity levels, from the simplest based on heuristic criteria to the most complex involving physical failure models. Developing a prognostic algorithm able to identify the precursors of an EMA failure and its degradation pattern is thus beneficial for anticipating the incoming failure and alerting the maintenance crew such to properly schedule the EMA replacement. This avoids a servomechanism failure in service, thereby ensuring improved equipment availability and minimizing the impacts onto the logistic line. To this effect, a model based failure detection/evaluation technique was developed that fuses several information obtained by comparing actual with expected responses of the EMA to recognize a degradation and estimate the remaining useful life. The choice of the best algorithms able to detect and evaluate a particular kind of incipient failure is driven by their ability to detect the failure itself, so proper tests are needed. The proposed algorithm is based upon:

- 1. Fourier spectral analysis (by means of FFT);
- 2. Correlation coefficient)

The Fourier Transform (FT) is a mathematical instrument, based upon the theory of Fourier series, which has many applications in physics and engineering (Welch 1967). Fourier Transform of a function f(t) is often calculated by means of the Discrete Fourier Transform (called DFT). Unlike the typical FT, the DFT requires as input a discrete function; this restrains the DFT to the analysis of a function on a limited and discrete domain. It must be noted that the input values of DFT are finite sequences of real or complex numbers, feature that makes it ideal for data processing on electronic calculators; in particular, this method is employed to analyze the frequencies composing a certain numerical signal by means of proper algorithms constituting the Fast Fourier Transform (FFT) (as shown by Cardona, Lerusse and Géradin 1998). In order to achieve the spectral analysis of the dynamic response of the actuation system to a given command, a dedicated numerical algorithm (based upon the FFT MATLAB implementation) has been conceived.

⁵ The proposed algorithm, implemented by means of the functions f(u) contained in the BLDC EM Model block diagram reported in figure 7, acts on the three back-EMF constants *Cei* (one for each branch) modulating their trapezoidal reference values *Ke_i* as a function of coil short circuit percentage, static rotor eccentricity ζ and angular position ϑ_r .

As mentioned earlier, the other instrument used to detect incipient failures or wear conditions is the correlation coefficient C. This coefficient, as proposed by Borello, Dalla Vedova, Jacazio and Sorli (2009) and Dalla Vedova et al. (2010), is defined as:

$$C = \frac{\int_0^T x_T x_M dt}{\int_0^T x_T^2 dt}$$
(3)

where x_T is the set of observed data and x_M is the theoretical data: in this work, they are respectively the results of the model that simulates the actual system and the data from the monitoring model. The data considered in the two vectors, depending on the case, could concern positions, velocities or other physical magnitudes of the system. The data representing the dynamic response of the actual system (fault sensitive) are compared with the results provided by the monitoring system (that simulates ideal conditions, since no progressive failures are considered): the more the failure is considerable, the more the results obtained from the simulated actual system differ from the theoretical data⁶. This difference, in order to be useful for prognostic analysis, should have a monotonic trend related to the corresponding failure increase. In order to allow a direct correlation between the growth of a defined failure and the corresponding value of the correlation coefficient, it is necessary to identify a physical magnitude (sensitive to the aforesaid failure) that, with increasing failure itself, generates a monotonic and easily detectable trend of C; to this purpose, the authors have conceived another dedicated numerical algorithm (developed in MATLAB environment) implementing equation (3).

6. FAILURES EFFECTS OF THE EMA BEHAVIOR

In order to recognize the effects produced by a failure on the dynamic behavior of the considered actuation system, the dynamic responses generated under such conditions are compared with those reported in nominal conditions (i.e. considering the nominal values of parameters and failures). The proposed EMA model has been tested with several simulations in nominal conditions (NC): the compliance between the actual behaviors of a real EMA and the corresponding simulated results have been evaluated by means of many types of Com; subsequently, these results have been compared with the system behavior in failure conditions. A step command input (figure 12) generates a dynamical response that, in NC (having proper values of dry friction torque and mechanical backlash and neglecting any phase short circuit or rotor static eccentricity), puts in evidence the system stability margin, the non-linear effects due to saturations and the position errors due to frictions

(this is because the authors model integrates the dry friction algorithm in a dynamic system able to take into account also the hard stops effects and their mutual interactions); by this way it is possible to discern between static and dynamic friction conditions and evaluate their effects on the system. Figure 13 puts in evidence the EMA numerical model ability to simulate the actual dynamics of the three-phase currents (*Ia*, *Ib*, *Ic*) taking into account the effects due to PWM regulation ad phase commutation, such as "two-phase on" effect shown by Haskew, Schinstock and Waldrep (1999) or Hemanand and Rajesh (2006).



Figure 12. Example of system dynamic behavior in condition of step position command.



Figure 13. Related reference and actual phase.

The ramp response analysis reveals that the proposed model is able to simulate both a high-slope ramp response (Fig. 14) and a stick-slip phenomenon (Fig. 15); the first case underlines the limits of the actuator in terms of maximum speed, while the latter shows what occurs when the ramp slope is lower enough to emphasize the frictional effects. Furthermore, the model allows to evaluate the incipient motion resolution of the servomechanism, i.e. the smallest command value producing an actuator's response. Obviously, this value becomes higher as frictional contribution is more significant, that is when the servomechanism undergoes increasing wear conditions.

⁶ If the vector of observed data exactly corresponds to the theoretical data, C is equal to 1. If this correspondence does not occur, the more the discrepancy between the two data sets is noticeable, and the more the value of C is different from 1: its value could be higher or lower than 1.



Figure 14. Example of system dynamic behavior in condition of high slope ramp command.



Figure 15. Example of system dynamic behavior in condition of very low slope ramp command.

At the same way, several periodic inputs have been examined confirming the model ability to simulate the behavior of the real actuation system and its sensitivity to nonlinear effects, command inputs (in terms dynamic response related to amplitude and frequency input) and external loads. The most interesting results are provided by FFT analysis performed on positions and velocities of motor and user. The algorithm employed to perform this task correctly records the most important spectral contribution of the analyzed magnitudes as a function of the corresponding command frequency: its amplitude is related to the command semi-amplitude. If the given command has an amplitude or a frequency too wide to be properly followed by the servomechanism, this analysis also records odd multiple harmonics of the command frequency (which typically appear if signals distortions have a half-wave symmetry). Checked the compliance of the proposed numerical model in NC, several analysis have been performed considering the four possible failures.

Firstly, the effects of wear conditions (friction and backlash) have been evaluated: the friction torque is defined as a percentage of the maximum motor torque, while the mechanical transmission backlash is modeled as localized downstream the gear reducer.

The high-slope ramp command provides significant results:

- 1. In terms of FFT analysis on velocities, the fundamental frequency recorded in nominal conditions is around 2040 Hz. This value slightly decreases as frictional effects increase, since angular velocity is reduced by friction. The amplitude related to this frequency monotonically increases with friction and increasing non-monotonic multiple harmonics arise (the second and the third ones have been recorded during FFT analysis). Backlash is not detected with FFT algorithm;
- 2. The investigation on the correlation coefficients reveals that on user position and velocity a negligible increase with friction has been found, while a definite decreasing monotonic trend can be recorded for motor torque. The same analysis performed on backlash has not provided any employable data, from a prognostic point of view. The correlation coefficient for reference current is always 1 for a ramp input, since the actuator follows a velocity regime and this fact is independent from the kind of failure implemented on the model.

Further analysis concern the sinusoidal response (the input has a frequency of 20 Hz and an amplitude of 0.001 rad):

- 1. FFT analysis cannot detect nor friction nor backlash, since only the command frequency prevails;
- 2. All the correlation coefficients generally show negligible variations (lower than 1%), regardless of changes in command frequency or amplitude. The exceptions are motor torque and reference current, which show similar monotonic, decreasing trends as friction grows: this behavior is due to the higher torque needed to follow the command. This trend, clearer for friction and less remarked for backlash, is similar for both the wear effects.

Secondly, the effects of electrical failures on the performances of the servomechanism have been evaluated, considering coil short-circuit and rotor static eccentricity. A typical behavior of the system undergoing electrical failures is the rise of sub-harmonics on the spectra of angular velocities. This phenomenon is clearly recorded with the FFT analysis on the high-slope ramp command:

- 1. 1/3 and 2/3 multiple of the fundamental harmonic are related to short-circuits; the 1/3 harmonic provides the most important contribution in terms of amplitude when the failure ratio is above 0.02;
- 2. 1/6 and 1/2 multiple harmonics concern the rotor static eccentricity. In this case, the 1/6 harmonic is the prevailing term for misalignments higher than 1%.

These sub-harmonic values could be explained by means of this relation:

$$\frac{f_{M}}{f_{\omega,M}} \cong 2 * p * n \tag{4}$$

where f_M is the fundamental frequency recorded by FFT motor velocity analysis, $f_{\omega,M}$ is the motor velocity in Hz, p=4 is the number of polar couples, n=3 is the number of phases. For sub-harmonics induced by coil failures, it is clear that they arise due to differences in the *n* motor phases, so the spectral analysis detects significant contributions at $\frac{i}{n} \cdot f_M$, i = 1, ..., n. The rotor static eccentricity, instead, is represented on the spectrum as combined by a sub-harmonic related to the number of polar couples p (i.e. the 1/6 subharmonic, for this motor) and the 1/2 sub-harmonic. The latter represents the effect of the eccentricity on a certain polar couple. In both cases the sub-harmonic amplitudes show a monotonic trend: this result allows to detect a possible electrical failure with a simple observation of FFT spectra. In this case, only the correlation coefficient for motor torque shows monotonic trends for both the failures. The sinusoidal command provides the following results:

- 1. As for wear detection, the FFT analysis fails due to the predominance of the command frequency;
- 2. Significant results are provided by the analysis on correlation coefficients: in particular, a significant decreasing monotonic trend can be recognized in reference current for coil failures.

Finally, the open-loop step response has been evaluated: all the analyzed magnitudes show monotonic trends in terms of correlation coefficients for both failures, but the variations are not significant enough to be employed in prognostics.

7. FAILURE MAPS

After the analysis performed on a single acting failure, this work focuses on the effects due to the simultaneous presence of different kinds of failures acting on the system. To the purpose to achieve a timely identification and evaluation of these failures, the authors developed a new faults detection technique based on failure maps (FMs). A failure map constitutes the graphical representation of how a system-representative parameter varies as a function of two different types of failures; in other words, if the measurement of the parameter of the real system is available, this instrument allows to suppose which extent a certain couple of failures has on the actuator. More exactly, a failure map displays the first failure G_1 on x-axis and the representative parameter P_1 on y-axis. Each map represents a set of curves $P_1 = f(G_1)$ which are parameterized with the second failure G_2 . A proper choice of P_1 is crucial in order to obtain a useful failure map. Firstly, this parameter should be a function of both G_1 and G_2 . It is preferable a parameter which is highly sensitive to changes in failure levels. In particular, its dependence from the two kinds of failure should be monotonic, i.e. the curves plotted on the maps should not intersect: this feature is the most important, since it allows to detect a specific area on the map containing all the possible failure levels.

The proposed prognostic technique, in order to identify system conditions with high enough accuracy, requires more than one of these maps for a specific couple of failures. When several maps are employed, it is important that they are independent from each other. Independent maps can be obtained when the actuator undergoes different command inputs: in this way, the parameter represented on each map is a magnitude that is not related to the others. By using three independent maps, i.e. representing three different parameters P_1 , P_2 and P_3 , an accurate area containing the possible failures is identified. The considered inputs are:

- 1. A sinusoidal input with a frequency of 20 Hz and an amplitude of 0.001 rad;
- 2. A high-slope ramp command at 10 rad/s;
- 3. A step command with an amplitude of 0.005 rad, with the actuator in open-loop configuration.

By using the results found during the single failure analysis to find the most suitable parameter for the map drawing, all the possible failure combinations have been investigated. It must be noted that, in many cases, the FMs were not suitable for prognostics; for few couples there were not enough independent maps (as for the couple *coil failure – rotor static eccentricity*, with only two employable maps). A couple on which the method has been successfully tested was the *friction – coil failure* couple, allowing to obtain more independent maps. Among these, three were chosen to apply the FMs method (G_1 = friction, G_2 i= coil failure ratio).

The first map (figure 16) concerns correlation coefficient C for reference current, P_1 , obtained with sinusoidal input.

The second map (figure 17) represents the correlation coefficient C for user position, P_2 , when a step input is given to the open-loop system (OL).

Finally, the last map (figure 18) shows the response to a high-slope ramp input in terms of the correlation coefficient C for user velocity, P_3 .



Figure 16. Correlation coefficient C failure map related to reference current – Sinusoidal input.


Figure 17. Correlation coefficient C failure map related to user position – OL Step input.



Figure 18. Correlation coefficient C failure map related to user velocity – High slope ramp input

After the maps have been obtained, they can be employed for the proposed procedure, which is now explained in detail. Firstly, the numerical model is simulated as affected by a known level of both friction and coil failure ratio, considering the three different command inputs: this step provides the parameters P_1 , P_2 and P_3 . As these values will employed on the failure maps, a certain statistical dispersion, equal to a $\pm 5\%$ of the maximum variation between the curves of each map is taken into account. Then, the first map is employed with the entering value of P_1 and an initial large area containing the possible failure levels for G_1 and G_2 is obtained. These two intervals are inserted on the second map, which requires also the value P_2 : their intersection provides narrower intervals of the two kinds of failure. The procedure applied on the third map (on which P_3 is considered) is the same seen for the second one. This method have been successfully employed on a number of combinations of friction and coil failure ratio, always resulting on an enough accurate detection of the failure levels acting on the actuator.

The example shown in figure 19 is referring to a friction torque equal to four times the nominal value (4·NC), a 4% of the coil failure ratio and a rotor static eccentricity ratio equal to 0.05: the *X* represented the supposed failure level.



Figure 19. Example of application of Failure Maps

It must be noted that the correlation coefficients considered are not significantly sensitive to the variations induced in the system by low levels of backlash or rotor static eccentricity; so, the levels of friction and coil short-circuit could be properly recognized neglecting their effects.

8. CONCLUSIONS

This work focuses on the research of system-representative parameters which are suitable for prognostic activities and on the development of a technique, allowing a prompt detection of gradually-increasing failures on aircraft actuators. The study has been performed on a numeric test bench (simulating the behavior of a real EMA actuator) that implements four kinds of failure: friction, backlash, coil short circuit, rotor static eccentricity; by means of proper simplifications, the aforesaid numerical model was then reduced obtaining the monitoring model. The proposed failure detection/evaluation algorithm has been developed mixing together the information derived from the spectral analysis of signals (performed by means of the FFT algorithm) and by direct comparison between EMA and monitoring model (through the correlation coefficient C); by means of these tools suitable fault precursors, useful for early recognition and quantification of the damage, have been identified. Finally, proper failure maps have been drawn to perform the analysis of combined failures. This method have been successfully applied to many different combinations of considered failures, guaranteeing always an enough accurate detection/estimation of their levels.

REFERENCES

- Çunkas, M., & Aydoğdu, O. (2010). Realization of Fuzzy Logic Controlled Brushless DC Motor Drives using Matlab/Simulink. *Mathematical and Computational Applications*, vol. 15, n. 02, pp. 218-229.
- Halvaei Niasar, A., Moghbelli, H., & Vahedi, A. (2009). Modelling, Simulation and Implementation of Four-Switch Brushless DC Motor Drive Based On Switching Functions. *IEEE EUROCON 2009*. May 18-23, St.-Petersburg (Russia), pp. 682 – 687.

- Borello, L., Maggiore, P., Dalla Vedova, M. D. L., Alimhillaj, P. (2009). Dry Fiction acting on Hydraulic Motors and Control Valves: Dynamic Behavior of Flight Controls. XX National Congress AIDAA. Milan (Italy)
- Borello, L., Maggiore, P., Villero, G., & Dalla Vedova, M. D. L. (2010). A comparison between Dry Friction Discontinuous Computational Algorithms. 27th International Congress of the Aeronautical Sciences ICAS 2010. September 19-24, Nice (France).
- Borello, L., & Dalla Vedova, M. D. L. (2012). A Dry Friction Model and Robust Computational Algorithm for Reversible or Irreversible Motion Transmission. *International Journal of Mechanics and Control* (*JoMaC*), vol. 13, n. 02, pp. 37-48, ISSN: 1590-8844.
- Borello, L., Dalla Vedova, M. D. L., Jacazio, G., & Sorli, M. (2009). A Prognostic Model for Electrohydraulic Servovalves. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. September 27-October 1, San Diego (USA).
- Dalla Vedova, M. D. L., Jacazio, G., Maggiore, P., & Sorli, M. (2010). Identification of Precursors of Servovalves Failures for Implementation of an Effective Prognostics. *International Conference of Recent* Advances in Aerospace Actuation Systems and Components. May 5-7, Toulouse (France), pp.116-126.
- Borello, L., & Dalla Vedova, M. D. L. (2006). Mechanical failures of flap control systems and related position errors: proposal of innovative configuration equipped with centrifugal brakes. *International Journal of Mechanics and Control (JoMaC)*, vol. 07, n. 02, pp. 7-20, ISSN: 1590-8844.
- Welch, P. D. (1967). The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms. *IEEE Transactions on audio and electroacoustics*, vol. AU-15, n. 2.
- Cardona, A., Lerusse, A., & Géradin, M. (1998). Fast Fourier nonlinear vibration analysis. *Computational Mechanics*, vol. 22, n. 02, pp. 128-142.
- Lee, B. K., Ehsani, M. (2003). Advanced Simulation Model for Brushless DC Motor Drives. *Electric Power Components and Systems*, vol. 31, n. 9, pp. 841–868, ISSN: 1532-5008.
- Hemanand, T., Rajesh, T. (2006). Speed Control of Brushless DC Motor Drive Employing Hard Chopping PWM Technique Using DSP. Proceedings of India International Conference on Power Electronics (IICPE 2006). December 19-21, Chennai (India), pp. 393-396.
- Haskew,T. A., Schinstock, D. E., & Waldrep E. M. (1999). "Two-Phase On" Drive Operation in a Permanent Magnet Synchronous Machine Electromechanical Actuator. *IEEE Transactions on on Energy Conversion*, vol. 14, v. 02.

BIOGRAPHIES



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Leveraging Next Generation Reasoning for Prognostics and Health Management of the Smart Grid

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ABSTRACT

With the increasing complexity from an evolving Smart Grid, the significance of providing real-time situational awareness and the ability to leverage advanced reasoning and prediction for control and automation will become key differentiators for service providers. Similar techniques are being applied within prognostics and health management (PHM) applications and are providing value by predicting and assuring system reliability, performing real-time detection and diagnosis of failure, and presenting current and predicted system states to users to aid in decision making. With the overlap in application and requirements for advanced software techniques, the smart grid industry is compelled to investigate products and processes applied to PHM across other domains. However, the complexity of grid management, the speed of technology development, the dynamic nature of electric power supply and demand - each of these contribute to the necessity for applying advanced reasoning capabilities that provide more flexibility to developers and users. Such advanced capabilities allow for leveraging all available information, enabling accurate predictions of future conditions and availability, and incorporating the necessary knowledge for making high level decisions. Object oriented, model-based reasoning systems have demonstrated value within the PHM community for handling such complexity, and in this paper the authors discuss a pragmatic approach for applying these next generation PHM techniques to the smart grid.

1. INTRODUCTION

Many years of PHM research in the aerospace industry has resulted in the development and validation of various Gilbert Cassar et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

learning algorithms and expert system reasoning platforms for the purposes of monitoring and predicting the health of complex aircraft systems (Ferrel, 1999). Among other things, such PHM systems have demonstrated the ability to detect anomalies from real-time comparisons between measured and expected process values (potentially derived from physics models), recognize and characterize fault signatures, utilize rules and algorithms for isolating root causes, make predictions about future health and remaining useful life, incorporate policy and mission objectives for generating advice, and automate actions according to real-time state assessment for ensuring safety, maximizing availability, and optimizing productivity (Vatchsevanos, Lewis, Roemer, Hess, & Wu, 2006), (Walker, 2010). Recently the application of aerospace PHM techniques has expanded to virtually every other industry where concern of availability and a desire to minimize the costs associated with repair exists (Walker, Advanced reasoning techniques are Kapadia, 2009). especially of value in applications where there is high data dimensionality, an availability of disparate information across subsystems or geographic regions, the need for making predictions based on recognized patterns, and/or the opportunity to optimally reconfigure systems based on well understood cost functions. One such industry where PHM technological advancements are readily applied is that of the so-called energy smart grid.

For smart grid, one of the key objectives is to effect real-time reconfigurations of the electrical grid (generation and distribution) based on the ability to proactively monitor and predict load demand. Additional input for making such decisions might also come from predictions and assessments of infrastructure health, allowing for reconfigurations of the grid based on component failure or anticipated outages. Advanced reasoning systems could also incorporate policybased rule logic that would guide such reconfigurations based on real-time knowledge of criticality measures, service agreements, or current pricing trends.

Forecasting in smart grid applications is typically performed by applying pattern recognition algorithms over historical usage data, in conjunction with making real-time predictions of availability of conventional and renewable energy sources. Similar pattern recognition techniques are often utilized by advanced reasoning systems for classifying fault signatures or making predictions regarding the onset of failure (Patterson-Hine, Aaseng, Biswas, Narashimhan, & Pattipati, 2007). PHM systems equipped with such advanced reasoning are therefore immediately applicable to the smart grid. Furthermore, anticipating and forecasting demand in such systems can also be utilized to augment predictions of component remaining useful life based on the effects of the anticipated usage.

Often the automated decisions required of smart grid management systems involve the processing of information that is aggregated across many grid components (e.g. meters, switches, and converters) and spans wide geographic areas. These are also characteristics of many large scale enterprise or fleet-wide PHM systems, as the goal of such systems is not just to assess the health of specific assets (vehicles, plants, processes, facilities), but to aggregate such health information into a higher level health assessment of the enterprise (or overall mission capability). Such systems are often architected in a distributed fashion and include supervisory level reasoners for aggregating information and performing high level management functions like generating reports, initiating maintenance actions, automating inventory and management of spares, and producing and presenting executive advisories.

While recent advances stemming from PHM research have successfully been applied for use in the smart grid marketplace, most of the engineered solutions are constrained by a lack of flexibility in the selection and configuration of learning and reasoning algorithms to be employed. Typically the inferences and predictions associated with the smart grid management problem require the application of multiple algorithms and reasoning approaches. However, a review of prominent research demonstrates that many of the smart grid solutions are restricted to single algorithms and characterized by rigid policies (NIST, 2012). Very often an algorithm that is selected or tuned for one application requires tweaking in order to produce similar results in another. It should also be noted that modification and extensibility of such systems typically requires costly reengineering efforts.

One PHM technology that can be used to overcome the limitations of current smart grid management solutions is that of the model-based reasoning platform. Model-based reasoning platforms that support rapid specification of logic through graphical programming languages not only can be used to reduce the cost of developing, testing, and validating software, but they also lend themselves as add-ins for extending existing solutions with limited or constrained flexibility. When such reasoning systems are built on top of goal-oriented expert systems technology, the user is readily able to abstract the management problem to even higher levels. The authors have coined the term "Objective Oriented 3rd Generation Expert Systems" to refer to such advanced model-based reasoning systems.

In the following sections we present some detail regarding the existing challenges presented to the smart grid management system provider, and provide insight as to how Objective Oriented 3rd Generation Expert Systems can be used to overcome those challenges. The implication is that such reasoning systems can be used to enable the full benefits of PHM to smart grid management providers, since the objectives of the smart grid are so inextricably linked to the measured and predicted health of the components, infrastructure, and topology of the grid.

2. CHALLENGES

Smart grids, which use intelligent transmission and distribution networks to deliver electricity, aim at improving the electric system's reliability, security and efficiency through two-way communication of consumption data and dynamic optimization of electric-system operations, maintenance, and planning (Khurana, Hadley, Lu, & Frincke, 2010). The underlying requirements of smart grids indicate a dependency on massive communications between components involving an enormous amount of data. This suggests the inevitability of an increase in fault propagation through the network, and an urgent demand for various technological enhancements that can assist in assessing the health of smart grids. At a high level, the design of smart grid PHM algorithms and products can be categorized into 2 areas: real time analysis and reasoning based prediction.

2.1. Real time analysis

Based on wide area situational awareness, smart grid management systems should be expected to be able to receive and analyze large amounts of real-time data and information from disparate sources. Such systems should also support increased adaptability when facing ever changing conditions. For example, pattern recognition and classification techniques can be effective in re-assignment of grid nodes dynamically and automatically when the load or the availability of renewable energy sources changes (Lu, Tinker, Apon, Hoffman, & Dowdy, 2005). However, with the real-time changes in the grid come changes in the amounts, quality, and availability of data – suggesting that the pattern recognition algorithms and event detection rules themselves be adaptable.

2.2. Reasoning prediction

The power of expert systems allows smart grid system designers to reason over the system process using embedded

domain expertise, generic rule based logic, and advanced model-based reasoning even in the presence of incomplete information. This combination of capabilities enables process health and performance prediction involving higher level abstractions of data and information, providing the end users with improved situational awareness and understanding. The ability to transform data and information into knowledge and understanding stems from the expert system's ability to leverage software models of the entire domain - including object associations, relationships, and roles (refer to Figure From the system maintenance side, outage and 1). node/equipment failure propagation can be prevented in advance, if historical event data is available. For energy management, demand from smart appliances and supply from renewable energy sources can be anticipated by investigating the pattern characterization of weather, human activity agenda, etc. Such advanced reasoning capabilities typically involve the incorporation of many business rules which not only need to accommodate ever changing conditions, but also ever changing objectives.



Figure 1. Reasoning - From data to wisdom.

The plethora of choices and the need for a wide variety of approaches presents some dilemmas for the smart grid management provider. Several of these are briefly discussed in the following paragraphs.

Dilemma 1 - Compatibility of multiple 'smart' designs

There are plenty of 'smart' designs appearing in the smart grid market, most of which focus on different objectives. For example, some applications focus on the efficiency, reliability, security and stability of the grid. Others focus more specifically on the energy efficiency, demand response, and load control for residential, commercial and industrial purposes (NIST, Technology, Measurements, and Standards Challenges for the Smart Grid, 2013). Some smart grid designs build up specific scenarios for the grid, which are not compatible with each other in many cases. The uncertainty of each promised scenario is often not clear or is difficult to compare. This general lack of compatibility presents some challenges to the implementer of smart grid PHM solutions, although such apparent incongruity can be successfully addressed with improved architectures equipped with advanced reasoning capabilities.

Dilemma 2 - Changing user objectives

It is also difficult for smart grid management system users/suppliers to define or clarify their objectives at an early design stage. Furthermore, it is typical that requirements and objectives have changed by the end of the development cycle. As in most industries, smart grid suppliers have to adjust their objectives with market requirements and local policies. In many cases their specific designs will need to target specific codes and standards. In other cases, the users/suppliers may have to satisfy multiple codes and standards- all while enduring rapidly changing local policies and grid market conditions. In addition, the grid has to stay open to new emerging grid technologies which introduce new data, requiring potentially new event detection approaches, and resulting in changes to policy and objectives. In general, as the smart grid evolves, users and providers place increasing demands on higher level management capabilities that involve new modeling constructs and policies. Smart grid management providers have to adjust with all of these challenges and opportunities in a short time and can be plagued by technologies that are not sufficiently flexible or extendable.

Dilemma 3 – Requirements for higher level management system interoperability

Another trend occurring across the smart grid landscape is the emergence of new alliances and the requirements for interoperability between management systems. One example is the trend for crossover corporations that combine services between multiple industries. In China, a new corporation has been proposed that combines the telecom industry with the smart grid in order to minimize the service line cost and share end user resources. In another case the convergence of solar, smart grid and healthcare IT in one offering or platform is also raising the attention and funding of the investors (Prabhu, 2013) Modifying or incorporating logic that addresses such interoperability is a challenge for most reasoning system platforms.

Dilemma 4 – Expensive design implementation

To embrace a novel PHM design with the existing grid system, there is much effort required prior to implementation. Design options vary, and with somewhat fluid requirements, implementation time can be excessive. Meanwhile, test requirements for PHM systems can be severe (Vatchsevanos, Lewis, Roemer, Hess & Wu, 2006). According to a typical solution delivery framework (SDF), the original design should be adjusted, tested and verified in the existing system environment. This process is always time consuming and costly. Ideally, the designers of smart grid management systems can make use of tools that allow for minimizing the labor associated with designing, implementing and testing solutions in the presence of such difficulties.

Dilemma 5 – Too much information

Due to the large numbers of components, the dynamic nature of supply and demand, and the increase in digital information being shared across the infrastructure, smart grid reasoning systems produce extremely large numbers of advisories and events. Since the goal of smart grid health management systems is to increase situational awareness, this inundation of alarms and information actually acts to degrade operator situational awareness. But ever increasing data and information is an unavoidable consequence when you consider the advancements being made with smart meters, new sensing technologies, and the proliferation of networked infrastructure components. When you add the requirement of real-time health monitoring of the grid and its components, the situation becomes even worse. The smart grid PHM designer requires tools that will aid in the reduction of alarms and events, principally through filtering, correlation and alarm subsumption.

Dilemma 6 - Advanced PHM out of reach

While the smart grid PHM designer expects to achieve benefits like root cause isolation (through the deployment of fault models), the ability to leverage supervised and unsupervised learning, and meaningful predictions regarding remaining useful life, very often these advanced capabilities remain out of reach. Ideally, the tools available to the smart grid PHM designer would enable higher level management capabilities such as Condition Based Maintenance. For example, advanced PHM systems should support real-time determinations regarding the most appropriate responses to current and predicted conditions. Typical responses might include differentiating between maintain, repair, and replace actions. To simplify decision making involving 'smart' designs and products, and to bring more opportunities for grid service providers, Objective-Oriented 3rd Generation Expert Systems can be utilized. These kinds of systems provide a powerful and reconfigurable environment that can speed up overall design and testing times as well as providing state-ofthe-art reasoning capabilities. Objective-Oriented 3rd Generation Expert Systems will be discussed in greater detail in the next section.

3. OBJECTIVE-ORIENTED THIRD GENERATION EXPERT SYSTEMS

Objective-Oriented 3rd Generation Expert Systems are used to create model-based reasoning solutions for interpreting data in real-time. Such systems can also readily leverage knowledge derived from historical data, and apply that knowledge to making better predictions. Model-based reasoning in such advanced reasoning systems can pave the way for a wider use of PHM design in smart grid management platforms by providing the tools needed to address the challenges mentioned in Section 2. In this section we discuss the main advantages of using Objective-Oriented 3rd Generation Expert Systems and how they can be applied to address the problems associated with delivering smart grid management solutions.

3.1. Compatibility

Objective-Oriented 3rd Generation Expert Systems can easily interface to standard supervisory control and data acquisition software (SCADA) and distributed control systems (DCS), making it possible to quickly set up data sources for your application. The software also supports standard databases such as Oracle and SQL server. Standard simulation designs can be captured and validated in graphical software development environment, allowing the instant re-use of preexisting designs. Whole infrastructures and processes can be modeled and simulated very quickly by using the wealth of reconfigurable graphical tools. These features can be used for operator training, education, process optimization, and also to validate and test a hypothesis.

Re-configurability

Vast libraries of mathematical and statistical functions are available for easy integration in an application. These can be used to analyze large quantities of real-time data such as the data generated by the sensors deployed over a smart grid. The main advantage of using such libraries is that algorithms can be quickly reconfigured or interchanged. Figure 2. shows a typical palette from which functions can be readily selected and used within an application. Most data mining and analysis applications rely on machine-learning algorithms to find patterns in the data and extract the valuable knowledge required for situational awareness. However, testing different machine learning algorithms on the same application can be very complex and time-consuming.



Figure 2. A palette of data mining functions.

With model-based platforms, different algorithms can be easily applied to the same application, making it possible to quickly test different approaches to your solution or to simultaneously apply multiple algorithms to the same problem. The platform can also enable real-time model selection and switching based on system state.

The re-configurability of Objective-Oriented 3rd Generation Expert Systems allows system designers to quickly adapt their software to changes in the technology, the objectives, and policies.

Objective-Oriented Design

One of the important aspects of modern reasoning systems is the ability to be configured based on user-defined objectives. Objective Oriented platforms typically leverage a graphical software development suite with vast auto configuration features that drastically reduce the amount of engineering time required to create or re-configure applications. Creating applications using model-based platforms results in a better cost-benefit ratio than in-house IT development, especially if developing software is not the core expertise or goal of your company.

Advanced Reasoning Capabilities

By adopting model-based reasoning, Objective-Oriented 3rd Generation Expert Systems provide a platform for accurate fault modelling and root cause analysis. Figure 3 shows the implementation of a Bow-Tie rule in one such expert system. Reasoning engines are used to analyze the model and automatically detect anomalies or even predict them ahead of time. These model-based reasoning capabilities can also be used to make automated decisions, for example: Condition-Based Maintenance (CBM) of equipment. CBM determines when maintenance should be carried out on equipment in order to ensure that the whole system keeps running without faults for as long as possible.



Figure 4. A bow tie rule.

Another added value that Objective-Oriented 3rd Generation Expert Systems can offer is Advanced Alarm Management (AAM). The generation of too many events and alarms in a system can confuse an operator and hinder their situational awareness rather than aiding it. The advanced reasoning mechanisms that are gained by adopting a PHM design allow AAM solutions to actively reduce the quantity of alarms presented to the operator and improve the quality of the alarm messages presented. Figure 6. shows an example of alarm grouping where alarms that provide the same information are grouped together (subsumed) so as to avoid presenting duplicate information to the operator. All of this is done at an advanced level that is often not possible with DCS and SCADA systems.



Figure 5. A simple analysis rule using SVM.

In order to provide the advanced reasoning capabilities required for smart grids, Objective-Oriented 3rd Generation Expert Systems should allow the implementation of a combination of rule-based schemes. Rules can be used to make applications react to abnormal situations in real-time. The decision making process can be based on logic, statistics, machine learning, or a combination of these and other algorithms. Figure 5 shows an example of how a Support Vector Machine (SVM) can be used to classify a situation based on readings from a set of data points in a model-based platform. The parameters are read from the data points, arranged into a row vector, and fed into a SVM block that computes what label best classifies the information shown in the input vector. The output is used to set a variable that can then be used in another rule for decision making.

16:20 21-06 Group Image: Compare the second	Ala	rm Cento	er	16:20	21-06-2010
	L4A	16:20 21-06 16:19 21-06 16:18 21-06 16:16 21-06 16:16 21-06 16:15 21-06	Group LOABS LOABS LLABS HIABS HIABS	COMPARING ALARY HIGH LEVEL SUMP COMPARING AND A A A A A A A A A A A A A A A A A A	<710

Figure 6. Alarm grouping.

4. CONCLUSION

The benefits and capabilities of PHM systems developed and demonstrated across multiple industries are readily applicable to the health and prognostics management of the electric grid. In addition, most of the algorithmic and reasoning technologies associated with assessing and predicting complex system health are also directly associated with the requirements and objectives of modern day service providers. These objectives include the assessment and prediction of optimal grid configuration in the presence of dynamic conditions associated with recent modernizations. Unification between existing smart grid management solutions and an overall grid PHM capability seems highly appropriate. However, the proliferation of new information and the demand for improved service in the presence of ever changing requirements present significant challenges to the developers of smart grid management systems. One proven solution to these challenges is the incorporation of advanced reasoning capabilities derived from Objective Oriented 3rd Generation Expert Systems. Such systems provide significant benefits to the smart grid management system developer, including rapid deployment; extensibility; scalability; and iterative, incremental development.

REFERENCES

- Ferrell, B. L. (1999), JSF Prognostics and Health Management. Proceedings of IEEE Aerospace Conference. March 6-13, Big Sky, MO. doi: 10.1109/AERO.1999.793190
- Khurana, H., Hadley, M., Lu, N., & Frincke, D. (2010). Smart Grid Security Issues. *IEEE Security and Privacy*.
- Lu, B., Tinker, M., Apon, A., Hoffman, D., & Dowdy, L. (2005). Adaptive automatic grid reconfiguration using workload phase identification. *First international conference on e-Science and Grid Computing*.
- NIST. (2012). NIST Framework and Roadmap for Smart Grid Interoperability Standards.
- NIST. (2013). Technology, Measurements, and Standards Challenges for the Smart Grid.
- Patterson-Hine, A., Aaseng, G., Biswas, S., Narashimhan, K., Pattipati, K.(2005). A Review of Diagnostic Techniques for ISHM Applications. *ISHM Forum 2005*, Napa, CA.
- Prabhu, R (2013) Smart Grid Receives \$434 Million in VC Funding, \$17 billion in M & A transactions recorded Retrieved from www.engrreview.com/Editorial _pages/2013/02/ER0213_Client-Tech_22.html
- Schwabacher, M., & Goebel, K. F. (2007). A survey of artificial intelligence for prognostics. *Proceedings of AAAI Fall Symposium*, November 9–11, Arlington, VA. www.aaai.org/Library/Symposia/Fall/2007/fs07-02-016.php
- Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). Intelligent fault diagnosis and prognosis for engineering system. Hoboken, NJ: John Wiley & Sons, Inc
- Walker, M., (2007). Model-based Reasoning Applications for Remote Intelligent Systems Health Management. *Proceedings of ASNE Intelligent Ships Symposium*. May 2007.
- Walker, M., Kapadia, R. (2009). Integrated Design of Online Health and Prognostics Management. *Proceedings of the Annual PHM Society Conference*, San Diego, CA. October 2009.

Walker, M. (2010). Next Generation Prognostics and Health Management for Unmanned Vehicles. *Proceedings of the IEEE Aerospace Conference*, Big Sky Montana, March 2010.

BIOGRAPHIES



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Multi-objective optimization of OEE (Overall Equipment Effectiveness) regarding production speed and energy consumption

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ABSTRACT

Using condition monitoring to track machine health and trigger maintenance actions is a proven best practice. By monitoring machinery health, costly failures are avoided and downtime due to outages is reduced. This results in an improved OEE (Overall Equipment Effectiveness). Many papers discuss the implementation of condition monitoring to prevent failures and optimize maintenance interventions. However, much less attention is paid to the use of condition monitoring information in order to optimize production capacity of a machine or a plant. This optimization is often translated in production plants by maximizing the production capacity (speed) and minimizing machine's downtime. As energy consumption is becoming more and an important decision criterion in modern more manufacturing plants, the former optimization needs to take this parameter into account. As such a trade-off has to be made between the gain in capacity and the cost of the additional energy consumed. Therefore, in this paper we will develop a multi-objective optimization of OEE to allow multiple-criteria decision making. More precisely, the goal of this paper is to establish the link between condition monitoring information and production capacity optimization by continuously adjusting production parameters (i.e. production speed) taking into account the machine's condition and the energy consumption.

1. INTRODUCTION

Condition-based maintenance (CBM) and predictive maintenance (PdM) approaches have been extensively developed these last two decades (Mobley, 1990; Sholom, et

al. 1998). The technical approach consists on monitoring the condition of an asset through a condition monitoring system and triggers a maintenance action when the condition monitoring signal crosses a critical value in case of CBM policy or uses this condition monitoring signal together with a prognostics model to predict when a maintenance action is needed in case of PdM policy (Blair, et al 2001; Goh, et al 2006, Bey-Temsamani, at al. 2009). Maintenance optimization based on these policies often consists of finding the optimal threshold, associated to the condition of the monitored asset, where maintenance should be triggered. In our previous works, this concept was successfully validated on packing machines (Van Horenbeek, et al. 2011) and extended with an optimal threshold determination taking into account the product quality. In this respect the end-user may decide to tolerate more degradation of the monitored asset if he judges the product quality is still acceptable. In some other industrial applications, the enduser prefers to control the degradation of the monitored assets by fixing a threshold on the condition monitoring signal (e.g. by implementing a thermal protection). In this case, if no optimization is implemented, a risk of 'too often' production stops could rise. In our previous work (Bey-Temsamani, et al. 2013), maximization of steel production capacity using temperature monitoring of production assets proved a production gain up to 21%. The technical approach followed in that work consists of optimizing the production (machine) speed taking into account the remaining time to trigger the thermal protection and the needed time to finish the product. If the first time is lower than the second, the machine speed should be adjusted accordingly. Although this approach would results on a high productivity gain, this does not mean a high profit could be obtained. Higher speed means directly higher energy consumption. The evolution of the energy price these last years is monotonically increasing. Therefore taking the energy consumption in the

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Figure 1. OEE concept and the six big production losses.

optimization scheme seems logical. In this paper we will extend our previous work by developing a multi-objective optimization taking into account production speed and energy optimization. This paper is structured as following. In Section 2, the OEE approach is explained. In Section 3, Run by Run (RbR) production concept is described. Singleobjective and multi-objective OEE optimizations applied to RbR production are explained in Section 5. Results of validation on a steel cord production machine are given in Section 6. Finally, conclusions are summarized in Section 7.

2. OVERALL EQUIPMENT EFFECTIVENESS (OEE)

Different measures of productivity exist in the available literature. The overall equipment effectiveness (OEE) concept has been widely used as a quantitative tool essential for measurement of productivity (Muchiri and Pintelon 2008). The OEE measurement tool evolved from the total productive maintenance (TPM) concept introduced by Nakajima (1988) and is defined as a measure of total equipment performance, that is, the degree to which the equipment is doing what it is supposed to do. It is a three part analysis tool in order to determine equipment performance based on its availability, performance and quality rate of the output. It is used to identify the related equipment losses for the purpose of improving and optimizing the total productivity and performance of the considered system. Six major categories of losses are identified within the OEE concept; these are depicted in Figure 1, and can be summarized as follows:

- Breakdown losses categorized as time losses and quantity losses caused by equipment failure or breakdown.
- Set-up losses occur when production is changing over from one item to another.
- Idling and minor stoppage losses occur when production is interrupted by temporary malfunction or when a machine is idling.

- Reduced speed losses refer to the difference between equipment design speed and actual operating speed.
- Quality defects and rework are losses in quality caused by malfunctioning production equipment.
- Reduced yield during start-up are yield losses due to machine start-up

Based on the definition of the six big losses, OEE can be defined as follows:

$$OEE = A \times P \times Q \tag{1}$$

Where:

Availability rate (A) =
$$\frac{Operating time(h)}{Loading time(h)} \times 100$$
 (2)

$$\frac{Performance(P) =}{\frac{Theoretical cycle time(h) \times Actualoutput(units)}{Operating time(h)}} \times 100$$
(3)

$$\begin{array}{l} Quality \ rate \ (Q) = \\ \frac{Total \ production \ (units) - Defect \ amount \ (units)}{Total \ production \ (units)} \times 100 \end{array} \tag{4}$$

By considering the six major losses defined in OEE an optimal performance of the process can be achieved by monitoring the availability, performance and quality rates. This can be done by defining an efficient maintenance schedule (Availability), a qualitative product output (Quality) and an optimal production speed (Performance). In order to optimize OEE in this paper, we target to reduce two specific losses (i.e. breakdown losses and reduced speed losses) defined within the OEE concept by considering condition monitoring information. This extension shows a direct added value when applied to the Run by Run (RbR) production concept (see Section 3). At every production run, the production speed can be optimized using the condition monitoring signal (avoid to reach risk zone for the monitored asset). This will result in minimal downtime losses due to failures and minimal speed losses. In order to be able to optimize OEE with regard to speed and



Figure 2. Run by Run (RbR) production concept

breakdown losses several important parameters have to be monitored, these are:

- Production versus time in each run
- Production speed versus time in each run
- Condition monitoring information on the degradation of the machine
- Degradation threshold beyond which normal operation of the machine is impossible

3. RUN BY RUN (RBR) PRODUCTION CONCEPT

The Run by Run (RbR) production concept is schematically shown in Figure 2. For every run, the production output (e.g. produced wire length measured as spool length at a given speed) and the condition monitoring signal (e.g. temperature of the bearing) are monitored. Based on these collected information from previous production runs, modeling the temperature using only its value at the start of the run and the production speed become possible. In our previous work (Bey-Temsamani et al., 2013), modeling the monitored temperature at a given run based on historical data was perfectly possible with a coefficient of determination (R^2 =0.9815) between modeled and measured temperature. This way it becomes possible to predict the temperature at the end of the run already at the start of the run. On the other side, production output (e.g. produced wire length) is possible to predict at the beginning of the run if the production set-point and the current production speed set-point are known. Once these two models are defined, the remaining time to reach condition monitoring signal threshold and remaining time to finish the production in a run are determined.

4. OEE OPTIMIZATION OF RBR PRODUCTION

4.1. Single-objective optimization of OEE

As explained in Section 3, The production speed optimization consists of proposing a production speed for the current and future cycles that maximizes machine's capacity without the risk of crossing the condition monitoring signal threshold. This threshold was determined by off-line analysis to avoid bearings overheating. Based on the condition at the start of the run and the production length, the condition during and at the end of the run can be determined, for a given speed, by a predictive model. This is a physics-based parametric model whose parameters were estimated using Restricted Maximum Likelihood Estimator (RMLE). The determination of the optimal production speed v^* , while avoiding the crossing of the condition monitoring signal threshold, can be formulated as a constrained maximization problem as follows and is also illustrated in Figure 2 and 3.

$$v^* = \{\max\{v | [t_r(v, l_p) < t_{th}(v, l_p, d_i)] \land (v \ge 0) \land (l_p \ge 0)\}$$

$$(5)$$

Where v is the production speed for the next production run, l_p is the production set point for the next production run and d_i is the initial degradation at the start of the production run. t_r is defined as the time to finish the production run and is function of v and l_p . t_{th} is defined as the time to reach the degradation threshold and is function of v, l_p and d_i .

This single-objective optimization of OEE based on condition monitoring information for run-by-run production systems is thoroughly described in (Bey-Temsamani, et al. 2013).

This single-optimization problem is also described in Figure 3 which illustrates the different times to finish production and to reach the critical threshold of the condition monitoring signal. The same information is depicted in Figure 4 where variations versus production time are depicted. In Figure 4, t_r , t_{th} , denote, respectively, the time to finish production and the time to reach the critical threshold (defined here as a failure) of the condition monitoring signal versus the production speed v and the production time t. This graph also indicates the optimal speed v^* where t_r , t_{th} need to be compared. The goal would be to set the optimal machine speed v^* such as the time to reach the temperature threshold t_{th} would be just lower than the time to finish the production spool t_r .

4.2. Multi-objective optimization of OEE

The major drawback of the OEE concept is that the increase in OEE is never linked to the necessary investment or cost in order to achieve this increase. In other words maximizing OEE (i.e. Section 4.1) in a single-objective problem structure could lead to major cost increases to reach the necessary increase in OEE. Hence, a trade-off should be made between the increase in OEE and corresponding costs of achieving these improvements. Therefore, extension of the approach described in Section 4.1 is needed. This extension consists of constructing a multi-objective optimization problem where two objective functions are minimized, these are energy consumption cost and lost capacity cost (i.e. OEE as described in Section 4.1), which can generally be combined into a single objective of profit maximization (i.e. if the cost of energy and lost capacity are known). Both functions depend on the production speed in the sense that when the production speed increases, the energy consumption increases and the lost capacity decreases. The multi-objective optimization problem can be formulated as follows:

$$\min(f_1(v), -f_2(v))$$

$$s.t. \ t_r(v, l_p) < (t_{th}(v, l_p, d_i)$$

$$v \ge 0$$

$$l_n \ge 0$$

$$(6)$$

Where $f_1(v)$ is the function that describes the energy consumption in relation to the production speed and $f_2(v)$ is the production capacity in relation to the production speed.

In the case study covered in this paper, $f_1(v)$ is derived from collected energy-speed data as depicted in Figure 6.



Figure 3 : Optimization problem formulation



Figure 4. Production speed maximization problem



5. VALIDATION ON STEEL PRODUCTION MACHINE

In this section the results of validating the multi-objective OEE optimization approach on RbR production are given.

The ultimate goal would be to set the production (machine) speed such that the productivity is maximized AND the energy consumption is minimized (maximizing the profit function described in Section 4.2. An illustration of the setup is given in Figure 5. The optimization algorithm could run in parallel to the machine's controller or be integrated in the machine's controller. In this work, the machine was emulated using data recorded in the production plant. The inputs to the optimization algorithm are the condition monitoring signals and its associated threshold, the production process values, and the energy consumption. In this work as energy was not recorded directly in production plant, it was calculated using some expert-knowledge from the production plant. This is shown in Figure 6 where R^2

denotes the coefficient of determination. The output of the optimization block is the optimal machine's speed set-point.

The production profit is defined as:

 $PROFIT = PR \times PU - ER \times CU$

Where:

- *PR*: production rate (m/min)
- *PU*: profit unit (\notin /m)
- *ER*: energy consumption (kW/min)
- CU: cost energy (\notin /kW)

The optimization has been validated on more than 6500 hours production data records. In Figure 7 the estimated production profits without optimization, with single-objective optimization and with multi-objective optimization are respectively shown.



Figure 6. Energy consumption versus machine speed

The results of both the single-objective (Section 4.1) as multi-objective (Section 4.2) optimization approach are compared to a reference scenario. The reference scenario is based on real measured production data. The results in terms of production per time unit (i.e. production capacity) and profit per time unit are shown in Figure 7 and Table 1. First of all, it is clear that the optimized solutions always outperform the reference scenario. This clearly illustrates the added value of using condition monitoring information to optimize the production speed of the machine. In terms of production capacity the single-objective approach is the optimal one (+28.18% compared to reference). This is the case because within the concept of OEE the better solution is always the one with the highest speed without considering costs. However, when considering the cost of energy consumption into the optimization problem it is clear that the multi-objective optimization outperforms the singleobjective optimization in terms of profit per time unit (+4.89%)compared to reference for multi-objective +1.67% single-objective optimization versus for optimization compared to reference), although the production capacity is lower. Hence, an additional increase in profit per time unit of 3.17% can be gained by considering multi-objective optimization rather than singleobjective optimization with limited focus on OEE (i.e. production capacity) maximization without considering relevant costs. As such a trade-off is made between the gain in capacity and the cost of the additional energy consumed



Figure 7. Production/time unit and profit/time unit versus time for three different scenarios.

	Capacity (m/min.)	Profit		
Reference	Single-objective	Multi-objective	Reference	Single-objective	Multi-objective
71,43	91,56	85,47	40,70	41,38	42,69
	+28.18%	+19.66%		+1.67%	+4.89%

Table 1: Production capacity (m/min.) and profit (€/min.) for the three different scenarios.

in the multi-objective optimization approach. Therefore, it is of major importance to consider costs associated to a possible increase in OEE to make a well thought and optimal decision.

6. CONCLUSIONS

Industrial productivity profit maximization was discussed in this paper using single-objective and multi-objective optimization concepts by considering condition monitoring information. These concepts were validated on a concrete industrial example where production speed and energy consumption were used in the optimization constraints while at the same time avoiding catastrophic failures. As such the usefulness of condition monitoring information is extended from purely avoiding breakdowns to process and production optimization. Hence, a multi-objective optimization model of OEE (Overall Equipment Effectiveness) regarding production speed and energy consumption is proposed in this paper. The results clearly illustrate the importance to consider the trade-off between the gain in capacity and the cost of the additional energy consumed by increasing the production speed. The results indicate a significant gain in profit by applying the developed model to the case study of a production machine. This paper establishes the link between condition monitoring information and production capacity optimization by continuously adjusting production parameters (i.e. production speed) taking into account the machine's condition and the energy consumption.

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NOMENCLATURE

- CBM Condition-Based Maintenance
- OEE Overall Equipment Effectiveness
- PdM Predictive Maintenance
- POM Prognostics for Optimal Maintenance
- RbR Run by Run
- TPM Total Productive Maintenance

REFERENCES

- R. K. Mobley, (1990). An introduction to predictive maintenance, Van Nostrand Reinhold.
- W. Sholom & I. Nitin, (1998). Predictive data mining: a practical guide. Morgan Kauffmann.
- J. Blair & A. Shirkhodaie, (2001). Diagnosis and prognosis of bearings using data mining and numerical visualization techniques, Proceedings of the 33rd Southeastern Symposium on System Theory, pp. 395-399.
- K. M. Goh, T. Tjahjono & Subramaniam, (2006). A review of research in manufacturing prognostics, IEEE International Conference on Industrial Informatics, pp.417-422.
- A. Bey-Temsamani, M. Engels, A. Motten, S. Vandenplas & A. P. Ompussunggu, (2009). A practical approach to combine data mining and prognostics for improved predictive maintenance, Proceedings of 15th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Workshop Data Mining Case Studies, pp. 37-44.
- A. Van Horenbeek, A. Bey-Temsamani, S. Vandenplas, L. Pintelon & B. De Ketelaere (2011). Prognostics for Optimal Maintenance: maintenance cost versus product quality optimization for industrial cases, Proceedings of the 6th World Congress on Engineering Asset Management.
- A. Bey-Temsamani, A. Van Horenbeek, B. De Ketelaere, L. Pintelon, A. Bartic (2013). Prognostics for optimal maintenance: industrial production capacity optimization using temperature condition monitoring, Proceedings of the Condition Monitoring and Diagnostics Engineering Management (COMADEM).
- Muchiri P, Pintelon L. Performance measurement using overall equipment effectiveness (OEE): literature review and practical application discussion. International Journal of Production Research. 2008;46:3517-35.
- Nakajima. Introduction to TPM: Total Productive Maintenance: Productivity Press; 1988.

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Designing for Human-Centred Decision Support Systems in PHM

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ABSTRACT

Prognostics and health management (PHM) represents a paradigm shift from legacy condition based maintenance (CBM) frameworks by expanding the potentials to accurately and robustly detect and diagnose incipient system faults. The ultimate goal of PHM is reliably predicting system failure times to allow for efficient maintenance scheduling either autonomously or by human decision makers (DM). In many industrial settings today the output from PHM systems constitutes a decision support system (DSS) used to aid DM, as entirely autonomous systems have not seen widespread industrial integration. However, there is relatively little support for engineers designing PHM systems in terms of human factors and how to provide the information in a way that actively supports human decisionmaking and this gap may result in limited use of PHM system by maintainers. The reliability of the information presented is a critical factor in the user acceptance and trust in a system. As a first step in developing such guidance, this paper reviews the implementation of other DSS and presents a design framework whereby PHM reliability levels are mapped against a suggested level of human input to the decision making process regarding required maintenance. The aim is to provide engineers with a guide to the level to which they should consider human factors and the presentation of information in the design of their PHM system. Fundamental to the suggested paradigm is that the uncertainties within a PHM system can be quantified, and as uncertainty increases, the requirement for DM to access additional information not explicitly tied to the PHM output increases. This information can form both explicit and tacit knowledge of a system or indeed industrial contexts

surrounding decision implications, such as acceptable maintenance intervention windows in busy production schedules. As the complexity of a system or component being monitored is likely to affect the uncertainty within the PHM system associated with it, we are considering the overall cumulative uncertainty of a model output as the metric through which the required level of human input can be inferred. Coupled to this is the fact that increased model uncertainty is a causal factor in distrust and potential nonuse of the model in industrial applications. It is the authors' belief therefore that designing for increased human-model interaction concurrent with increasing model uncertainty may lead to a better engagement with PHM decision support capabilities, thereby offering the full advantages that PHM has to offer. The framework presented in this paper is an initial step towards facilitating the design of more usable and useful PHM systems.

1. INTRODUCTION

Human factors (HF) considerations remain wholly underutilised within PHM framework design. More specifically, a human factors integration (HFI) approach, as outlined in ISO standard 9241-210 (International Standards Organisation, 2010) is rarely if ever considered as part of the PHM design process. Although much of the technological developments in the field to date relate to mathematical and computational scheme advancements, HF is a discipline which cannot be overlooked if maintenance decision support is to continue its necessary evolution in the coming years.

Recent developments in measurement devices, data storage capacities, data processing, and computational capabilities have occurred concurrently with advancements in industrial internet technologies. These developments are encouraging high risk industries in particular, such as the military,

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nuclear, oil and gas, chemical, automotive, pharmaceutical, and aerospace to adopt Prognosis and Health Management (PHM) systems for increasing system availability, minimizing unscheduled shutdowns, reducing maintenance costs, and increasing safety (Walker & Kapadia, 2009). In these high risk industries detecting and isolating faults and subsequently predicting the remaining useful life (RUL) of critical components is a crucial task. If logistical support services, predominantly maintenance activities and associated spare parts inventory management, are to operate as efficiently as possible to achieve this goal, active contributions from multiple disciplines are required. These are typically cited as being from the engineering sciences, computer science, reliability engineering, communications, management sectors etc. (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006). The main bulk of current research activity in industry and academia towards PHM focuses on the availability of run-to-failure data, accelerated ageing environments, real-time prognostics algorithms, uncertainty representation and management (URM) techniques, prognostics performance evaluation, and methods for verification and validation (Saxena, Roychoudhury, & Celaya, 2010). Performance assessments of PHM systems currently evaluate the technical and economic feasibility of diagnostic and prognostic technologies (Vachtsevanos et al., 2006), with little to no consideration given to end-user requirements or ergonomic issues. While this work is critical and valid from a technical standpoint, we propose that the human factors discipline also has a key role to play in the efficacy of PHM systems, particularly if they are to have a defining role in new global industrial systems. The authors believe it is necessary to take a holistic view of PHM system design and implementation if they are to enjoy widespread industrial integration in the coming years and lessons can be learned in this regard from DSS developed for other applications. Even though many successful R&D activities in the PHM domain are carried out by numerous major companies such as GE, Boeing, Lockheed, and Honeywell, PHM still lacks widespread acceptance as a technology standard (Vachtsevanos et al., 2006).

2. PHM OVERVIEW

Prognostics and Health Management (PHM) has been defined as 'an approach to system life-cycle support that seeks to reduce/eliminate inspections and time-based maintenance through accurate monitoring, incipient fault detection, and prediction of impending faults' (Kalgren, Byington, Roemer, & Watson, 2006). To do so, different information and data sets relating to the past, present and future behaviour of the equipment in question are required. An accurate PHM system requires the availability of sufficient and relevant statistical equipment failure data. However, the common scarcity of such data, particularly of critical components in the nuclear industry for example, has led to the development of numerous approaches based on different sources of information and data, modelling and computational schemes, and data processing algorithms (Zio, 2012). A typical PHM scheme consists of three main facets, Fault Detection (D), Fault Diagnosis (FD), and Fault Prediction (FP). Fault detection normally includes fault isolation, which is a task to locate the specific component that is faulty. Fault detection in a broader sense indicates whether something is going wrong in the monitored system, and fault diagnosis determines the nature of the fault after it has been detected. Prognostics deals with fault prediction, and is a task to determine whether a fault is impending and estimate how soon and how likely that fault is to occur. Diagnostics therefore can be defined as posterior event analysis and prognostics as prior event analysis. Prognostics is much more efficient than diagnostics in achieving zerodowntime performance. Diagnostics, however, is required when fault prediction of prognostics fails and a fault occurs, and is important from a root cause analysis (RCA) perspective to avoid future failures of a similar nature (Jardine, Lin, & Banjevic, 2006).

2.1. Fault Detection

fault detection. several empirical Within signal reconstruction models have been explored to estimate the expected values of measured variables under both changing and steady state process conditions, such as: Auto-Associative Kernel Regression (AAKR) (Baraldi, Di Maio, Pappaglione, Zio, & Seraoui, 2012); Artificial Neural Networks (ANNs) (Hines & Garvey, 2006); Evolving Clustering Method (ECM) (Zhao, Zio, & Baraldi, 2011); Principle Component Analysis (PCA) (Garcia-Alvarez, 2009; Jain, Duin, & Mao, 2000); Independent Principle Component Analysis for redundant sensor validation (Ding, Hines, & Rasmussen, 2003); Support Vector Machines (SVMs) (Laouti, Sheibat-Othman, & Othman, 2011); and Fuzzy Similarity (Baraldi, Di Maio, Genini, & Zio, 2013).

For robust determination of anomaly detection certainty several methods can be found in the literature. For example, in threshold-based methods (Montes de Oca, Puig, & Blesa, 2012; Puig, Quevedo, Escobet, Nejjari, & de las Heras, 2008), the process of an anomaly is concluded when the residual values exceed a predefined threshold. Another example is using statistical methods such as sequential probability ratio test (SPRT) (Hines & Garvey, 2006) in which anomaly detection is concluded if the probability distribution function of the residual differs from the probability distribution function calculated during normal conditions. However, these methods have some practical difficulties such as setting of the threshold value in threshold-based methods and some parameters (e.g., SPRT), and when no information about the confidence on FD outcomes (e.g., threshold-based) is provided.

2.2. Fault Diagnostics

System diagnostics lead to increased overall equipment effectiveness (OEE) in a number of ways. This is because when an alarm is triggered due to an identified system event, a decision must be taken to (Zio, 2012):

- Ignore the alarm. This increases the chances for potential accidents and catastrophic equipment failure in the case of a true alarm event.
- Stop the equipment. This will lead to additional utilised manpower resources, lost production time, and extra costs in the case of a false alarm.
- Further manual investigations without stopping the system, which, in the case of false alarms, again leads to extra costs and manpower.

An automated event diagnosis system is therefore used after an event detection module concludes that there are sufficient abnormal conditions in a system at a time t, in order to identify the root cause(s) of the occurred abnormality, on the basis of the observed signals which are representative of the system behaviour. This can be considered as a classification problem in which specific classes of event are associated with specific values of observed measured variables (Baraldi, Di Maio, Rigamonti, & Zio, 2013; Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003).

2.3. Fault Prognosis

Upon fault detection and diagnosis, prognostics becomes a fundamental task of a PHM system which aims to reliably and accurately forecast the RUL of the equipment/system (Kalgren et al., 2006) so that it may function for as long as its design intended (Zio, 2012). RUL is typically a time, cycle, or some other specific context driven expression. The RUL is the prediction of a component or systems functional/operational usage expectancy based on measured, detected, modelled, and/or predicted health state. The RUL is dependent on the intended set of operating conditions or mission to be performed (Kalgren et al., 2006).

It is not pertinent within this work to give a further detailed treatise of PHM and its constituents. For this purpose the interested reader is referred to the work of Zio (2012) and Vachtsevanos et al (2006).

3. PHM AND THE FOURTH INDUSTRIAL REVOLUTION

PHM must meet the challenge facing industry in the first half of the 21st century. This challenge, commonly labelled 'Industry 4.0', (German Federal Ministry of Education and Research, 2013) is what has been termed as the fourth industrial revolution, where future industrial production will be characterised by industrial internet driven smart factories

centred around adaptability, resource efficiency and ergonomics. ProcessIT Europe, an innovation centre focusing on manufacturing automation solutions for EU process industries, outline the elements expected to be key in the expansion of large-scale automation systems required to drive Industry 4.0 (ProcessIT Europe, 2013). Among these are improvements in automation system functionality to enable the integration of traditionally separated systems, along with greater internet compatibility and open standards, such as those developed under EU funded projects SIRENA, SODA, SOCRADES, and AESOP (Bohn, Bobek, & Golatowski, 2006; Deugd, Carroll, Kelly, Millett, & Ricker, 2006; Souza, Spiess, Guinard, Moritz, & Karnouskos, 2008; Karnouskos, Colombo, Jammes, Delsing, & Bangemann, 2010). Machine to machine communications (M2M) using Internet of Things (IoT) principles will form the so called Cyber-Physical Systems (CPS) predicted to enable new automation archetypes and improve plant operations in terms of increased OEE. One component of this is a need for improvement in humanmachine interface development, which must continue to improve the possibilities for efficient plant operations through the visualisation, virtualisation, and simulations of a plant and its automation systems (ProcessIT Europe, 2013). GE outlined their own similar initiative titled 'The Industrial Internet' (Evans & Annunziata, 2012). Central to this initiative is an integration of three fundamental elements which embody the essence of the Industrial Internet, 'Intelligent Machines', 'Advanced Analytics', and 'People at Work'. Evans and Annunziata (2012) argue that humanmachine interaction will be a critical step in blending the hardware and software components required to support the minimal input and undesired output of future industrial automation systems.

Lee and Lapira (2014) argue that adoption of the IoT ideology within Industry 4.0 presents a unique opportunity for organisations to create tools and technologies that can identify and quantify organisational uncertainties, to determine an objective estimation of the assets and processes and the resultant manufacturing readiness of the organisation. The authors argue that interactive PHM systems are the next phase in the industry's evolution that will provide transparency in the factory, giving DM the opportunity to proactively implement mitigating or countermeasure solutions to prevent production losses.

Tying into this, ISO 9241-210 (International Standards Organisation, 2010) describes six key principles to ensure that the design of such interactive systems are user centred, which are:

- The design is based upon an explicit understanding of users, tasks and environments.
- Users are involved throughout design and development.

- The design is driven and refined by user-centred evaluation.
- The design process is iterative.
- The design addresses the whole user experience.
- The design team includes multidisciplinary skills and perspectives.

In terms of addressing the whole user experience, the standard outlines the following: 'the concept of usability used in ISO 9241...can include the kind of perceptual and emotional aspects typically associated with user experience'. This is an important point, as for a system to be fully utilised, it has to be more than 'easy to use', it has to engage with users in multiple ways. One of the best examples of this is through operator trust in a system. This concept is discussed later in the paper.

4. UNCERTAINTY IN PHM

The ultimate goal of PHM is to increase component availability, maintenance minimise reduce costs, unscheduled shutdowns, and increase safety. The importance of uncertainty quantification in this context should not be understated. Monitoring the health state of systems, subsystems, and components, the classification of the different types of faults that may occur in these components, and estimating the RUL along with other prognostic metrics such as the End-of-Prediction (EoP) time index, can be extremely helpful to support DM in assessing whether maintenance intervention is necessary or not. In ever more complex environments, operators need to quickly make thousands of decisions to maintain optimal decision performance. Although this challenge can be overcome by enabling a DSS to perform select operations with human consent (Evans & Annunziata, 2012), without quantifying the associated uncertainties, remaining life projections have little practical value within PHM systems (Engel, Gilmartin, Bongort, & Hess, 2000). It is the comprehension of the corresponding uncertainties that is at the heart of being able to develop a business case that addresses prognostic requirements. The assumption of data monitoring without uncertainty is particularly problematic, as this forces maintenance planning to become an exercise in decision making under uncertainty with sparse data (Sandborn, 2005).

As stated previously, PHM systems are usually implemented in three stages for the holistic health state management of a component of interest: fault detection, fault diagnosis, and system lifetime prognosis. Several methods have been widely developed in the last few decades to increase the reliability of PHM systems. In this paper, we define the reliability of the PHM system models as the cumulative reliability of the following; Fault Detection: the ability to confidently monitor the health condition of a system with low false and missing alarm rates with respect to the detection of normal or abnormal conditions.

Fault Diagnosis: the ability to identify the fault type/class with a low misclassification rate

Fault Prediction: the ability to predict the probability of system failure and the RUL with low inaccuracies, taking into account the set of missions needed to be completed.

This cumulative information will provide the organisation with the information required to decide if maintenance intervention is necessary and if so, when to perform maintenance actions (Zio, 2012). It is worth mentioning that assessing the reliability of the PHM system is made a priori during model development using the previously mentioned methods dedicated to each part of the PHM system. In this respect, the different sources of uncertainty which exist within the varied fault detection, diagnosis, and prognosis methodologies have to be taken into account. For example, those sources may influence the performance of the PHM system, causing false or missing alarms, and hence impact the overall reliability. In the false alarm case, the output of the PHM system indicates that a healthy component is experiencing abnormal conditions, causing potential unwarranted downtime, whereas in the missing alarm case the output of the PHM system indicates that an unhealthy component is operating under normal conditions, potentially leading to catastrophic unexpected failures of the component/system with associated large downtimes, high cost, as well as possible safety and environmental implications (Zhao et al., 2011).

For these reasons, it is necessary to manage the different sources of uncertainty that may arise in the PHM system stages. In practice, the possible sources of uncertainty that may arise in a PHM system are:

- Uncertainty in the signal measurements: incomplete, noisy, and imprecise measurements
- Uncertainty in the models adopted at each data management stage, such as:
- Model Structures: un-modelled phenomena, approximations, simplifications, hypotheses, assumptions, etc.
- Model parameters: the Kernel Bandwidth in Auto Associative Kernel Regression (AAKR) methods, the threshold parameter in threshold-based methods classification and detection algorithms such as Support Vector Machines (SVM) etc.
- Uncertainty due to the inherent stochasticity of the physical processes: stochasticity in the current and

future states of the system, unforeseen future loads and environmental conditions etc.

• Human decision errors relating to the decisions made given the PHM system output

Uncertainty quantification research currently, both in industry and academia, focuses on the shortcomings in the availability of run-to-failure data, accelerated ageing environments, real-time prognostics algorithms, uncertainty representation and management (URM) techniques, prognostics performance evaluation, and methods for verification and validation (V&V) (Saxena et al., 2010).

Essentially, the inherent uncertainties which propagate through PHM systems mean that the PHM output can never be perfectly reliable (Aven, Baraldi, Flage, & Zio, 2014; Gertler, 1998; Jardine et al., 2006; Sankararaman & Goebel, 2012). Even if it were, in practice a PHM system is being applied in complex industrial environmental contexts and there will almost always be human DMs at the system interface who may choose not to follow the guidance of the PHM system, because of a possible lack of trust in the system output or because they have knowledge extraneous to the modelled parameters. Context drivers in this regard include financial pressures to delay maintenance activities, unexpected environmental conditions which could affect the reliability/uncertainty of the algorithms, a change in the maintenance policies of the organisation, cost of shutting down at a particular time, resource availability, time available for production intervention activities (including time of the year), audit timing within regulated industries, management interests, corporate politics etc. With this in mind, it is important to consider the application of the PHM system within the overall socio-technical system of the maintenance organisation. Only by providing a PHM system that is calibrated against the actual usage of the system can the full benefit be achieved.

Sandborn (2005) asks; given that the forecasting ability of PHM is fraught with uncertainties in the sensor data collected, the data reduction methods, the models applied, the material parameters assumed in the models, etc., how can PHM results be interpreted so as to provide value? Sandborn argues that this problem partly reduces to one of determining optimal safety margins and prognostic distances for health monitoring. This determination is intrinsically contextually driven. Engel, Gilmartin, Bongort, and Hess (2000) also argue that the calculation of system RUL in PHM systems alone does not provide sufficient information to form a decision or to determine corrective action. They state that without comprehending the corresponding measures of the uncertainty associated with the calculation, DSS outputs have little practical value.

5. HUMAN FACTORS OVERVIEW

Human factors is defined as 'the scientific discipline concerned with the understanding of the interactions among humans and other elements of a system, and the profession that applies theoretical principles, data and methods to design in order to optimize human well-being and overall system performance' (International Ergonomics Association, 2000). Within multiple high risk industries such as nuclear, oil and gas, and the medical domains, there is an existing recognition of the importance of HF, not just from a safety perspective, but also from a systems performance perspective. A recent directorate of the Nuclear Installations Inspectorate (NII) of the Health and Safety Executive (HSE) of Great Britain (2010) outlines how HF needs to be incorporated in all industrial projects in the field, throughout the full project lifecycle, to achieve both the aims of increased safety and reliable energy production. The objective is again reiterated about considering HF as an integral part of all projects, and not just an afterthought. The issue that we see repeated is that if the requirements of system operators are only accounted for at the end of system design, then it is unlikely that it will be a useable system.

PHM systems aim to be highly autonomous up until the point that a decision is required regarding maintenance intervention. In this way PHM systems can assist maintainers to determine the optimum time to perform maintenance given a host of constraints, providing the operator with confidence bounds on the availability of critical assets to meet production schedules. Ideally autonomous diagnostic and prognostic capabilities are to be implemented within an integrated maintenance and logistics system that supports critical complex systems throughout their lifetimes (Vachtsevanos et al., 2006). However, there is little to no evidence that it has as yet proven possible in practice to achieve this level of autonomy, and some degree of human intervention is typically required. In fact, a complete prognostic health management system still does not exist (Saxena et al., 2010). For this reason this paper draws on the human factors discipline in order to propose a set of design rules for the incorporation of human factors into PHM, particularly with regards to data visibility during the decision making process.

5.1. Human Factors in PHM

The application of human factors has traditionally been in safety critical industries, where a variety of methods and techniques are applied to understand human interactions within a system and the potential for human error, and recommendations are made to improve the system, environment, organisation or tasks to improve human performance. It has long been recognised that maintenance tasks are vulnerable to human error, particularly in the aircraft maintenance domain (Australian Government Civil Aviation Authority, 2013; Ben-Daya, Duffuaa, Raouf, Knezevic, & Ait-Kadi, 2009; International Civil Aviation Organization (ICAO), 2003; Latorella & Prabhu, 2000; Rankin, Hibit, Allen, & Sargent, 2000) and maintenance of the protection systems in nuclear industries (Khalaquzzaman, Kang, Kim, & Seong, 2011; Rasmussen, 1975). In these instances human factors principles have been applied in order to reduce both the rate and impact of human errors.

However, there has not been a strong input from human factors in the domain of PHM. Most of the PHM literature, when it considers human interactions within the system at all, considers that a benefit of PHM is the potential reduction in required maintenance interventions, thereby reducing the opportunity for human errors in the maintenance process (Leão, Fitzgibbon, Puttini, & de Melo, 2008). While true, this view of human factors does not consider the possibility of harnessing human intelligence and reasoning abilities to improve the overall maintenance system, or of modelling human interactions with the system to improve both the prediction of faults and effectiveness of the system output. Only Zhao, Tian, and Zeng (2013), and Yu, Syed Zubair, and Yang, (2013) suggest that human factors could be included as an uncertainty in the PHM system itself, although ultimately both works neglected to use HF as a modelling parameter. Research in this area could investigate the feasibility of incorporating some of the existing HRA techniques in a PHM model, or could use another approach whereby there is feedback from the maintainer/installer in order to generate a confidence interval for the possibility of human error having occurred.

Despite the potential in these areas, in this paper, we propose a more general framework for the level of human interaction with a PHM system based on the calculated reliability (or inversely speaking the calculated uncertainties) of the PHM system, and from this the requirements for the outputs from the PHM algorithms and the feedback to the human maintainer. There are several papers that consider the important issue of the user interface through which PHM analysis is displayed to the maintenance staff (Bechhoefer & Morton, 2012; Mathur, Cavanaugh, Pattipati, Willett, & Galie, 2001; Saxena et al., 2010). Mathur et al (2001) recognise that human factors considerations need to guide the development of interface components and accessibility requirements. They provide an example of a web-based design of servers which support a distributed, multi-platform, three-tier architecture. Saxena et al (2010) detail four key parameters driving the requirements for prognostics from a technical engineering perspective, but alludes to the fact that classifying software requirements based on functionality, e.g. feature set, capabilities, generality, security, and usability e.g. human factors, aesthetics, consistency, and documentation, is also important. Bechhoefer and Morton (2012) studied the lack of adoption of condition monitoring systems relating to wind turbines in the renewable energy sector. They concluded that as no single condition indicator (CI) can detect all failure modes, a user display requirement is necessary to view, threshold, and trend information that incorporates more than just spectral data or one CI. They specify the need for a data reduction methodology that is intuitive and user friendly, citing the use of the health indicator (HI) concept, which is the integration of several condition indicators into a single value. The HI provides the health status of the component to the end user. In contrast to these works, which focus on providing a user friendly interface at the end of the system, we propose that early consideration of how the operator will use system outputs in practice should drive the whole philosophy of the PHM system and hence influences not just the design of the interface, but the decisions on what data to present and at what level of detail.

5.2. PHM as a Decision Support System

Sandborn (2005) states that methods used to obtain and store large amounts of information has largely been perfected, and as a result, a sort of information overload is prevalent, where it is not uncommon that a lot more information exists than organisations know how to use. Sandborn states that the trick now is to figure out how to make decisions based on that information. The goal of applied PHM technology is to provide decision support. Therefore, the final form of the output from a PHM system, driven by the context of the user, is actionable information that supports improved decision making (Kalgren et al., 2006). Decision Support Systems (DSS) are designed to support the intelligence, design, or choice phases of human decision makers (DM) (Mintzberg & Simon, 1977).

A comprehensive study was conducted by Ketteler (1999) on the requirements for equipment monitoring and decision support systems in the machining/manufacturing domain regarding their reliability, flexibility, and user friendliness, using the input of industries from Japan, the USA, Canada, and Europe. Data from machine builders, end-users, and monitoring system suppliers was collected and analysed. The main conclusions are applicable across multiple industries, dealing with the theme of industrial integration, and lack thereof, of online decision support capabilities aiding maximum throughput. Ketteler concludes that less than 38% of end-users were at the time satisfied with available monitoring systems, the main reasons for this being the lack of system reliability, too many false alarms, and the complicated nature of the monitoring systems. Reliability was defined as high detection rates with low false alarms. While the number of satisfied end-users may have increased in the preceding decade, Ketteler's conclusions on end-users general expectations leading to their satisfaction in monitoring systems and DSS are still applicable today. The most important expectations for endusers when using DSS were less downtime of the production equipment, less scrap production, higher

productivity, easier DSS operability, and less false alarms. Given the need for greater operability, DSS and associated technologies need to move out of the realm of esoterica, enabling full implementation and management environments within organisations. Many analytics technologies still focus on the technical aspects with insufficient regard for the monitoring of model performance and the sharing of information in a collaborative environment. Although this is one of the less glamorous aspects of predictive technologies, in many ways it is one of the most important, as without the establishment of the confidence levels in predictive models the technology will always be underexploited and untrusted (Butler, 2013).

5.2.1. Human Factors Considerations in Decision Support Systems

Human interaction with automation as a whole, of which PHM can be considered a branch, and the use of DSS has been widely researched in human factors. Many lessons can be learned by PHM system designers from the introduction of automated systems in the aviation industry for example, and there is a large volume of knowledge which exists in the HF literature on the subject. One of these lessons is whether total system safety is always enhanced by allocating functions to automatic devices rather than human operators (Wiener & Curry, 1980). Research on DSS information output indicates that DSS which indicate the status of a system are preferable to those that advise operators on how to respond (Crocoll & Coury, 1990). Similar findings in high-risk industries where the information is imperfect suggest that status displays are better than command displays (Sarter & Schroeder, 2001). DSS which incorporate a high degree of decision autonomy have failed frequently in industrial settings, as discussed earlier. In theory, a DSS acts as a 'prosthesis' to aid a human DM who is purportedly characteristically flawed and inconsistent in his/her decision making. As such, more precise algorithms are the preferred research objectives of PHM, as opposed to a greater understanding of the power of human cognition (Salvendy, 2012). This type of reasoning is common in the PHM literature. However, the level of automation required with such an approach conflicts in reality with the amount of situations the algorithms must face. The great danger here is that a DSS will make wrong decisions about situations it has not been modelled to compute. Tied to this is the fact that removing the responsibility of decision making from a human DM in high-risk industrial settings has been shown to have negative consequences as people will simply blame erroneous decisions on the automation.

This phenomenon has been labelled as automation bias (AB), essentially the tendency to over-rely on automation, and has been studied in various academic fields. Although most research shows overall improved operator and system performance with the use of automation, there is often a failure to recognise the new errors that DSS can introduce.

This problem can also be described as automation-induced complacency or insufficient monitoring of automation output. User factors which directly influence AB include operator trust and confidence in the DSS. Environmental mediators include workload, task complexity, and time constraints, which pressurise the cognitive resources of the end users. Mitigating factors of AB includes implementation factors such as training and emphasising user accountability, and DSS design factors such as the position of the advice on the screen, updated confidence intervals of the DSS output, and the provision of information versus recommendation (Goddard, Roudsari, & Wyatt, 2012). The 'information versus recommendation' degree of automation where the DM is used to critique the output of a DSS has met with more success in terms of industrial integration, particularly in high-risk situations (Salvendy, 2012). For example, Guerlain et al. (1999) created a DSS for blood type identification in a blood bank. When used as a critiquing tool, where the DSS presented the users with different hypotheses regarding the data available rather than defined solutions, the operators made correct decisions 100% of the time. This was in contrast to a DSS which did not allow the operators to critique the decisions, which led to wrong decision being made between 33% and 63% of the time.

This gives us an interesting insight into the power of human cognition, one of a number of seemingly intangible elements important for successful businesses (Pecht, 2008). With regard to the power of human cognition in the decision making process, it has been written that the human recognition process relies heavily on context, knowledge, and experience. The effectiveness of using contextual information in resolving ambiguity and recognizing difficult patterns is therefore the major differentiator between the recognition abilities of humans and systems (Jain et al., 2000). With this in mind, the fundamental research issue in building intelligent DSS should centre on linking the domain-specific knowledge of experts with the normative power of analytical decision techniques to improve the quality of decisions (Yam, Tse, Li, & Tu, 2001). It has been said that the complex human decision process largely follows a Bayesian approach, as given a set of information, human decision makers tend to duplicate Bayesian predictions if they are provided adequate information in appropriate representations (Martignon & Krauss, 2003). The strength of this approach is demonstrated in recent research which illustrated that human reasoning in complex situations, in this case complex ribonucleic acid (RNA) folding schemes related to HIV and cancer research, outperformed specifically formulated RNA folding algorithms almost by an order of magnitude. The research focused on allowing humans to come up with complex folding patterns for RNA through a crowdsourcing application, and not only were humans able to develop better models of RNA folding than previous computer algorithms, but design rules formulated by the online

community have even been used to construct a new algorithm, EteRNABot, and in some cases represent completely new understandings about RNA folding that have yet to be explained mechanically (Lee et al., 2014).

Formal methodologies have been developed, called knowledge-based expert systems, in an attempt to capture human knowledge to draw conclusions in a formal methodology framework. An expert system is a DSS that essentially mimics the cognitive behaviour of a human expert. It consists of a knowledge base, a set of if-then-else rules, and an inference engine which searches through the knowledge base to derive conclusions from given facts (Venkatasubramanian, Rengaswamy, & Kavuri, 2003). This essentially forms a sort of indirect fusion approach, which uses information sources like a-priori knowledge about the environment and human input into a DSS (Teti, Jemielniak, O'Donnell, & Dornfeld, 2010). Again we see however that the problem with this kind of knowledge representation is that it does not have any understanding of the underlying physics of the system, and therefore fails in cases where a new condition is encountered that is not defined in the knowledge base. Therefore, this kind of knowledge is referred to as 'shallow' since it does not have a deep, fundamental understanding of the system which it is attached to (Venkatasubramanian, Rengaswamy, & Kavuri, 2003).

Similarly Billings (1991) describes what he terms as 'human-centred automation' in the aviation industry. Automation systems in Billings definition include systems which have intelligence, or some capacity to learn and then to proceed independently to accomplish a task. Such reasoner systems are evidenced frequently in PHM literature. Billings argues that the quality and effectiveness of an automation system depends largely on the degree to which the system takes advantage of the combined strengths of humans and automation technologies, and equally compensates for the weaknesses of both elements. Though Billings admits that humans are far from perfect sensors, decision-makers and controllers, he argues that they possess a number of vital attributes which automation systems do not. These are that humans are excellent detectors of signals in the presence of noise, can reason effectively given uncertainties, are capable of abstraction and conceptual organisation, can cope with failures not envisioned by system designers, possess the ability to learn from experience and thus the ability to respond quickly and successfully to new situations, recognise and bound the expected, cope with the unexpected, and to innovate and to reason by analogy when previous experience does not cover a new problem. Humans thus provide a degree of flexibility with regards to decision making and system control that cannot be attained by computational DSS alone, except in narrowly and well defined, well understood domains and situations. These uniquely human attributes each provide a reason to retain the human in a central position in systems

which are neither directly controllable nor fully predictable (Billings, 1991).

The reliability of automation and decision support tools has long been understood to be a key factor in the success of the tool (Wickens & Dixon, 2007). Madhavan and Wiegmann (2007a) and Wickens and Dixon (2007) both conducted a meta-analysis of numerous research studies relating the reliability of diagnostic automation and its effect on the performance of human operators. The main conclusion from both studies indicates that below an optimal threshold of 70% reliability, performance degrades to the point that DSS are largely disused. Balfe et al (2012) describe a set of principles for automation systems, designed for rail automation but applicable to other domains. Among these are the importance of reliability of the automation, and feedback to the human operator in terms of making the base information, raw data that has been transformed in to useful information, visible and providing understandable outputs to the operator. Bechhoefer and Morton (2012) explicitly mention the need for end-user confidence in PHM systems to be high in order to preserve the value of the system. They refer to the need to reduce false alarm rates (type I errors) and increase the sensitivity to actual faults (type II errors), i.e. increasing PHM system reliability. They also specify that to achieve widespread deployment of CMS, it is necessary to change the perception of end-users by convincing them of the value proposition supporting PHM. One of the facets enhancing a strong proposition that they note is an improved user interface, greater system reliability, and greater access to more actionable information.

5.2.2. Trust in Decision Support Systems

A review of trust in automation systems was conducted by Balfe (2010), of which DSS can be considered a branch. Table 1 below outlines the key findings from research on the factors leading to operator trust in automation systems. It can be argued that the usage of DSS under uncertainty relies on the same tenets to realise integration into the working environment. Balfe (2010) concludes that the effect of system uncertainty on trust and subsequent usage has been conclusively proven, and that evidence exists to support the notion of human competence as a key dimension in trust as understanding automation systems can improve the rating of trust.

Key Finding	Author		
There is a correlation between trust in and usage of automation.	(De-Vries, Midden, & Bouwhuis, 2003; Muir & Moray, 1989)		
High reliability and competence are fundamental requirements for trust in automation.	(Muir & Moray, 1989; Wiegmann, Rich, & Zhang, 2001)		
Operator self-confidence and the usefulness of the automation also influence usage.	(Lee & Moray, 1992, 1994)		
For complex systems, explicit feedback is required to develop trust.	(Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Sarter, Woods, & Billings, 1997; Sheridan, 1999)		
Trust must be well calibrated to ensure optimal use of automation.	(Lee & See, 2004; Madhavan & Wiegmann, 2007b)		
Accurate mental models are important to ensure correct calibration of trust.	(Sheridan & Parasuraman, 2006)		
Individual differences influence trust.	(Merritt & Ilgen, 2008)		

Table 1: Summary of key research on trust in automation,
adapted from (Balfe, 2010)

Decision making given large uncertainties has been widely studied in the medical literature, many of whose conclusions on DSS integration into the working environment agree with those of Balfe (2010). One example of this is evidence based medicine (EBM), where clinicians integrate individual clinical expertise with the best available external clinical evidence from systematic research. Combining both individual expertise with external evidence allows clinicians to improve the accuracy and precision of diagnoses and prognoses (Sackett, Rosenberg, Gray, Haynes, & Richardson, 1996). EBM has led to the creation of clinical decision support systems (CDSS), interactive computer software systems designed to aid doctors with medical decisions, designed to impact clinician decision making about individual patients at the point in time that decisions are made (Berner, 2007). They are similar in scope and design to their industrial counterparts, albeit the system inputs are clinical metrics related to the human body. This same approach can be utilised by maintenance and management personnel involved in decision making related to defective components or equipment. Uckun, Goebel, and Lucas (2008) and Popov, Fink, and Hess (2013) draw similar comparisons.

While CDSS have many proven benefits, their uptake by GPs (general practitioners) is limited. Shibl, Lawley, and Debuse (2013) researched how and why GPs accept DSS via a UTAUT (Unified Theory of Acceptance and Use of Technology) based model. The insights into the reasons why GPs do not use DSS are transferable to other industries

for the development of strategies to enable greater widespread adoption of DSS. Shibl et al. (2013) conclude that the four main factors influencing DSS acceptance and use include usefulness, facilitating conditions (including training), ease of use, and trust in the DSS output. Similarly, Alexander (2006) concludes that a clinician's level of trust in CDSS is affected by how knowledge is represented, the CDSS' ability to make reasonable decisions, and how they are designed. Again, usage issues arise if end-users do not understand how to use the CDSS.

Dreiseitl and Binder (2005) investigated how physicians react when faced with DSS suggestions that contradict their own diagnoses. They found that in 24% of the cases in which the physicians' diagnoses did not match those of the DSS, the physicians changed their diagnoses. Physicians were significantly less likely however to follow the decision system's recommendations when they were confident of their initial diagnoses. They conclude that given uncertainties, people are most likely to trust their own judgement. False trust leads to wrong diagnoses, therefore uncertainty quantification is critical. Quality assurance and validation of such systems is therefore of paramount importance.

The challenge of increasing system reliability concurrent with decreasing system complexity allowing greater usability cannot be understated. For while the algorithms and methods behind the three facets of PHM, detection, diagnosis, and prognosis, must become more robust and potentially more complex as they seek to reduce and ultimately eliminate uncertainties, so too must their outputs become flexible, reconfigurable, and subjectively easy to interpret. While one can argue that this approach would dictate the use for a 'black box' style methodology to DSS, this too is also not favourable. This is because the complexity of the mathematical models involved, coupled with end-user perception of high missed detection and false alarm rates, leads to mistrust and eventual non-use of DSS. Consequently a more open interface is required where PHM outputs are viewed as non-esoteric. This essentially means the transformation of data to usable information, useable information being context driven. As such the management of DSS must be addressed to providing the right information in the right form to the right people at the right time in the right place to support maintenance-related decision-making across different organisational levels (ProcessIT Europe, 2013). Uckun et al. (2008) similarly state the need for PHM to become less of an art and more of a science. They conclude that one of the main issues with PHM today is the lack of standardisation governing the research, and that it is often impossible to derive actionable conclusions based on the research results.

6. PROPOSED DESIGN FRAMEWORK

The aim of PHM systems is to provide information for maintenance decisions and ideally, the information would be totally reliable. However, although a perfectly reliable PHM system is a noble aim, it is unfortunately unlikely to always be possible. The uncertainties within any system mean that a PHM methodology acting as a DSS can never be perfectly reliable, either due to technical difficulties in creating an accurate model or external factors which influence the reliability of the output. With this in mind, it is important to consider the application of the PHM system within the overall socio-technical system of the maintenance organisation and develop the system against a design philosophy appropriate for the context of use.

The design framework presented here is intended to assist the developer of a PHM system in considering the feedback requirements based on the expected reliability of the PHM algorithms and hence set a design philosophy. This is a crucial first step in correctly setting the user requirements and designing the HMI. We propose that as the level of reliability of the algorithm increases, the required feedback to the operator decreases as per a simple proportional relationship. It is important to note that in this paper we deal with this concept purely in the notional sense. The reliability of the PHM system is intended to be calculated after it has been developed, and before the detailed design of the user interface for presenting the results. This is an adaptation of the well-known pilot control and management continuum developed by Billings (1991) for NASA, which directly relates levels of automation and human involvement in flight control systems for pilots.



PHM Reliability Figure 1: Proposed Design Framework

Figure 1 describes this proportional relationship and suggests five categories of PHM system. The categories begin with a low PHM reliability and a corresponding high level of human involvement. In this case the system would probably not benefit from a PHM system at all; however this decision must be made at a local level. At the other end of the scale, very high PHM reliability (e.g. very low levels of model uncertainty) could successfully achieve an autonomous PHM system in which human input is not required.

The lower level of reliability considered in this model is suggested to be 70%, on the basis of the previously discussed research (Madhavan & Wiegmann, 2007a; Wickens & Dixon, 2007) which provides evidence that automation below this level is not useful. The same research by Wickens & Dixon (2007) describes how the benefits of automation increase as the reliability level increases and on the basis of their analysis, we describe a suggested banding of the reliability levels to support the model in Table 2. The banding is intended as a guide and not a hard and fast rule.

Table 2: Banding of Reliability Levels

Reliability	Feedback Required
< 70%	Manual Monitoring
70-80%	Component Condition Data
80-90%	PHM Recommendation
90-99%	PHM Decision
>99%	Autonomous PHM

Each of these bandings is described below:

- Manual Monitoring below a 70% reliability threshold it is proposed that traditional methods of system maintenance are employed, such as corrective and/or scheduled maintenance approaches. The development of a PHM system with such an amount of present uncertainties is unlikely to add significant value to the maintenance decision process;
- Component Condition Data between 70% and 80% reliability, it is proposed that a PHM DSS use component condition data in conjunction with traditional methods of system maintenance to provide an additional data source to aid human decision makers. This generates requirements in terms of the data presented to the decision maker which must be at a sufficient level of detail for them to interpret. A combination of these two elements might take the form of scheduled maintenance intervals, in which maintenance will always be performed, interspersed with the use of CBM technologies to help ensure the component does not fail between maintenance windows.

- PHM Recommendation when reliability levels are expected to reach 80%, the PHM system can provide a primary recommendation on proposed maintenance actions, and there is no need for the inclusion of maintenance approaches. traditional The recommendation should be provided in conjunction with supporting information for a final decision by the human decision maker, and at the lower levels of the band should be presented reliability alongside alternative hypotheses. Again, this suggests requirements on presentation of the PHM analysis in a manner which facilitates the human decision maker in interpreting the data;
- PHM Decision above 90% reliability, a decision can be made by the DSS and be provided to the human decision maker for confirmation. Supporting information is not required at this stage and the human decision maker would be expected to seek out additional information if they believed it was necessary with regard to a particular decision. The interface requirements are perhaps less demanding in this case, but is still necessary to provide access to interpretable data when required;
- Autonomous PHM if the reliability of the PHM system is proven to be above 99%, the system can be considered for implementation as an autonomous system, with directions for maintenance interventions passing directly from the system to the maintenance team, without the involvement of any human decision maker. There is also scope in such a system to coordinate with inventory management systems and/or a logistics knowledgebase for complete synchronisation of the maintenance effort. Such a system would be particularly efficacious in the self-maintaining systems envisioned as the next generation in intelligent industrial equipment enabling the fourth industrial revolution (Lee, Ghaffari, & Elmeligy, 2011)

Identification of the correct banding is key to developing the correct design philosophy and presenting the PHM data to the human decision maker in a way which optimises operator trust in and use of the system. However, regardless of the banding, the system should still facilitate the user in 'drilling-down' in to the source data in order to support understanding and trust in the system. Again, this is to avoid the use of a 'black-box' style approach. The design framework detailed here proposes that the source data can become gradually more hidden as reliability increases. We believe this framework can act as a useful guide for PHM system designers, and that further research is needed in the area if PHM is to continue its advance to becoming a standard industrial methodology in the coming years.

7. CONCLUSION

In this paper we conducted a comprehensive review tying together for the first time the literature within the HF, automation, decision support, and PHM domains. We have presented unique findings from these disciplines across multiple domains that will aid in the acceptance, widespread industrial integration, and ultimate end-use of PHM systems which act as maintenance DSS. Some of the key findings in this paper include the factors which govern the acceptance of automation and DSS technologies in multiple applications, including presentation of information considerations and developing operator trust in those systems. From the knowledge and insights gained we demonstrated how such HF elements must be considered from the outset of system development, and why it is important to consider the application of a PHM system within the overall complex socio-technical-economic contexts existing within today's organisations. We presented a theoretical blueprint which is a useful first step in designing and deploying successful PHM systems in industry, where using a quantitative assessment of PHM reliability, based on PHM system uncertainties, one can alter the system outputs to cater for the needs of both endusers and the organisation as a whole.

While an important step in bridging the gap for the first time between human factors and PHM, this work represents early theoretical research. Further research activity can be focused towards the identification of applicable industrial case studies to provide empirical evidence in support of the model, generating a more detailed model of guidance for implementation of PHM systems, and combining HF metrics as inputs into PHM systems in order to increase the reliability of decision outputs. In addition, the different types of uncertainty (e.g. false positive and false negative rates in diagnosis, accurate prognosis horizons in prediction, receiver operating curves, etc.) may have different implications for how the information is presented. Future work will look at the sources of uncertainty in terms of detection, diagnosis, and prognosis and expand the model presented here to include guidance on the human factors concerns relating to different types of uncertainty.

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REFERENCES

- Alexander, G. L. (2006). Issues of trust and ethics in computerized clinical decision support systems. *Nursing Administration Quarterly*, *30*(1), 21–9. Retrieved from
- http://www.ncbi.nlm.nih.gov/pubmed/16449881 Australian Government Civil Aviation Authority. (2013).
- Safety Behaviours: Human Factors for Engineers Resource Guide.
- Aven, T., Baraldi, P., Flage, R., & Zio, E. (2014). Uncertainty in Risk Assessment. (T. Aven, P. Baraldi, R. Flage, & E. Zio, Eds.). Chichester, United Kingdom: John Wiley & Sons, Ltd. doi:10.1002/9781118763032
- Balfe, N. (2010). Appropriate Automation of Rail Signalling Systems: A Human Factors Study. University of Nottingham.
- Baraldi, P., Di Maio, F., Genini, D., & Zio, E. (2013). A Fuzzy Similarity Based Method for Signal Reconstruction during Plant Transients. In *Prognostics and System Health Management Conference PHM-2013* (pp. 889–894). doi:10.3303/CET1333149
- Baraldi, P., Di Maio, F., Pappaglione, L., Zio, E., & Seraoui, R. (2012). Condition monitoring of electrical power plant components during operational transients. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 226(6), 568–583. doi:10.1177/1748006X12463502
- Baraldi, P., Di Maio, F., Rigamonti, M., & Zio, E. (2013). Transients Analysis of a Nuclear Power Plant Component for Fault Diagnosis. *Chemical Engineering Transactions*, 33, 895–900. doi:10.3303/CET1333150
- Bechhoefer, E., & Morton, B. (2012). Condition monitoring architecture: To reduce total cost of ownership. In 2012 IEEE Conference on Prognostics and Health Management (pp. 1–9). Denver, CO: IEEE. doi:10.1109/ICPHM.2012.6299509
- Ben-Daya, M., Duffuaa, S. O., Raouf, A., Knezevic, J., & Ait-Kadi, D. (2009). *Handbook of Maintenance Management and Engineering* (1st ed., p. 768). London: Springer. Retrieved from http://books.google.ie/books?id=WE2M8YAD7jQC
- Berner, E. S. (Ed.). (2007). Clinical Decision Support Systems: Theory and Practice (2nd ed., p. 269). New York, NY: Springer New York. doi:10.1007/978-0-387-38319-4
- Billings, C. E. (1991). Human-Centered Aircraft Automation : A Concept and Guidelines. NASA Technical Memorandum 103885.
- Bohn, H., Bobek, A., & Golatowski, F. (2006). SIRENA -Service Infrastructure for Real-time Embedded Networked Devices : A service oriented framework for different domains. In *Proceedings of the*

International Conference on Networking, International Conference on Systems and International Conference on Mobile Communications and Learning Technologies (ICNICONSMCL'06) (p. 43). Washington, DC, USA.

- Butler, M. (2013). Predictive Analytics in Business: Strategy, Methods, Technology (p. 28). Retrieved from http://butleranalytics.com/wpcontent/uploads/2013/08/Predictive-Analytics.pdf
- Crocoll, W. M., & Coury, B. G. (1990). Status or Recommendation: Selecting the Type of Information for Decision Aiding. In *Proceedings of the 34th Annual Meeting of the Human Factors & Ergonomic Society* (pp. 1524–1528). Santa Monica, CA: Human Factors and Ergonomics Society.
- Deugd, S. De, Carroll, R., Kelly, K. E., Millett, B., & Ricker, J. (2006). SODA : Service-Oriented Device Architecture. *Pervasive Computing, IEEE*, 5(3), 94– 96.
- De-Vries, P., Midden, C., & Bouwhuis, D. (2003). The effects of errors on system trust, self-confidence, and the allocation of control in route planning. *International Journal of Human-Computer Studies*, 58(6), 719–735.
- Ding, J., Hines, J. W., & Rasmussen, R. (2003). Independent component analysis for redundant sensor validation. In *Proceedings of the 2003 Maintenance* and Reliability Conference (MARCON 2003). Knoxville, TN.
- Dreiseitl, S., & Binder, M. (2005). Do physicians value decision support? A look at the effect of decision support systems on physician opinion. *Artificial Intelligence in Medicine*, *33*(1), 25–30. doi:10.1016/j.artmed.2004.07.007
- Dzindolet, M. T., Peterson, S. A., Pomranky, R. A., Pierce, L. G., & Beck, H. P. (2003). The role of trust in automation reliance. *International Journal of Human-Computer Studies*, 58(6), 697–718.
- Engel, S. J., Gilmartin, B. J., Bongort, K., & Hess, A. (2000). Prognostics, the Real Issues Involved with Predicting Life Remaining. In *Proceedings of IEEE Aerospace Conference* (pp. 457–469).
- Evans, P. C., & Annunziata, M. (2012). *Industrial Internet : Pushing the Boundaries of Minds and Machines* (p. 37).
- Garcia-Alvarez, D. (2009). Fault detection using principal component analysis (PCA) in a wastewater treatment plant (WWTP). In *In Proceedings of the International Student's Scientific Conference.*
- German Federal Ministry of Education and Research. (2013). Zukunftsbild "Industrie 4.0" Hightech-Strategie (p. 36).
- Gertler, J. (1998). Fault Detection and Diagnosis in Engineering Systems (p. 504). New York: Marcel Dekker Inc.

Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: a systematic review of frequency, effect mediators, and mitigators. *Journal of the American Medical Informatics Association : JAMIA*, *19*(1), 121–7. doi:10.1136/amiajnl-2011-000089

Guerlain, S. A., Smith, P. J., Obradovich, J. H., Rudmann, S., Strohm, P., Smith, J. W., ... Sachs, L. (1999). Interactive Critiquing as a Form of Decision Support: An Empirical Evaluation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *41*(1), 72–89. doi:10.1518/001872099779577363

Hines, J. W., & Garvey, D. R. (2006). Development and Application of Fault Detectability Performance Metrics for Instrument Calibration Verification and Anomaly Detection. *Journal of Pattern Recognition Research*, 1, 2–15.

International Civil Aviation Organization (ICAO). (2003). Human Factors Guidelines for Aircraft Maintenance Manual. Montréal, Quebec.

International Ergonomics Association. (2000). What is ergonomics? Retrieved from http://www.iea.cc/browse.php?contID=what_is_ergon omics#sthash.gpOFBKYx.dpuf

International Standards Organisation. (2010). Ergonomics of human-system interaction - Part 210: Human-centred design for interactive systems. ISO Standard 9241.

Jain, A. ., Duin, R. P. W., & Mao, J. (2000). Statistical Pattern Recognition : A Review. *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, 22(1), 4–37.

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510. doi:10.1016/j.ymssp.2005.09.012

Kalgren, P., Byington, C., Roemer, M., & Watson, M. (2006). Defining PHM, A Lexical Evolution of Maintenance and Logistics. In 2006 IEEE Autotestcon (pp. 353–358). IEEE. doi:10.1109/AUTEST.2006.283685

Karnouskos, S., Colombo, A. W., Jammes, F., Delsing, J., & Bangemann, T. (2010). Towards an architecture for service-oriented process monitoring and control. In *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society* (pp. 1385–1391).
Glendale, AZ: Ieee. doi:10.1109/IECON.2010.5675482

Ketteler, G. (1999). Analysis of Requirements for Monitoring Systems. In H. Van Brussel & P. Valckenaers (Eds.), *Proceedings of the Second International Workshop on Intelligent Manufacturing Systems* (pp. 721–725). Leuven, Belgium: Katholieke Universiteit Leuven - Departement Werktuigkunde.

Khalaquzzaman, M., Kang, H. G., Kim, M. C., & Seong, P. H. (2011). Optimization of periodic testing frequency

of a reactor protection system based on a risk-cost model and public risk perception. *Nuclear Engineering and Design*, 241(5), 1538–1547. doi:10.1016/j.nucengdes.2011.02.003

Laouti, N., Sheibat-Othman, N., & Othman, S. (2011). Support vector machines for fault detection in wind turbines. In *Proceedings of IFAC World Congress* (pp. 7067–7072).

Latorella, K. A., & Prabhu, P. V. (2000). A review of human error in aviation maintenance and inspection. *International Journal of Industrial Ergonomics*, 26(2), 133–161.

Leão, B. P., Fitzgibbon, K. T., Puttini, L. C., & de Melo, G. P. B. (2008). Cost-benefit analysis methodology for PHM applied to legacy commercial aircraft. In *IEEE Aerospace Conference* (p. 12).

Lee, J. D., & Moray, N. (1992). Trust, control strategies and allocation of function in human-machine systems. *Ergonomics*, 35(10), 1243–1270.

Lee, J. D., & Moray, N. (1994). Trust, self-confidence, and operators' adaptation to automation. *International Journal of Human-Computer Studies*, 40(1), 153–184.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, 46(1), 50–80.

Lee, J., Ghaffari, M., & Elmeligy, S. (2011). Selfmaintenance and engineering immune systems: Towards smarter machines and manufacturing systems. *Annual Reviews in Control*, *35*(1), 111–122. doi:10.1016/j.arcontrol.2011.03.007

Lee, J., Kladwang, W., Lee, M., Cantu, D., Azizyan, M., Kim, H., ... Das, R. (2014). RNA design rules from a massive open laboratory. In *Proceedings of the National Academy of Sciences* (pp. 2–7). doi:10.1073/pnas.1313039111

Lee, J., & Lapira, E. (2014). Recent Advances and Trends in Predictive Manufacturing in Industry 4.0 Environment. *Uptime Magazine*, 16–21.

Madhavan, P., & Wiegmann, D. A. (2007a). Effects of information source, pedigree, and reliability on operator interaction with decision support systems. *Human Factors*, 49(5), 5773–5785.

Madhavan, P., & Wiegmann, D. A. (2007b). Similarities and differences between human-human and humanautomation trust: An integrative review. *Theoretical Issues in Ergonomics Science*, 8(4), 277–301.

Martignon, L., & Krauss, S. (2003). Can l'homme eclaire be fast and frugal? Reconciling Bayesianism and bounded rationality. In S. Schneider & J. Shanteau (Eds.), *Emerging perspectives on judgment and decision research* (pp. 108–122). Cambridge: Cambridge University Press.

Mathur, A., Cavanaugh, K. F., Pattipati, K. R., Willett, P. K., & Galie, T. R. (2001). Reasoning and modeling systems in diagnosis and prognosis. In P. K. Willett & T. Kirubarajan (Eds.), *Proceedings of SPIE—The* International Society for Optical Engineering: Component and Systems Diagnostics, Prognosis, and Health Management (Vol. 4389, pp. 194–203). Orlando, Florida. doi:10.1117/12.434239

- Merritt, S. M., & Ilgen, D. R. (2008). Not all trust is created equal: Dispositional and history based trust in humanautomation interactions. *Human Factors*, 50(2), 194– 210.
- Mintzberg, H., & Simon, H. a. (1977). The New Science of Management Decision, Revised Edition. Administrative Science Quarterly, 22(2), 342. doi:10.2307/2391966
- Montes de Oca, S., Puig, V., & Blesa, J. (2012). Robust fault detection based on adaptive threshold generation using interval LPV observers. *International Journal of Adaptive Control and Signal Processing*, 26(3), 258– 283. doi:10.1002/acs.1263
- Muir, B. M., & Moray, N. (1989). Operators' trust in and use of automatic controllers. In *Proceedings of the* 22nd Annual Conference of the Human Factors Association of Canada (pp. 163–166). Ontario: Human Factors Association of Canada.
- Pecht, M. G. (2008). *Prognostics and Health Management* of *Electronics* (p. 300). Hoboken, New Jersey: John Wiley & Sons, Inc.
- Popov, A., Fink,, W., & Hess, A. (2013). PHM for Astronauts – A New Application. In S. Sankararaman & I. Roychoudhury (Eds.), Annual Conference of the Prognostics and Health Management Society 2013 (pp. 566–572). New Orleans LA: PHM Society. Retrieved from http://www.phmsociety.org/sites/phmsociety.org/files/

phm_submission/2013/phmc_13_083.pdf

- ProcessIT Europe. (2013). European Roadmap for Industrial Process Automation (p. 52).
- Puig, V., Quevedo, J., Escobet, T., Nejjari, F., & de las Heras, S. (2008). Passive robust fault detection of dynamic processes using interval models. *IEEE Transactions on Control Systems Technolog*, 16, 1083–1089.
- Rankin, W., Hibit, R., Allen, J., & Sargent, R. (2000). Development and evaluation of the Maintenance Error Decision Aid (MEDA) process. *International Journal* of Industrial Ergonomics, 26(2), 261–276. doi:10.1016/S0169-8141(99)00070-0
- Rasmussen, N. C. (1975). Reactor safety study. An assessment of accident risks in U. S. commercial nuclear power plants. Executive Summary. WASH-1400 (NUREG-75/014) (p. 10). Rockville, MD, USA.
- Sackett, D. L., Rosenberg, W. M. C., Gray, J. A. M., Haynes, R. B., & Richardson, W. S. (1996). Evidence based medicine: what it is and what it isn't. *BMJ*, *312*(7023), 71–72.
- Salvendy, G. (Ed.). (2012). *Handbook of Human Factors* and Ergonomics (4th ed., p. 1752). Hoboken, NJ,

USA: John Wiley & Sons, Inc. doi:10.1002/0470048204

- Sandborn, P. (2005). A decision support model for determining the applicability of prognostic health management (PHM) approaches to electronic systems. In Annual Reliability and Maintainability Symposium, 2005. Proceedings. (pp. 422–427). Arlington, VA: IEEE. doi:10.1109/RAMS.2005.1408399
- Sankararaman, S., & Goebel, K. (2012). Why is the Remaining Useful Life Prediction Uncertain? In Annual Conference of the Prognostics and Health Management Society 2013 (pp. 1–13). New Orleans, LA: PHM Society.
- Sarter, N. B., & Schroeder, B. (2001). Supporting Decision Making and Action Selection under Time Pressure and Uncertainty: The Case of In-Flight Icing. *Human Factors*, 43(4), 573–583.
- Sarter, N. B., Woods, D. D., & Billings, C. E. (1997). Automation surprises. In G. Salvendy (Ed.), *Handbook of Human Factors and Ergonomics* (2nd ed., pp. 1926–1943). New York: John Wiley & Sons, Inc.
- Saxena, A., Roychoudhury, I., & Celaya, J. R. (2010). Requirements Specifications for Prognostics: An Overview. In AIAA Infotech @ Aerospace (pp. 1–16). Atlanta, Georgia.
- Sheridan, T. B. (1999). Human supervisory control. In A. P. Sage & W. B. Rouse (Eds.), *Handbook of Systems Engineering and Management* (pp. 645–690). New York: John Wiley & Sons, Inc.
- Sheridan, T. B., & Parasuraman, R. (2006). Humanautomation interaction. In R. S. Nickerson (Ed.), *Reviews of human factors and ergonomics* (1st ed., pp. 89–129). Santa Monica, CA: Human Factors and Ergonomics Society.
- Shibl, R., Lawley, M., & Debuse, J. (2013). Factors influencing decision support system acceptance. *Decision Support Systems*, 54(2), 953–961. doi:10.1016/j.dss.2012.09.018
- Souza, L. M. S. de, Spiess, P., Guinard, D., Moritz, K., & Karnouskos, S. (2008). SOCRADES : A Web Service Based Shop Floor Integration Infrastructure. In C. Floerkemeier, M. Langheinrich, E. Fleisch, F. Mattern, & S. E. Sarma (Eds.), *Internet of Things* 2008 Conference (pp. 50–67). Zurich, Switzerland.
- Teti, R., Jemielniak, K., O'Donnell, G., & Dornfeld, D. (2010). Advanced monitoring of machining operations. *CIRP Annals - Manufacturing Technology*, 59(2), 717–739. doi:10.1016/j.cirp.2010.05.010
- The Nuclear Installations Inspectorate of the Health and Safety Executive. (2010). Safety Assessment Principles for Nuclear Facilities Technical Assessment Guide T/AST/058 - Human Factors Integration. Bootle, Merseyside: Office for Nuclear Regulation.

Uckun, S., Goebel, K., & Lucas, P. J. F. (2008). Standardizing research methods for prognostics. In 2008 International Conference on Prognostics and Health Management (pp. 1–10). Ieee. doi:10.1109/PHM.2008.4711437

Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent Fault Diagnosis and Prognosis for Engineering Systems* (1st ed., p. 456). Hoboken, New Jersey: John Wiley & Sons, Inc. doi:10.1002/9780470117842.app1

Venkatasubramanian, V., Rengaswamy, R., & Kavuri, S. N. (2003). A review of process fault detection and diagnosis Part II : Qualitative models and search strategies. *Computers & Chemical Engineering*, 27(3), 313–326.

Venkatasubramanian, V., Rengaswamy, R., Yin, K., & Kavuri, S. N. (2003). A review of process fault detection and diagnosis Part I : Quantitative modelbased methods. *Computers & Chemical Engineering*, 27(3), 293–311.

Walker, M., & Kapadia, R. (2009). Integrated Design of Online Health and Prognostics Management. In Annual Conference of the Prognostics and Health Management Society (pp. 1–15). San Diego, CA.

Wickens, C. D., & Dixon, S. R. (2007). The benefits of imperfect diagnostic automation: a synthesis of the literature. *Theoretical Issues in Ergonomics Science*, 8(3), 201–212. doi:10.1080/14639220500370105

Wiegmann, D. A., Rich, A. M., & Zhang, H. (2001). Automated diagnostic aids: The effects of aid reliability on users' trust and reliance. *Theoretical Issues in Ergonomics Science*, 2(4), 352–367.

Wiener, E. L., & Curry, R. E. (1980). Flight-deck automation: Promises and problems. *Ergonomics*, 23(10), 995–1011.

Yam, R. C. M., Tse, P. W., Li, L., & Tu, P. (2001). Intelligent Predictive Decision Support System for Condition-Based Maintenance. *The International Journal of Advanced Manufacturing Technology*, *17*(5), 383–391. doi:10.1007/s001700170173

Yu, B. Y., Syed Zubair, M. H. S., & Yang, M. C. (2013). A Framework for System Design Optimization Based On Maintenance Scheduling With Prognostics and Health Management. In Proceedings of ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (p. 12). Portland, Oregan.

Zhao, F., Tian, Z., & Zeng, Y. (2013). Uncertainty Quantification in Gear Remaining Useful Life Prediction Through an Integrated Prognostics Method. *IEEE Transactions on Reliability*, 62(1), 14.

Zhao, W., Zio, E., & Baraldi, P. (2011). Confidence in signal reconstruction by the Evolving Clustering Method. In 2011 Prognostics and System Health Managment Conference (pp. 1–7). IEEE. doi:10.1109/PHM.2011.5939535 Zio, E. (2012). Prognostics and Health Management of Industrial Equipment. In S. Kadry (Ed.), *Diagnostics* and Prognostics of Engineering Systems: Methods and Techniques (pp. 333–356). IGI Global. doi:10.4018/978-1-4666-2095-7

BIOGRAPHIES



Darren McDonnell graduated from the Dublin Institute of Technology, Ireland, with a B.Eng.Tech in Mechanical Engineering (2008) and a B.Eng (Hons.) in Manufacturing and Design Engineering (2010), for which he won the Institute of

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Development of Diagnostics & Prognostics for Condition-Based Decision Support

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ABSTRACT

The market for civil and military aerospace applications shows an increasing demand for service-based contracting ("Performance Based Contracting" - PBC). These contractual-concepts are based on guaranteed performance indicators over a fixed period, enabling a share of the financial risk between the system provider and the operator. The realization of efficient condition monitoring capabilities and reliable prognostics for prediction of spares and personnel demands has been identified as one key enabling factor for a successful implementation of PBC-concepts. To ensure an optimal incorporation of the diagnostic & prognostic functions needed for this purpose, the integration has to be considered as a standard design task during the development and certification phase, rising the need to adapt existing development processes. This adaption includes the extension of certification guidelines, definition of dedicated requirements and realization of innovative verification strategies. During the last years Airbus Defence & Space was working on the definition of a development process for integration of an innovative health management strategy into new aircraft systems to support condition-based operations. Following a summary of condition monitoring and prognostic techniques, selected requirements and guidelines for development of diagnostic & prognostic functions will be presented and discussed.

1. INTRODUCTION

For the civil aerospace sector, the highly competitive situation and simultaneously continuously growing market are motivating factors for the development of new and attractive business models. The global competition has also an increasing relevance for the military sector but the only annually available funding of the governmental customers is an additional regulating factor. To realize new development programs under these conditions and in despite of more and more limited budgets, future activities have to ensure minimized and predictable costs for development and operation & support. PBC-concepts are one possible solution to reduce the financial and operational risk for the operator, while providing technical sophisticated systems. The main attributes of such PBC-concepts are therefore defined through cost efficiency and operational performance, whereas the respective contents of the contract are application specific.

Beside the system design itself, the strategy for maintenance and on-demand provisioning of resources is one of the fundamental aspects to control operation & support costs and system availability (Lee et. al, 2008). Hence provisioning of spare parts and qualified personnel at the right place and the right time without any oversupply to avoid excessive costs for personnel, production and logistics, is one major challenge for the successful implementation of PBC-concepts (Reimann et. al, 2009). This demand can be fostered through an efficient health management system with failure prognosis capabilities (Jazouli & Sandborn, 2011 and Wilmering & Ramesh, 2004). A maximum capitalization of the information provided by the health management system can only be achieved with an integrated solution for condition-based maintenance and mission management. An appropriate development process is a mandatory prerequisite to integrate these capabilities into a new system design. The establishment of such a process for the development and certification of integrated diagnostic & prognostic functions to enable condition-based decision-making is still an ongoing task. The majority of publications in the field of Prognostics & Health Management (PHM) are discussing modelling, simulation and algorithms for various applications. Only very few authors have discussed the topic of validation & verification as part of a development process to an extent that can be applied to aerospace applications (Kacprzynski et. al, 2004, Leao et. al, 2008 and Saxena et. al, 2010). The aim of this paper is to detail an approach that

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allows for inclusion and verification of design requirements for PHM functions into the development process for new or legacy systems. After an introduction to the principles of Condition-Based Operations a review of the current status within the emerging field of diagnostics & prognostics will be given. According to the main aim of the paper, the status reviews are followed by the derivation of appropriate design requirements and established validation & verification strategies.

2. DESIGN ELEMENTS OF CONDITION-BASED OPERATIONS

The main elements of condition-based operations as considered by Airbus Defence & Space are depicted in Figure 1:

- 1. On-board health management functions and data transmission.
- 2. Evaluation of health management information using prognostic functions to enable predictive decision support.
- 3. Decision Support including evaluation of different options for dynamic mission and maintenance scheduling.
- 4. Performance Based Logistics for an optimized resource and supply chain management.
- 5. Certification of condition-based decision-making and configuration control to ensure continued airworthiness.



Figure 1. Design elements of condition-based operations

The main technology challenges can be seen in the development of on-board monitoring functions, regularizations for data security, integration of off-board functions for predictive maintenance and mission management and the on-demand strategy for supplier and logistic supply chain management. Apart from the technology maturation, all design elements need to be developed under the guidelines of the respective authorities

to ensure certifiability for new products and continued airworthiness for upgrades of legacy systems. The field of diagnostics & prognostics is one important contributor for the realization of condition-based operations, as the information from the health management system is one of the main inputs to dynamically optimize maintenance and mission planning.

As for the development of other on-board and off-board functions, diagnostics & prognostics also require the definition of verifiable design requirements. Airbus Defence & Space has developed a virtual framework to support the validation & verification of design requirements for a health management system (Mikat et. al, 2012). The model described in (Mikat et. al, 2012) has been validated against a certified environment and the requirements and concepts described in this paper are now an integral part of the framework to support the development of diagnostic & prognostic functions. The implementation is done as shown in Figure 2. The contents of this paper are discussing selected requirements and concepts from the elements marked with "Requirements Application".



Figure 2. Development process for diagnostic & prognostic functions

The following chapters will focus on a status review of condition monitoring in general and prognostics as an integral part for condition-based operations. The main requirements for definition of diagnostic & prognostic functions that can be applied to any design task from this field are presented and discussed. The discussion includes the implementation of a general approach to evaluate the performance of prognostic concepts.

2.1. Condition Monitoring

Today's condition monitoring systems for aircraft applications are based on a combination of Built-In-Tests (BIT) and health monitoring systems (Srivastra, 2009). Therefore dedicated instrumentations and data analysis concepts are considered during the system design stage. The BIT shall ensure that all relevant failure modes become evident to the flight operator. Different classes of BITs ("Power-Up BIT" during component or system start, "Continuous BIT" during continuous operation and "Initiated BIT" during specific operating conditions) are considered and evaluated according to a predefined monitoring concept. The results from the BIT monitors are compared with specified thresholds, to decide whether the respective function can be supported as required. Repeatability and reliability of the BIT is ensured by the fixed test procedures and thresholds for unacceptable conditions that have been defined and verified during component and system qualification. The evaluation of BIT information is a mandatory input to continuously verify the airworthiness of the operating system.

In addition to BITs, selected parameters and conditions are subject to a continuous monitoring and assessment of the remaining margin to predefined damage or performance thresholds (COndition Monitoring function - COM). Examples are the "Usage Monitoring" for structural parts (Hunt & Hebden, 1998) or "Engine Trend Monitoring" for jet engines (Kühl & Pakszies, 2011).

The main difference between these two approaches can be seen in the high reliability of the BIT to distinguish between two conditions (operative or non-operative) and the capability of the COM to continuously quantify changes in the operating conditions before a failure or malfunction occurs. The impact of BIT and COM on maintenance intervals and the useful life consumption is shown in Figure 3. The BIT would indicate the failure when the predefined threshold is exceeded, causing an operational interruption due to a failure event, while the COM avoids the failure and maximise the availability by the initiation of a preventive maintenance action. The waste of useful life E can be minimized with increasing accuracy of the diagnostic & prognostic function. For real world applications E will always be greater than zero, affecting the useful life consumption of the monitored equipment adversely but avoiding unacceptable degradation levels. Therefore the design aim for COM functions should be to maximize the component utilization (which is equivalent to minimizing E), while also ensuring a simple and robust monitoring concept with a minimum impact on the system design and operation.



Figure 3. Condition Monitoring concepts and impact on the operating system

2.1.1. Classification of Condition Monitoring

In general condition monitoring techniques can be classified into data-driven and model-based approaches (Venkat et. al Part I, 2003 and Schaab, 2010):



Figure 4. Classification of diagnostic approaches

The class of qualitative data-driven approaches is robust and easy to implement. Limit checking and plausibility checks are used for numerous industrial applications (Münchhof, 2006). These concepts require usually no complex algorithms and the main effort can be seen in the derivation of reasonable thresholds to decide whether the monitored function is satisfying its requirements or not.

The quantitative methods are utilizing extensive datasets with and without failure signatures to identify whether the observed process has a nominal or faulty behaviour. The health assessment is done based on pattern recognition algorithms, by analyzing selected features from the collected data (Venkat et. al Part III, 2003). The concept for feature generation is very problem specific and needs to ensure that the fault signature is evident to the algorithms for pattern recognition. Commonly used classification methods include but are not limited to Bayesian Decision Theory (Pipe, K., 2003), Neural Networks (Ypma, 2001) and Support Vector Machines (Schaab, Harrington & Klingauf, 2007).

Model-based approaches are utilizing a logical or mathematical description of the monitored process to compare the expected behaviour with actual measurements. The results of this comparison are used to derive estimates for the actual health status.

Qualitative models are an abstracted version of the underlying process and are used if no detailed physical modeling is needed or the complexity of the process does prohibit the model development (Venkat et. al, Part II, 2003). One example are logical graphs, which include information about the cause-effect relationship of failure modes that can be used for fault detection and isolation (Chung-Chien & Cheng-Ching, 1990).

Quantitative model-based methods are based on a detailed mathematical model, which represents a virtual redundancy of the monitored process. The models are used to derive a residual, which describes in case of a fault occurrence the difference between the nominal and faulty behaviour. The residual is then used to isolate and quantify deteriorations or malfunctions of the process. Various examples like parity equations (Isermann, 2006), recursive Bayesian estimation (Crepin & Kreß, 2000) or parameter estimations techniques (Isermann, 1992) have been discussed.

Following the above given definition for BITs and COM, the BIT can usually be seen in the context of qualitative methods, enabling detection and isolation of an already occurred failure. The capability to detect, isolate and quantify a deviation from the nominal behaviour requires a deeper analysis of the monitored process and therefore COM approaches would be expected to come from the field of quantitative methods.

2.1.2. Development of Condition Monitoring

The development of the above mentioned capabilities needs the establishment of design requirements for validation & verification of the diagnostic performance. To support this task, the following qualitative requirements have been identified as relevant for the development of Diagnostic Functions (DF) for all COM monitored items:

- The DF shall indicate the minimum detectable damage size.
- The DF shall quantify the remaining margin until the damage size exceeds a maximum allowable limit.
- The DF shall enable root cause isolation on component level.
- The DF shall provide the confidence level of damage size quantification.
- Each DF shall be provided with a value for the critical damage size of the monitored feature.

Once the requirements for DFs have been defined, the particular monitoring concepts and applied algorithms combination is very problem specific, therefore the task needs a case by case solution. The following set of quantitative requirements is considered as a generic baseline to verify the diagnostic performance of DFs:

- The system shall ensure a Diagnostic Capability Rate (DCR) of more than X%.
- The DF shall achieve a probability of detection of more than X%.
- The number of COM false alarms shall be less than X% of all COM failure detections.
- All DF shall ensure an error for damage quantification of less than X%.
- All DF shall ensure an uncertainty for damage quantification of less than X%.
- All DF shall ensure a probability of failure detection of more than X%.

The following definitions are used for these requirements:

• The DCR is defined as (FR_D = Failure Rates of components with diagnostic capabilities; FR_{SYS} = System Failure Rate):

$$DCR = \frac{\sum FR_{D}}{FR_{SYS}} \cdot 100 \tag{1}$$

- Probability of detection shall be defined as the probability to detect the minimum detectable damage size.
- Uncertainty of damage quantification shall be defined as the X% probability for correct damage assessment.
- Probability of failure detection shall be defined as the probability to detect an exceedance of the maximum allowable damage size.

The capability to quantify incipient failures is seen as a prerequisite for prognostics, as the output from the DF will be used to predict the future state of the degradation.

2.2. Prognostics

The task of prognostics is to determine the point in time, from where on the specified requirements of a function cannot be satisfied anymore. The criterion of failure can be defined through an unacceptable deviation from any operating condition or the loss of functionality.

2.2.1. Classification of Prognostics

The different concepts for the implementation of prognostics can be divided into data-driven, model-based

and hybrid approaches (Schwabacher, 2005, Medjaher et. al, 2013 and Goebel, Saha & Saxena, 2008):



Figure 5. Classification of prognostic approaches

The Reliability Analysis is based on a statistical evaluation of collected failure modes and correlation with recorded operating conditions to derive an estimate of the useful life for a given usage profile. No information about the real status will be used. Conservative assumptions can minimize the risk of failure but the useful life consumption is overestimated and a mismatch between the real and theoretical usage profile rises the risk for a failure during operation (Jaloretto et. al, 2009). The Weibull analysis is one of the most popular methods for Reliability Analysis (Groer, 2000).

Trend Monitoring uses time series regression of selected features to extrapolate an observed trend to a predefined threshold. With a meaningful selection of features, it is possible to gain sufficient knowledge about the real status of the system and about the future trend of the health status. As Trend Monitoring is usually adapted to the incoming observations, the potential for inclusion of prior knowledge is limited (Maio & Zio, 2010). Trend monitoring is applied if the degradation process is not sufficiently known or the used parameters are built up by numerous processes and no comprehensive data-base for the development of damage propagation models is available. Various methods from the field of auto-regression are common practice for Trend Monitoring tasks (Pandian & Ali, 2010).

The Lifetime Analysis establishes a direct link between the current condition and the Remaining Useful Life (RUL) of the monitored item, without considering the real path of the degradation process (Gebraeel & Lawley, 2008).

Concepts from the data-driven Process Analysis domain are utilizing collected information about the degradation path and relevant operating conditions to identify a suitable damage propagation model. The identified model is then used to predict the degradation trend as a function of operating conditions and the current health status, until a predefined threshold is exceeded. Commonly used methods are Neural Networks (Rao et. al, 2012), Support Vector Machines (Khawaja & Vachtsevanos, 2009) or Fuzzy-Inference Systems (Javed et. al, 2011). The Gaussian Process is a quite new and powerful method for data-model identification through non-parametric regression (Liu et. al, 2013). The strength of data-driven process analysis can be seen in the wide field of applications and in the fact that no or only very limited prior knowledge about the underlying process is needed to derive a suitable model. Restrictions are mainly resulting from the limited applicability for extrapolation beyond the training data sets and the blackbox character of the identified models. Additionally it cannot be guaranteed that the identified solution represents a global optimum of the problem, causing single fractions of the training data to have a higher weighting. Especially in the case of prognostics, this can cause divergence of the results (Wang & Wang, 2012).

Model-based techniques utilize detailed knowledge about the relationship between measurements, design parameters and the degradation trends to derive functional or physical models. The identification of model parameters and states shall enable an exact assessment of the monitored indicator and related uncertainties (model errors, measurements errors, bandwidth of operating conditions). For optimal support of the respective tasks, different models are used for identification (process model) and prediction (damage model) (Daigle et. al, 2012). The monitored state and all related uncertainties are estimated with the process model. The damage model is used to determine the degradation path until a predefined criterion is met. The most popular approaches are using recursive Bayesian estimators like the Kalman Filter for linear models (Celaya et. al, 2011), Extended Kalman Filter (Bechhoefer, 2008) and Unscented Kalman Filter for nonlinear models (Zhang & Pisu, 2012) and particle filter for non-Gaussian distributed variables and states (Zhu et. al, 2013).

Hybrid estimation schemes with multiple-model approaches optimize the local applicability of single models, improving quality of the overall prognostic performance and robustness (Li & Jilkov, 2003 and Chen, 2011).

Expert systems are based on a detailed technical understanding of the relationship and interactions between a Condition Indicator (CI) and the RUL. Fixed model structures or predefined decision trees are used to generate the estimate, without the capability to adapt the model structure to a new observation. With sufficient knowledge and experience, these approaches can enable an optimized prognosis but have a very limited robustness against model and measurement uncertainties (Brotherton, 2000).

Hybrid approaches combine the strengths from data- and model-based concepts to provide an optimized solution for the prognostic task. Common implementations are compensating measurement uncertainties or performing parameter estimation for data-driven concepts with adaptive filtering (Liu et. al, 2013) or provide data-modules to extend model structures with elements that cannot be modelled (Anger, Schrader, & Klingauf, 2012).

A qualitative overview about the fields of application for data-driven, model-based and hybrid concepts in general is depicted in Figure 6.


Figure 6. Areas of application for prognostic concepts

All mentioned prognostic approaches can be classified into two main categories:

- Lifetime calculation
- Failure prognosis

Only approaches that are enabling the prediction of the path for a CI under consideration of future operating conditions are accounted for the category of failure prognosis. This includes trend monitoring, selected data-driven process analysis concepts as well as model-based approaches, which are using damage propagation models or suitable expert systems.

Exact determination of the CI and related uncertainties for damage quantification through appropriate DFs are a prerequisite for failure prognosis. The period for which the prognosis can satisfy certain accuracy and precision requirements is called prognostic horizon and indicates the potential for predictive measures like spare parts ordering or maintenance scheduling. For a definition of prognostic horizon the reader should refer to section 7 or to Saxena, Celaya, Balaban, Goebel, Saha B., Saha S. and Schwabacher 2008.

Every failure prognosis accumulates and integrates all uncertainties for damage quantification, prediction of damage trends and impact of future operating conditions: Prognostics deals therefore with uncertainty. In the last step of the DF, before the prognosis is started, uncertainties come from the imperfect data acquisition and representation of the underlying process of damage quantification as well as uncertain knowledge of future inputs. Since these sources of uncertainty cannot be avoided, the full prognostic task deals with variables like remaining useful life and end of life that are random in nature. For these reasons, every prognostic algorithm must account for these inherent uncertainties. Moreover every conceived algorithm contributes to increase the uncertainty of the overall framework: the conceived algorithm has in fact just a partial knowledge of the state of the system at the time in which a prediction is initialized, of the future input statistics, of the description of the underlying process and above all it does not know exactly which model the system will follow during the time interval of prediction.

All the above-mentioned considerations make then the prognostic process a highly stochastic task. The final aim of the full prognostic process is to support the risk management for predictive planning, by means of the reliable determination of the expected RUL and related confidence limits: therefore making decisions based on uncertain information needs the characterization of the uncertainty itself. Hence, a failure prognosis shall provide not simply the trend of a CI but the whole time-dependent probability density function of the predicted feature, with an over time increasing variance (Lybeck et. al, 2007).

The way in which uncertainty is handled is therefore of paramount importance: however not so many papers in the literature are dealing with uncertainty propagation (Sankararaman et. al, 2011, Saha, Quach & Goebel, 2012, Luo e. al, 2008, Edwards, Orchard, Tang, Goebel, & Vachtsevanos, 2010, Daigle, Saxena, & Goebel, 2012 and Candela, Girard, Larsen & Rasmussen, 2003) as far as the authors knowledge is concerned. In what follows a discussion regarding this topic will be provided. In particular, the problem of propagating the first two statistical moments (mean and variance) of a CI will be addressed together with the final derivation of the timedependent probability of failure information (giving then the expected RUL, End of Life and the corresponding confidence limits).

First task of a generic prognostic process is to forecast the statistics of the CI: that is in other words to derive for future time instants its mean and variance or, if possible, the full Probability Density Function (PDF), that provides also the moments of higher order of the distribution.

Assuming that a model equation is available for the process describing the CI, the propagation of its statistics could be accomplished by considering the general equation (Eq. 3) proposed in the ISO Guide to the Expression of Uncertainty in Measurement (ISO/IEC Guide 98-3, 2008): an example of a generic model equation is here considered. The model equation is a function of Z number of inputs z_{ζ} , namely: x_{χ} ($\chi=1, 2, ..., X$); the time index k_t and the value that the function itself assumed a time-step before (a generic lag-dependency of course can here be considered).

$$CI = CI(z_1, z_2, ..., z_Z) = ...$$

$$CI(k_t, x_1, x_2, ..., x_X, CI(k_{t-1}))$$
(2)

Considering the simplified circumstances in which inputs have no cross-correlation, the uncertainty u of the CI can be expressed by means of the following equation:

$$u(CI) = \sqrt{\sum_{\zeta=1}^{\zeta=Z} \left[\left(\frac{\partial CI}{\partial z_{\zeta}} \right) \cdot u_{\zeta}^{2}(z_{\zeta}) \right]}$$
(3)

In which the uncertainty corresponding to each input propagates through the partial derivative with respect to the input itself; the derivative can be therefore thought as a sensitivity factor. Following the test-case suggested by (Eq.4), in



Figure 7 the result from the uncertainty propagation of a model equation with X=2 is shown (reasonable u_{x1} and u_{x2} values have been assumed regarding the inputs uncertainty, 30% and 15% of the respective definition's domains of x_1 and x_2), whilst time index is considered a certain information).

$$CI = CI_{1}(x_{1}) + CI_{2}(x_{2}) + \dots$$

$$CI_{3}(k_{t}, x_{1}, x_{2}) + CI_{4}(CI(k_{t-1}))$$

$$CI_{1} = c \cdot e^{x_{1}} + \sum_{r=0}^{r=R} a_{r} \cdot x_{1}^{r}; \quad CI_{2} = \sum_{s=0}^{s=S} b_{s} \cdot x_{2}^{s};$$

$$CI_{3} = 2 \cdot k_{t} + x_{1} \cdot x_{2} \cdot k_{t}^{2}; \quad CI_{4} = d \cdot \sqrt{CI(k_{t-1})}$$
(4)

More in detail, the upper couple of pictures shows the prediction for a model equation with R=S=5 (highly nonlinear; see Eq. 4) whilst the lower couple of pictures has R=S=2. The upper pictures stress the possible issues with this approach (in what follows as uncertainty has been always considered three times the value of the corresponding standard deviation): the reliability and accuracy of the uncertainty propagation decreases as the non-linearity of the system increases. The more the system has a non-linear behavior, the more the uncertainty propagation through the use of the partial derivatives fails, since the first derivative alone is not able to capture the full dynamic. As a matter of fact, the predicted uncertainty takes values apart from the *real ones* that are calculated by means of a Monte-Carlo simulation. Moreover, the approach here used, and based on the ISO Guide above mentioned, tackles only situations, in which we have at our disposal a closed form equation. If a recursion takes place, for example if a state-space-based system is used in which the previous state estimation is used as input to the current estimation step, then the approach, as here has been presented, is not applicable.



Figure 7. Mean and variance propagation

However, the above requirements are not always fulfilled, and therefore for many models the predictive density can only be approximated using Monte-Carlo sampling, local expansions or variational approaches. In these cases a Bayesian approach is generally followed (Daigle, Saxena, & Goebel, 2012 and Candela, Girard, Larsen & Rasmussen, 2003); the Bayesian kernel methods have proven to be very efficient nonlinear models (Rasmussen, 1996 and Ouinonero-Candela & Hansen, 2002) with flexible approximation capabilities and high generalization performance. As known, recursive sequential Bayesian filters are probabilistic approaches adopted to estimate an unknown PDF recursively over time; they make use of a mathematical process model and of incoming measurements. The estimation consists of two steps, namely prediction and correction: within the prediction step, the system state is projected in time towards a future state using the process model; then, by means of the incoming measurements, the statistics of the system are updated. The described framework could then be adapted within a prognostic task, applying a multi-step ahead prediction,

assuming no more measurements will be available. The mathematics beneath the Bayesian filter remains the same, but the correction step. In fact, having no measurements, the error is assumed to be zero. This way the mean and variance of a CI are reasonably forecasted.

Remaining within the Bayesian modelling, in (Daigle, Saxena, & Goebel, 2012) a different approach is proposed. Here the authors have developed a sample-based algorithm for predicting the remaining useful life distribution, accounting for the different sources of uncertainties. By adopting the unscented transformation (Julier & Uhlmann, 2004), the method allows one to sample from future input trajectories, maintaining at the end of the prediction the statistics as well. Moreover, having the unscented transformation deterministically accomplished, RUL predictions are deterministically bounded as well (and this is - in safety-critical systems - of great importance, if we think to the verification, validation, and certification protocols in the aerospace domain). In (Candela, Girard, Larsen & Rasmussen, 2003), Gaussian Process and Relevant Vector Machine approaches are used to propagate uncertainty. The paper aims to increase the prediction reliability by taking into consideration also the uncertainty associated to predicted values that are recursively used within the multiple-step ahead forecasting. A novel analytical expression is in fact derived for the predicted mean and variance.

Regardless of the approach followed, the first task of a prognostic process is to forecast the statistics of the CI, so that one has at his disposal the PDF of CI for future time (PDF_{CI,t}). In order to determine the so called Probability of Failure (PoF) of the unit under investigation, the statistics (in terms - for example - of the Cumulative Distribution Function - CDF) of the value assumed by the CI corresponding to failed conditions CDF_{CI} has to be known; this can be derived experimentally or assumed with common engineering sense.

This way PoF_t , indicating the probability that the monitored component fails at time *t*, can be derived:

$$PoF_{t} = \int_{CI=0}^{CI=\infty} PDF_{CI,t} \cdot CDF_{CI} \cdot \partial CI$$
(5)

From this distribution could be derived then the expected RUL (that is corresponding to the time at which the PoF i.e. is equal to 0.5 or 50%) and/or other needed confidence limits. In the following figure, the resulting PoF is shown, together with two different forecasted PDFs of the CI and the probability density function from which the CDF_{CI} is

derived.



Figure 8. Failure Prognosis with distributed threshold

To maximize the use of prognostics, the expected RUL has to be estimated with high accuracy and low uncertainty. The quality of prognosis increases with the prognostic horizon and the level of convergence of the expectation value and confidence limits against the real degradation path. The most important aspect for capitalization of prognostics is the accurate RUL estimation when the spare parts are ordered and condition-based maintenance is scheduled. The potential for optimization of the logistic and maintenance process is inversely proportional to the deviation between the real and predicted values and the related uncertainties. These interrelations are depicted in Figure 9.



Figure 9. Impact of prognostic performance on logistics and maintenance scheduling

2.2.2. Development of Prognostics

The development of prognostics can be seen as a special case of software development, as the verification of the prognostic capabilities usually is very cost and time consuming and requires many test cases to prove the accuracy and precision of prediction. Since legacy systems usually do not provide the type and quality of information that is needed to support the development of failure prognosis, then the need to perform destructive testing for a new system design will highly adversely affect the development cost and time schedule for the certification of the operating system. The limiting factors for the realization of a predictive decision support are shown in Figure 10. The overall limit for the development of prognostic concepts is

represented by the technology's maturation regarding data collection and available prognostic algorithms; for this reason the particular design, expressed through the required prognostic performance, will be defined by the application for economical, mission or safety critical functions. Moreover, due to the fact that autonomous mission support functions would require on-board applications, the integration into the off-board environment will enable the usage of more computing resources, extending so the list of applicable concepts and access to stored data.



Figure 10. Considerations for development of Prognostics As discussed in section 2.2.1, a variety of different approaches exist to implement Prognostic Functions (PFs). The quality/quantity of available degradation data and prior knowledge about the physics of degradation are determining whether data-driven or model-based approaches should be favored. After the initial decision about the type of solution that will be followed, a concept is needed to investigate advantages and disadvantages of different implementations and assess their prognostic performance during the design phase. Airbus Defence & Space has developed a framework to support these tasks and to enable prioritization of the most suitable prognostic approach without consideration of cost elements (see Figure 11).



Figure 11. Framework for assessment of prognostic performance

The shown process aims for a stepwise evaluation of selected performance metrics, successively enhancing the database for prognosis by increasing the number of used training datasets. The verification of prognostic capabilities is done for each test dataset k = 1:Q, whereas each single set is composed of i = 1:N time increments for starting the prognosis.

In what follows, a set of general definitions will be provided (see Figure 12) regarding the conceived process: up to time t_0 , diagnostic information is collected and used to derive the current health status and uncertainties for damage quantification, the item fails at EoL with a real remaining useful life of RUL. The prognosis starts at t_0 and estimates the predicted remaining useful life RUL*, with EoP (End of Prediction) as the point in time when the forecasted indicator distribution (the PDF of CI) is such that the cumulative of the PoF exceeds 50%. The upper and lower confidence limits of RUL* predictions are denoted by RUL_{UL}* and RUL_{LL}* respectively (UL (or ul): Upper Limit; LL (or ll): Lower Limit).



Figure 12. Definitions for prognostics

According to the general approach for system identification tasks, a prerequisite for performance evaluation is to classify the available data into "known" training data and "unknown" test data. All training data can be used for the development of prognostic concepts, while the test data should be used for verification of the prognostic performance. The classification into training and test data should follow a structured approach, to ensure that the information content is comparable and the results are representative for the achievable performance of the tested prognostic concept. Dedicated test cases for evaluation of limitations and robustness can be added at a later stage.

To simplify the comparison of results for different test runs k, the time dependency of the datasets can be normalized, by replacing the usage time T (in calendar time, cycles or operating hours) by a unitless value λ for all time increments:

$$\lambda_{1:N,k} = \frac{T_{1:N,k}}{RUL_k} = [\lambda_0, ..., 1]$$
(6)

with:

 $T_{1,k} = t_{0k}$

$$T_{N,k} = EoL_k$$

The prognostic error ε needs to be calculated for each individual test run and λ -step of RUL*_{i.k}:

$$\varepsilon_{i,k} = RUL_k - RUL^*_{i,k} \tag{7}$$

The same is required for the upper and lower confidence limits of RUL predictions:

$$\mathcal{E}ul_{i,k} = RUL_k - RUL_{UL} *_{i,k}$$
(8)

$$\mathcal{E}ll_{i,k} = RUL_k - RUL_{LL} *_{i,k}$$
(9)

For a consistent prognosis, the relative difference between EoL and EoP should reduce towards zero with increasing damage size, as the equipment approaches EoL. To account for that higher relevance of later predictions (increasing λ), an exponential scaling factor ρ is introduced:

$$\rho_{1:N,k} = \exp((\lambda_{1:N,k} - \arg\max\{\lambda_{1:N,k}\}) \cdot w)$$
(10)

Where w denotes a factor for relevance weighting of the different predictions (see Figure 13).



Figure 13. λ relevance weighting for performance criteria

Based on the contents of (Saxena et. al, 2008), the following criteria have been derived to support the identification of the most suitable prognostic approach:

1. Mean Absolute Percentage Error (MAPE):

$$MAPE_{k} = \frac{\sum_{i=1}^{N} \rho_{i} \cdot \left| \frac{\varepsilon_{i,k}}{RUL_{i,k}} \right| \cdot 100}{\sum_{i=1}^{N} \rho_{i}}$$
(11)

2. Sample Standard Deviation (SSD):

$$SSD_{k} = \sqrt{\frac{\sum_{i=1}^{N} \rho_{i} \cdot (\varepsilon_{i,k} - \overline{\varepsilon}_{k})^{2}}{\sum_{i=1}^{N} \rho_{i} - \overline{\rho}}}$$
(12)

with:

$$\overline{\rho} = \frac{1}{N} \cdot \sum_{i=1}^{N} \rho_i$$

 $\overline{\varepsilon}_{k} = \frac{1}{N} \cdot \sum_{k=1}^{N} \varepsilon_{i,k}$

The SSD criterion is applicable for Gaussian distributions of $\mathcal{E}_{i,k}$.

3. Mean Absolute Deviation from Median (MAD):

$$MAD_{k} = \frac{\sum_{i=1}^{N} \rho_{i} \cdot \left(\varepsilon_{i,k} - \widetilde{\varepsilon}_{k}\right)}{\sum_{i=1}^{N} \rho_{i} - \overline{\rho}}$$
(13)

with:

 $\widetilde{\boldsymbol{\varepsilon}}_{k} = median(\boldsymbol{\varepsilon}_{1:N,k})$

The MAD criterion is applicable for non-Gaussian distributions of $\varepsilon_{i,k}$.

4. False Positives (FP):

$$FP_{k} = \sum_{i=1}^{N} \delta_{FPi,k} \begin{cases} \delta_{FPi,k} = 1, \forall \varepsilon ul_{i,k} > 0\\ \delta_{FPi,k} = 0, \forall \varepsilon ul_{i,k} \le 0 \end{cases}$$
(14)

The FP criterion identifies the predictions that would cause an unacceptable early replacement, affecting operational availability adversely.

5. False Negatives (FN):

$$FN_{k} = \sum_{i=1}^{N} \delta_{FNi,k} \begin{cases} \delta_{FNi,k} = 1, \forall \mathcal{E}ll_{i,k} < 0\\ \delta_{FNi,k} = 0, \forall \mathcal{E}ll_{i,k} \ge 0 \end{cases}$$
(15)

The FN criterion identifies the predictions that would cause an unacceptable late replacement, affecting safety adversely.

6. $\alpha \cdot \lambda$ Performance:

The α - λ metric is used to identify the point in time from where on the predicted RUL remains within the confidence limits given by f_1 and f_2 (Eq. (16) & Eq. (17), see shaded region in Figure 14):

$$f_{1,1:N,k} = \left[\left(1 + \alpha \right) \cdot \frac{\left(RUL_{1:N,k} + t_{0k} \right)}{EoL_k} \right] \cdot 100$$
(16)

$$f_{2,l:N,k} = \left[\left(1 - \alpha \right) \cdot \frac{\left(RUL_{l:N,k} + t_{0k} \right)}{EoL_k} \right] \cdot 100$$
(17)

Two performance values can be derived from the α - λ analysis (see Figure 14):

Prognostic Accuracy (PA):

Point from where on the average of RUL predictions remains stable within the given α -limits ($\lambda_{PA,k}$).

Prognostic Precision (PP):

Point from where on both confidence limits of RUL predictions remain stable within the given α -limits ($\lambda_{PP,k}$).



Figure 14. α - λ plot with α = 10%

7. Prognostic Horizon (PH):

The PH-metric indicates the point in time $(\lambda_{PH,k})$ from where on the predictions stay stable within the confidence limits given by g_1 and g_2 (Eq. (18) & E. (19), see shaded region in Figure 15):

$$g_{1,1:N,k} = \left[\frac{\left(RUL_{1:N,k} + t_{0k}\right)}{EoL_k} + \alpha\right] \cdot 100 \tag{18}$$

$$g_{2,1:N,k} = \left[\frac{\left(RUL_{1:N,k} + t_{0k}\right)}{EoL_k} - \alpha\right] \cdot 100$$
(19)



Figure 15. Prognostic Horizon plot with $\alpha = 10\%$

The resulting performance values $p_{l,l:M}$ are simply the arithmetic means of the applied "Prognostic Performance Metrics".

Additional criteria are needed if the evolution of the prognostic performance with an increasing number of training datasets j = 1:M shall be considered. These criteria are defined as "Data Frame Size Metrics" to account for the dimensions of the training datasets. Therefore the weighted average v_l of each criterion $p_{l,1:M}$ and each training dataset $m_{1:M}$ is used to assess the capability for continuous improvement during the life cycle:

$$v_{l} = \frac{\sum_{j=1}^{M} q_{j} \cdot p_{l,j}}{\sum_{j=1}^{M} q_{j}}$$
(20)

with $q_i = \exp((\dim(m_i) - \arg\max\{\dim(m_i)\}) \cdot w)$

Where q_j denotes a weighting factor, addressing more relevance to the datasets including more information with $dim(m_i)$ as the dimension of training data used in dataset m_i .

If a unique resulting performance value is needed to simplify the comparison of different approaches, a weighted average of all criteria $v_{I:L}$ can be used. The individual weighting should reflect the relevance of the respective criterion. Independent of the type of application, the FN and PH criteria shall have a high weighting, as they are representing the risk for failure during operation and the prognostic lead time for predictive planning.

Similar to other conventional design tasks from the field of HW or SW development, prognostics do also need the definition of design requirements, which can be used to perform validation & verification during the design stage of a new system. To support this task, the following qualitative requirements have been identified as relevant for the development of PF:

- The unit for RUL estimations (time-based, cycle-based or calendar-based) shall be predefined for each PF.
- The PF shall enable prognosis from entering into service without availability of comprehensive data sets.
- The PF shall provide capabilities for continuous improvement over the life cycle of the operating system.
- The PF shall enable evaluation of different future operating profiles.
- Determination of a suitable condition indicator for damage quantification and related uncertainties shall be the task of a diagnostic system and be provided to the PF.
- The process for achieving prognostic capabilities as well as the prognosis itself must not be real-time capable.
- The PF shall provide uncertainty estimates for RUL predictions to support risk analysis for logistics and maintenance scheduling.
- Evaluation of selected criteria shall enable assessment of the prognostic performance and design requirements.

These conceptual requirements can be seen as general design guidelines for the development of PF. One major issue for the development of prognostics is the need to verify the capability to predict future states with a predefined accuracy and robustness. Therefore quantitative requirements are needed in addition to the set of qualitative ones given above, that enable the evaluation of uncertain test results. Based on previous studies regarding suitable approaches for performance assessment of prognostic functions (Saxena et. al, 2008), Airbus Defence & Space has derived a set of quantitative requirements that can be used for verification of the performance of any PF:

- The system shall ensure a Prognosis Capability Rate (PCR) of more than X%.
- The absolute Percentage Error (PE) of RUL predictions shall always be less than X% of the actual RUL.
- The Uncertainty of RUL Predictions (PU) shall always be less than X% of the predicted RUL.
- The prognostic function shall achieve a False Positives Rate (FPR) of less than X%.
- The prognostic function shall achieve a False Negatives Rate (FNR) of less than X%.

The following definitions are used for these requirements:

 The Prognosis Capability Rate PCR is defined as (FR_P = Failure Rates of components with prognostic capabilities; FR_{SYS} = System Failure Rate):

$$PCR = \frac{\sum FR_{P}}{FR_{SYS}} \cdot 100 \tag{21}$$

• The Percentage Error of RUL predictions PE is defined as:

$$PE = \frac{RUL_{50\% PoF} - RUL}{RUL} \cdot 100$$
(22)

• The Uncertainty of RUL Predictions PU is defined as:

$$PU = \frac{RUL_{95\% PoF} - RUL_{5\% PoF}}{RUL_{50\% PoF}} \cdot 100$$
(23)

• False Positives Rate is defined as:

$$FPR = \frac{RUL_{50\% PoF} - RUL}{RUL} \cdot 100 < -X\%$$
(24)

• False Negatives Rate is defined as:

$$FNR = \frac{RUL_{50\% PoF} - RUL}{RUL} \cdot 100 > +X\%$$
(25)

These requirements are covering all relevant aspects that are needed to verify the performance and robustness of a PF during the development stage and for performance monitoring during service.

3. CONCLUSION

The implementation of enhanced health monitoring and failure prognosis functions is one prerequisite to enable condition-based operations. The motivation for the development of such capabilities is driven from the need to establish competitive solutions for aerospace applications, enhancing availability and mission reliability, while reducing operation & support costs. The development of an integrated health management system requires dedicated requirements and processes for identification of the optimal problem specific solutions for diagnostics & prognostics and to enable validation & verification during the system design stage. The concept for requirements definition and prognostic performance evaluation presented in this paper has been successfully applied during preceding development programs. Future research activities will focus on the extension of the requirements framework with concepts for cost-benefit analyses to further maturate the development framework for diagnostic & prognostic functions.

NOMENCLATURE

Symbols

- α Accuracy value for performance evaluation
- ε Prognostic error
- *E* Waste of useful life
- *L* Number of Prognostic Performance Criteria
- *m_j* Training dataset for prognostics
- *M* Number of datasets for training of prognostics
- *p* Prognostic performance criterion
- *Q* Number of datasets for testing of prognostics
- T Operating Time
- v Data frame size metric

Abbreviations

BIT	Build-In-Test
CDF	Cumulative Distribution Function
CI	Condition Indicator
СОМ	COndition Monitoring Function
DCR	Diagnostics Capability Rate
DF	Diagnostic Function
EoL	End of Life
EoP	End of Preditiction
FN	False Negatives
FP	False Positives
FPR	False Positives Rate
FNR	False Negatives Rate
LL (ll)	Lower Limit
MAD	Mean Absolute Deviation from Median
MAPE	Mean Absolute Percentage Error
PA	Prognostic Accuracy
PBC	Performance Based Contracting
PCR	Prognostics Capability Rate
PDF	Probability Density Function
PE	Absolute Percentage Error of RUL predictions
PF	Prognostic Function
PH	Prognostic Horizon
PHM	Prognostics and Health Management
PP	Prognostic Precision
PU	Uncertainty of RUL predictions
RUL	Remaining Useful Life
RUL*	Remaining Useful Life predictions
SSD	Sample Standard Deviation
UL (ul)	Upper Limit

REFERENCES

Anger, C., Schrader, R. & Klingauf, U. (2012). Unscented Kalman Filter with Gaussian Process Degradation Model for Bearing Fault Prognosis. *Proceedings of the First European Conference of the Prognostics and Health Management Society 2012*. July 2-5, Dresden, Germany

Bechhoefer, E. (2008). A Method for Generalized Prognostics of a Component Using Paris Law. *Proceedings*

of American Helicopter Society 64th Annual Forum 2008. April 29 - May 1, Montreal, Canada

Brotherton, T. (2000). Prognosis of Faults in Gas Turbine Engines. *Proceedings of IEEE Aerospace Conference*. March 18-25, Big Sky, Montana, USA. doi: 10.1109/AERO.2000.877892

Candela, J.Q., Girard, A., Larsen, J. & Rasmussen, C.E. (2003). Propagation of uncertainty in Bayesian kernel models - application to multiple-step ahead forecasting. *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing*. April 1-6, Hong Kong, China

Celaya, J.R., Kulkarni, C., Biswas, G., Saha, S. & Goebel, K. (2011). A Model-based Prognostics Methodology for Electrolytic Capacitors Based on Electrical Overstress Accelerated Aging. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. September 25-29, Montreal, Quebec, Canada

Chen, H. (2011). A Multiple Model Prediction Algorithm for CNC Machine Wear PHM. *International Journal of Prognostics and Health Management 2011*, issue 2. ISSN2153-2648

Chung-Chien, C. & Cheng-Ching, Y. (1990). On-Line Fault Diagnosis Using the Signed Directed Graph. *Industrial & Engineering Chemistry Research*, vol. 29, pp. 1290-1299. doi: 10.1021/ie00103a031

Crepin, P.Y. & Kreß, R. (2000). Model Based Fault Detection for an Aircraft Actuator. *Proceedings of the International Council of the Aeronautical Sciences*. August 28 - September 1, Harrogate, UK

Daigle, M., Saha, B. & Goebel, K. (2012). A Comparison of Filter-based Approaches for Model-based Prognostics. *Proceedings of IEEE Aerospace Conference*. March 3-10, Big Sky, Montana, USA. doi: 10.1109/AERO.2012.6187363

Daigle, M., Saxena, A. & Goebel, K. (2012). An Efficient Deterministic Approach to Model-based Prediction Uncertainty Estimation. *Proceedings of the First European Conference of the Prognostics and Health Management Society*. July 2-5, Dresden, Germany

Edwards, D., Orchard, M. E., Tang, L., Goebel, K., & Vachtsevanos, G. (2010). Impact in input uncertainty on failure prognostic algorithms: Extending the remaining useful life of nonlinear systems. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. October 10-16, Portland, Oregon, USA

Gebraeel, N.Z. & Lawley, M.A. (2008). A Neural Network Degradation Model for Computing and Updating Residual Life Distributions. *IEEE Transactions on Automation Science and Engineering*, vol. 5, issue 1, pp. 154-163 Goebel, K., Saha, B. & Saxena, A. (2008). A Comparison of three Data-Driven Techniques for Prognostics. *Proceedings* of the 62nd Meeting of the Society for Machinery Failure Prevention Technology. April 6-8, Virginia Beach, Virginia, USA

Groer, P.G. (2000). Analyses of Time-To-Failure with a Weibull Model. *Proceedings of the Maintenance and Reliability Conference*. May 8-10, Knoxville, Tennessee, USA

Hunt, S.R. & Hebden, I.G. (1998). Eurofighter 2000 An Integrated Approach to Structural Health and Usage Monitoring. *RTO AVT Specialists Meeting on "Exploitation* of Structural Leads/Health Data for Reduced Life Cycle Costs". May 11-12,. Brussels, Belgium

Isermann, R. (1992). *Identifikation dynamischer Systeme I - Grundlegende Methoden*. Springer-Verlag

Isermann, R. (2006). Fault Diagnosis Systems. Springer-Verlag

ISO/IEC Guide 98-3:2008 Uncertainty of measurement -Part 3: Guide to the expression of uncertainty in measurement (GUM:1995)

Jaloretto, M.R., Bizarria, C. & Galvao, R. (2009). Trend Analysis for Prognostics and Health Monitoring. *Brazilian Symposium on Aerospace Eng. & Applications*. September 14-16, S.J. Campos, SP, Brazil

Javed, K., Gouriveau, R., Zemouri, R. & Zerhouni, N. (2011). Improving Data-Driven Prognostics by Assessing Predictability of Features. *Annual Conference of the Prognostics and Health Management Society*. September 25-29, Montreal, Quebec, Canada

Jazouli, T. & Sandborn, P. (2011). Using PHM to Meet Availability-Based Contracting Requirements. *Proceedings* of *IEEE Aerospace Conference*. March 5-12, Big Sky, Montana, USA

Julier, S. J. & Uhlmann, J. K. (2004). Unscented filtering and nonlinear estimation. *Proceedings of the IEEE*, vol. 92, issue 3, pp. 401–422. doi: 10.1109/JPROC.2003.823141

Kacprzynski, G.J., Liberson, A., Palladino, A., Roemer, M.J., Hess, A.J. & Begin, M. (2004). Metrics and development tools for prognostic algorithms. *Proceedings of IEEE Aerospace Conference 2004*. March 6-13, Big Sky, MT, USA. doi: 10.1109/AERO.2004.1368198

Khawaja, T. & Vachtsevanos, G. (2009). A novel Architecture for on-line Failure Prognosis using Probabilistic Least Squares Support Vector Regression Machines. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. September 27 – October 1, San Diego, California, USA Kühl, T. & Pakszies, A. (2011). Condition Monitoring of Civil Jet Engines during Flight. *LTH Triebwerkstechnologie*, AT 58 100-01

Leao, B.P., Yoneyama, T., Rocha, G.C. & Fitzgibbon, K.T. (2008). Prognostics Performance Metrics and their Relation to Requirements, Design, Verification and Cost-Benefit. *International Conference on Prognostics and Health Management*. October 6-9, Denver, CO, USA. doi: 10.1109/PHM.2008.4711429

Lee, S.G., Ma, Y.-S., Thimm, G.L. & Verstraeten, J. (2008). Product lifecycle management in aviation maintenance, repair and overhaul. *Computers in Industry*, vol. 59, issues 2–3, pp. 296–303

Li, X.R. & Jilkov, V.P. (2003). A Survey of Maneuvering Target Tracking-Part V: Multiple-Model Methods. *IEEE Transactions on Aerospace and Electronic Systems*, vol. 41, issue 4, pp. 1255-1321. doi: 10.1109/TAES.2005.1561886

Liu, D., Guo, L., Pang, J. & Peng, Y. (2013). A Fusion Framework with Nonlinear Degradation Improvement for Remaining Useful Life Estimation of Lithium-ion Batteries. *Proceedings of the Annual Conference of the Prognostics and Health Management Society 2013*. October 14-17, New Orleans, Louisiana, USA

Liu, D., Pang, J., Zhou, J., Peng, Y., Pecht, M. (2013). Prognostics for State of Health Estimation of Lithium-Ion Batteries based on Combination Gaussian Process Functional Regression. *Microelectronics Reliability*, vol. 53, Issue 6, pp. 832-839

Luo, J., Pattipati, K. R., Qiao, L., & Chigusa, S. (2008). Model-based prognostic techniques applied to a suspension system. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 38, Issue 5, pp. 1156-1168. doi: 10.1109/TSMCA.2008.2001055

Lybeck, N., Marble, S., Morton, B. (2007). Validating Prognostic Algorithms: A Case Study Using Comprehensive Bearing Fault Data. *IEEE Aerospace Conference 2007*. March 3-10, Big Sky, Montana, USA

Zio, E., Maio, F.D., (2010). A Data-Driven Fuzzy Approach for Predicting the Remaining Useful Life in Dynamic Failure Scenarios of a Nuclear System. *Reliability Engineering & System Safety*, vol. 95, Issue 1, pp. 49-57

Medjaher, K., Zerhouni, N., Baklouti, J. (2013). Data-Driven Prognostics Based on Health Indicator Construction: Application to PRONOSTIA's Data. *European Control Conference 2013*. July 17-19, Zurich, Switzerland

Mikat, H., Siddiolo, A.M., Buderath, M. (2012). Virtual Framework for Validation and Verification of System Design Requirements to enable Condition Based Maintenance. *European Conference of the Prognostics and Health Management Society 2012*. July 3-5, Dresden, Germany Münchhof, M. (2006), *Model-based Fault Detection for a Hydraulic Servo Axis*. Doctoral dissertation. Technische Universität Darmstadt, Darmstadt, Germany

Pandian, A., Ali, A. (2010). A Review of Recent Trends in Machine Diagnosis and Prognosis Algorithms. *Reliability Engineering & System Safety*, vol. 95, Issue 1, pp. 49-57

Pipe, K. (2003). Measuring the Performance of a HUM System - Features that Count. *Proceedings of the 3rd DSTO International Conference on Health and Usage Monitoring*. February 17-18, Melbourne, Australia

Quinonero-Candela, J., Hansen, L.K. (2002). Time series prediction based on the relevance vector machine with adaptive kernels. *International Conference on Acoustics, Speech, and Signal Processing*, vol. 1, pp. 985-988, doi: 10.1109/ICASSP.2002.5743959

Rao, B.K.N., Srinivasa, Pai, P., Nagabhushana, T.N. (2012). Failure Diagnosis and Prognosis of Rolling - Element Bearings using Artificial Neural Networks: A Critical Overview. *Journal of Physics: Conference Series*, vol. 364, Issue 1

Rasmussen, C.E. (1996). *Evaluation of Gaussian Processes and Other Methods for Non-linear Regression*. Doctoral dissertation., University of Toronto, Toronto

Reimann, J., Kacprzynski, G., Cabral, D., Marim, R. (2009). Using Condition Based Maintenance to Improve the Profitability of Performance Based Logistic Contracts. *Annual Conference of the Prognostics and Health Management Society 2009.* September 27-October 1, San Diego, California, USA

Saha, B., Quach, C. C., & Goebel, K. (2012). Optimizing battery life for electric UAVs using a Bayesian framework. *Proceedings of the IEEE Aerospace Conference 2012*. March 3-10, Bis Sky, Montana, USA

Sankararaman, S., Ling, Y., Shantz, C., & Mahadevan, S. (2011). Uncertainty quantification in fatigue crack growth prognosis. *International Journal of Prognostics and Health Management 2011*, vol. 2, Issue 2

Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S. and Schwabacher, M. (2008). Metrics for Evaluating Performance of Prognostic Techniques. *International Conference on Prognostics and Health Management 2008*. October 6-9, Denver, Colorado, USA

Saxena, A., Roychoudhury, I., Celaya, J.R., Saha, S., Saha, B. (2010). Requirements Specifications for Prognostics: An Overview. *American Institute of Aeronautics and Astronautics*

Schaab, J. (2011). Trusted Health Assessment of Dynamic Systems Based on Hybrid Joint Estimation. Doctoral dissertation. Technische Universität Darmstadt, Darmstadt, Germany Schaab, J., Harrington, M. and Klingauf, U. (2007). Onboard Health Assessment of an Electro-mechanical Actuator Using Wavelet Features. *Proceedings of the 1st CEAS European Air and Space Conference 2007*. September 10-13, Berlin, Germany

Schwabacher, M.A., (2005). A Survey of Data-Driven Prognostics. American Institute of Aeronautics and Astronautics

Srivastra, A.N., Mah, R.W., Meyer, C. (2009). Integrated Vehicle Health Management. *NASA Aviation Safety Program*, Technical Plan 2009

Venkat, V., Raghunathan, R., Kewen, Y. and Suryari, N.K. (2003). A review of process fault detection and diagnosis Part I: Quantitative model-based methods. *Computers and Chemical Engineering 2003*, vol. 27, Issue 3, pp. 293-311

Venkat, V., Raghunathan, R., Kewen, Y. and Suryari, N.K. (2003). A review of process fault detection and diagnosis Part II: Qualitative models and search strategies. *Computers and Chemical Engineering 2003*, vol. 27, Issue 3, pp. 313-326

Venkat, V., Raghunathan, R., Kewen, Y. and Suryari, N.K. (2003). A review of process fault detection and diagnosis Part III: Process history based methods. *Computers and Chemical Engineering 2003*, vol. 27, Issue 3, pp. 327-346

Wang, Y., Wang, W. (2012). Failure Prognostic of Systems with Hidden Degradation Process. *Journal of Systems Engineering and Electronics*, vol. 23, Issue 2, pp. 314-324, doi: 10.1109/JSEE.2012.00039

Wilmering, T.J., Ramesh, A.V. 2004. Assessing the Impact of Health Management Approaches on System Total Cost of Ownership. *IEEE Aerospace Conference 2005*. March 5-12, Big Sky, Montana, USA

Ypma, A. (2001). *Learning Methods for Machine Vibration Analysis and Health Monitoring*. Doctoral dissertation. Technische Universiteit Delft, Delft, Netherlands

Zhang, X., Pisu, P. (2012). An Unscented Kalman Filter Based Approach for the Health-Monitoring and Prognostics of a Polymer Electrolyte Membrane Fuel Cell. *Annual Conference on Prognostics and Health Management 2012.* September 23-27, Minneapolis, Minnesota, USA

Zhu, J., Yoon, J.M., He, D., Qu, Y., Bechhoefer, E. (2013). Lubrication Oil Condition Monitoring and Remaining Useful Life Prediction with Particle Filtering. *International Journal of Prognostics and Health Management 2011*, vol. 4, Special Issue Wind Turbine PHM

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Aircraft Preventive Diagnosis Based on Failure Conditions Graphs

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ABSTRACT

Modern aircraft are designed to be fault-tolerant. Current maintenance systems provide diagnosis of existing faults, capabilities to do trend monitoring, but no information about the real-time remaining tolerance margin knowing the existing faults, and regarding next incoming MMEL (Master Minimum Equipment List) items that impact aircraft dispatch capabilities.

This paper presents a new concept of aircraft preventive diagnosis based on failure conditions graphs with the associated logical framework. The complete method was successfully applied by Airbus on A380 use cases. The first part of the present paper gives the formal logical definitions for the aircraft preventive diagnosis and remaining margin, distance, risk rate. The second part gives an application example based on the landing gear system of an aircraft and also the lessons learnt from Airbus on A380. Finally, the last section provides a logical integration of preventive diagnosis with prognosis that opens new perspectives.

1. INTRODUCTION

Aircraft manufacturers design modern aircraft to be faulttolerant. Historically, the first reason for that came from *safety* considerations. *Availability* is the second reason.

Aircraft are designed with high reliability equipment and with system redundancies. Nonetheless, failures can still occur, and flight delays or cancellations lead to higher operating costs for airlines. For an aircraft, the MEL (Minimum Equipment List) is a document certified by airworthiness authorities enabling the pilot-in-command to determine whether a flight may be commenced or continued from any intermediate stop, should any instrument, equipment or systems become inoperative. "Experience has proved that some unserviceability can be accepted in the short term when the remaining operative systems and equipment provide for continued safe operations" (refer to Vincent Chérière et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Attachment G to ICAO Annex 6). The primary objective of the MEL is to, therefore, reconcile an acceptable level of safety with aircraft profitability, while operating an aircraft with inoperative equipment. The MMEL (Master Minimum Equipment List) is an operational document, based on the JAR OPS-1. It is an approved deviation of the aircraft Type Certificate.

Aircraft manufacturers took benefit from last technologies and last interdependent systems architectures in order to make the aircraft able to fly under MMEL conditions, although some faults without impacting effect may remain present. This has been possible thanks to more and more cooperative aircraft systems, that are more and more interconnected, sharing modular avionics, exchanging hydraulic power, electrical power, mechanical forces. On the one hand, this gives the possibility to define alternative system's functioning modes in case of fault and then a more fault-tolerant aircraft, but, on the other hand, this makes aircraft diagnosis more difficult. Indeed, it is much more complex to isolate failures when failures propagate and even more when faults accumulate.

2. BACKGROUND

It is undesirable for aircraft to be dispatched with inoperative equipment and such operations are permitted only as a result of careful analysis of each item to ensure that the acceptable level of safety, as intended in the applicable JAR, is maintained. A fundamental consideration is that the continued operation of an aircraft in this condition should be minimized. Therefore, the airline operators need help from aircraft diagnostic systems in order to isolate failures, identify faults and manage the fault-tolerance remaining margins on the aircraft.

The last on-board maintenance systems provide some information enabling preventive maintenance. On Airbus A380 aircraft, the centralized maintenance system provides the list of pending items to fix before they combine with next failures and lead to MMEL items impacting aircraft dispatch. The aircraft condition monitoring system generates preventive reports that include aircraft parameters enabling the airline to do trend monitoring on some parameters, so that preventive maintenance can be done upon preventive conditions. Ground tools like Airbus AIRMAN provide statistical functions enabling analysis of the history of aircraft maintenance messages over the aircraft fleet. These statistical indicators can be used to trigger preventive maintenance actions.

Nevertheless, none of these systems provide information about the real-time remaining tolerance margin before the occurrence of the next impacting MMEL item, in terms of additional remaining failures of line replaceable units, failure combination, and quantified risk. This status about the remaining margins is very important for the preparation of an optimized preventive maintenance planning and the associated maintenance job orders.

3. NEED FOR AN INTEGRATED LOGICAL FRAMEWORK AND RELATED WORK

To answer these expectations, it is needed to find a framework that:

- Enables to reason on failure combinations and propagation in the aircraft,
- Enables to abduce remaining tolerance margins that are possible thanks to remaining healthy equipment in the aircraft,
- Can be extended to Prognostics so that aircraft diagnostic and prognostic reasoning are integrated, ensuring logical consistency, and taking benefit from integrated and common aircraft knowledge,
- Enables to quantify risk with respect to future aircraft dispatch, integrating information from Diagnostics and Prognostics.

The main contribution of this paper is to define a logical framework that answers these needs.

The logical framework defined in the rest of this paper is based on the theory of model-based diagnosis defined by Reiter et al. (1992) that settled fundamental concepts of consistency-based diagnosis, worked on and improved by the DX' research community for more than 20 years.

Many research works have been done on Diagnostics, on the one hand, and on Prognostics on the other hand. Few of them propose to integrate Diagnostics reasoning with Prognostics reasoning, for instance in (P. Ribot, Y. Pencolé, M. Combacau, 2008, 2009), (N. Belard, Y. Pencolé, M. Combacau, 2011), or (I. Roychoudhury & M. Daigle, 2011). But, to the best of our knowledge, very few enable to reason on multiple failures combining with multiple degradations propagating in a fault-tolerant system, and to quantify remaining risks as it is needed there.

4. LOGICAL FRAMEWORK

4.1. Definition 1. (Aircraft)

An aircraft is a triple (SP, AO, DM) where:

- SP, the aircraft system pattern, is a finite set of first-order sentences
- AO, the accusable objects, is a finite set of constants
- DM, the detection mapping, is a finite set of first-order sentences

4.2. Definition 2. (Accusable Object)

An accusable object is a logical constant designating an object that can be suspected by the diagnostic function. Accusable objects are organized according to the following groups:

- Hardware Fault Candidates, including the line replaceable units handled by line maintainers
- Software Fault Candidates, including the software that can be loaded by line maintainers
- Wiring Fault Candidates
- Regular Inoperative Conditions Example: System safety test in progress.
- Environmental Conditions Example: Icing conditions.
- Operational Conditions Example: Overspeed.
- On-going Maintenance Conditions
 Example: Circuit-breaker open and locked.

4.3. Definition 3. (Predicate Ab(.))

We adopt Reiter et al. convention that Ab(a) is a literal which holds when Accusable Object a is behaving abnormally.

Ab(.) is a unary predicate. Semantically, Ab(.) represents the abnormality of an Accusable Object; while \neg Ab(.) represents its normality.

4.4. Definition 4. (Failure Condition)

A Failure Condition is a logical constant that designates a condition having an effect on the airplane and/or its occupants, either direct or consequential, which is caused or contributed to by one or more failures or errors, considering flight phase and relevant adverse operational or environmental conditions, or external events.

4.5. Definition 5. (Dispatch Condition)

A Dispatch Condition is a logical constant that designates the set of conditions to be fulfilled as specified by MMEL, in order to allow aircraft operation with a specific inoperative item.

Example of dispatch condition: *Cargo Door Inoperative In Closed Position.*

A Dispatch Condition may have one Dispatch Status that can be:

- no dispatch (also denoted "NO GO")
- dispatch under conditions (maintenance (m) or operational (o), it is also denoted "GO IF"),
- dispatch (also denoted "GO").

4.6. Definition 6. (Observation)

An observation is a logical constant.

Observations are of two main types: automatic reported observations (e.g. ECAM messages on Airbus A380) and human observations (e.g. check done during the pre-flight inspection).

Examples of observations:

- ECAM Message *APU FAULT*
- Human inspection reporting an *Hydraulic leakage in* brake circuit
- First-order assertion of the Aircraft Condition Monitoring System: *Command Voltage* > 5V
- Built-In Test Software Fault Report Code reported by a sub-system of the aircraft: *3231F542*.

4.7. Definition 7. (Predicate Reported(.))

The logical predicate Reported(.) applies on Observations and is defined as follows: Reported(o) is a literal which holds when Observation o is reported.

4.8. Definition 8. (Detection Mapping)

A Detection Mapping is a finite set of first-order sentences $\{DM_i\}_i$ complying with the following production rules:

Let O_i be an Observation and FC_i be a Failure Condition

$$DM_i = (FC_i \vDash Reported(O_i))$$
 (1)

$$DM_i = (\neg FC_i \vDash Reported(O_i)) \quad (2)$$

4.9. Definition 9. (System Pattern)

A System Pattern is a finite set of first-order sentences ${SP_i}_i$ complying with the following production rules:

Let AO_i be some Accusable Objects. Let FC_i , FC_j , FC_k be some Failure Conditions. Let DC_p , DC_q , DC_r be some Dispatch Conditions.

$$SP_i = \left(Ab(AO_i) \vDash FC_j\right) \tag{3}$$

$$SP_i = \left(FC_i \models FC_j\right) \tag{4}$$

$$SP_i = \left(FC_i \land FC_j \models FC_k\right) \tag{5}$$

$$SP_i = \left(\neg FC_i \land FC_j \vDash FC_k\right) \tag{6}$$

$$SP_i = (FC_i \models DC_n) \tag{7}$$

$$SP_i = \left(DC_p \models DC_q\right) \tag{8}$$

$$SP_i = \left(DC_p \land DC_q \models DC_r \right) \tag{9}$$

5. FROM FAULT TOLERANCE TO MARGIN VERSUS EFFECTS

5.1. Definition 10. (Aircraft Diagnosis)

Let *R* be a set of reported Observations.

$$R = \{Reported(o_i)/o_i \text{ is an Observation}\}$$

A diagnosis Δ for an aircraft (*SP*, *AO*, *DM*) with given reported Observations R, is a set of Accusable Objects such that:

$$SP \cup DM \cup \left\{ \bigwedge_{f \in \Delta_F} Ab(f) \right\} \cup \left\{ \bigwedge_{h \in \Delta_H} \neg Ab(h) \right\} \vDash R$$
(10)
$$\Delta = \Delta_F \cup \Delta_H$$
$$\Delta_F \cap \Delta_H = \emptyset$$

 Δ_F is called the set of *faulty* Accusable Objects, Δ_H is called the set of *healthy* Accusable Objects.

5.2. Definition 11. (Aircraft Preventive Diagnosis)

Let *DC* be a set of Dispatch Conditions.

Let *R* be a set of reported Observations.

 $R = \{Reported(o_i)/o_i \text{ is an Observation}\}.$

A preventive diagnosis Δ_P preventing from *DC* for an aircraft (*SP*, *AO*, *DM*) with given reported Observations R, is a set of Accusable Objects such that:

$$SP \cup DM \cup \left\{ \bigwedge_{f \in \Delta_{PF}} Ab(f) \right\} \cup \left\{ \bigwedge_{h \in \Delta_{PH}} \neg Ab(h) \right\} \vDash R \cup DC \quad (11)$$
$$\Delta_{P} = \Delta_{PF} \cup \Delta_{PH}$$
$$\Delta_{PF} \cap \Delta_{PH} = \emptyset$$

 Δ_{PF} is called the set of *preventive faulty* Accusable Objects, Δ_{PH} is called the set of *preventive healthy* Accusable Objects.

5.3. Solving Aircraft Diagnosis or Aircraft Preventive Diagnosis

A possible solving process for Aircraft Diagnosis or Aircraft Preventive Diagnosis can be the General Diagnostic Engine (GDE, J. de Kleer and B. C. Williams, 1987), as proven in (N. Belard, 2012).

5.4. Definition 12. (Remaining Margin)

Let DC be a set of Dispatch Conditions.

Let *R* be a set of reported Observations.

Let A_c be an aircraft (SP, AO, DM).

Let *D* be the set of all Aircraft Diagnosis for A_c with given reported *R*.

Let *P* be the set of all Aircraft Preventive Diagnosis preventing from *DC* for A_c with given reported *R*.

For a given Δ_P in P, a Remaining Margin μ is a set of Accusable Objects in *AO* such that:

 $\mu = \{o \in AO\}$

$$\exists \Delta_P \epsilon P \text{ such that } \forall o \in \mu, o \epsilon \Delta_P \text{ and } Ab(o) \quad (12)$$

$$\nexists \Delta \in D \text{ such that } \forall o \in \mu, o \in \Delta$$
 (13)

In other words, all objects *o* are suspected within an aircraft preventive diagnosis but the objects *o* are not suspected in any aircraft diagnosis.

5.5. Definition 13. (Remaining Distance)

The Remaining Distance d_{μ} of a Remaining Margin μ is defined as the cardinality of μ :

$$d_{\mu} = |\mu| \tag{14}$$

5.6. Definition 14. (Remaining Risk Rate)

Let suppose that a failure rate is attributed to every Accusable Object in the aircraft.

$o\epsilon AO \rightarrow \lambda(o)\epsilon]0,1[$

The Remaining Risk Rate ρ_{μ} of a Remaining Margin μ is the scalar product of the failure rates of all Accusable Objects in the Remaining Margin:

$$\rho_{\mu} = \prod_{o \in \mu} \lambda(o) \tag{15}$$

6. Representation based on oriented graphs

For a more intuitive representation that is easier to handle by aircraft systems engineers, we use oriented graphs to represent the logical model defined by a given aircraft with reported observations.

The industrial method to build the oriented graphs was defined by Airbus and is available in (Cheriere et al, 2010, 2012).

6.1. Oriented Graph of an Aircraft

Let A_c be an Aircraft (SP, AO, DM).

The oriented graph for the aircraft A_c is composed such that the nodes are defined by:

- Ab(A) where A is any Accusable Object,
- Failure Conditions,
- Dispatch Conditions,
- Reported(o) where o is any Observation,
- Logical connector AND
- Logical connector OR
- Logical NOT

And the oriented edges are defined by the entailments given in the System Pattern and the System Mapping, knowing that the logical connectors "AND", "OR", and "NOT" are treated as logic gates.

NB: Other Gates like "XOR" (exclusive OR), \geq N (N true at least) can be obtained thanks to the usual basic logic gates.

6.2. Interface Failure Condition

Any Failure Condition node in the Aircraft Graph that has no successor is named *Interface Failure Condition*.

Indeed, the Aircraft Graph may cover only a part of all aircraft systems and these nodes stand for the interfaces with external systems.

6.3. Example

6.3.1. Introduction

Let's base the example on an aircraft landing gear system. The Figure 1 depicts an example of landing gear system of the Airbus A380.



Figure 1. A380 body and wing landing gears. Source: Wikipedia, Florian Lindner, March 2014

The position of a landing gear door is sensed thanks to proximity sensors. The Figure 2 shows the principle of a proximity sensor.



Figure 2. Principle of Proximity Switch Sensor. Source: Crane Aerospace and Electronics, March 2014. www.craneaerospace.com

The Proximity Switch Sensor is connected to a remote data concentrator that is an avionics unit providing the sensor with electrical power. The sensor gives a different current if the target (fixed on aircraft body) is close or not to the sensor (fixed on the actuated door). This information is used within the control loop of the door by the corresponding side of the landing gear control system.

For a same position, there are two redundant proximity switch sensors that are reporting to two redundant remote data concentrators.



Figure 3. Redundancy Principle for the Feedback of Proximity Sensors

As soon as the door position is lost from one redundant side of the system, the pilot will be informed of this failure by a dedicated ECAM message displayed in the cockpit.

The aircraft dispatch with no landing gear available control is not allowed by the Minimum Equipment List.

It means that it is not allowed to dispatch the aircraft with the ECAM message "LOSS OF LANDING GEAR CONTROL 1+2".

6.3.2. Accusable objects

If we limit our Aircraft to the objects at stake in Figure 3, the list of accusable objects is:

- AO₁₁: Hardware Proximity Sensor 1
- AO₂₁: Hardware Remote Data Concentrator 1
- AO_{31} : Software hosted on Remote Data Concentrator 1
- *AO*₄₁: Wiring from Proximity Sensor 1 to Remote Data Concentrator 1
- A0₅₁: Wiring from Proximity Sensor 1 to Remote Data Concentrator 2
- A0₆₁: On-going Maintenance Condition: Remote Data Concentrator 1 initiated test in progress

The objects are symmetrical for the side 1 and the side 2. The side 2 will give the symmetrical set of accusable objects.

- AO₁₂: Hardware Proximity Sensor 2
- AO₂₂: Hardware Remote Data Concentrator 2
- AO_{32} : Software hosted on Remote Data Concentrator 2
- *AO*₄₂: Wiring from Proximity Sensor 2 to Remote Data Concentrator 1
- A0₅₂: Wiring from Proximity Sensor 2 to Remote Data Concentrator 2

• A0₆₂: On-going Maintenance Condition: Remote Data Concentrator 2 initiated test in progress

6.3.3. Failure Conditions

In the example, the failure conditions that would be considered are:

- FC₁₁: Inconsistent current from Proximity Sensor 1
- *FC*₂₁: Current provided by Proximity Sensor 1 is not processed by Remote Data Concentrator 1
- *FC*₃₁: Current provided by Proximity Sensor 1 is incorrectly acquired by Remote Data Concentrator 1
- *FC*₄₁: Loss of electrical continuity between Proximity Sensor 1 and Remote Data Concentrator 1
- *FC*₅₁: Loss of electrical continuity between Proximity Sensor 1 and Remote Data Concentrator 2
- *FC*₆₁: Position information provided by Proximity Sensor 1 is incorrectly processed by Remote Data Concentrator 1
- *FC*₇₁: Feedback of door position on side 1 does not correspond to real door position
- *FC*₈₀ : Door position information are inconsistent between Side 1 and Side 2

The side 2 will bring symmetrical failure conditions (replace 1 by 2).

- FC_{12} : Inconsistent current from Proximity Sensor 2
- *FC*₂₂: Current provided by Proximity Sensor 2 is not processed by Remote Data Concentrator 2
- *FC*₃₂: Current provided by Proximity Sensor 2 is incorrectly acquired by Remote Data Concentrator 2
- *FC*₄₂: Loss of electrical continuity between Proximity Sensor 2 and Remote Data Concentrator 1
- *FC*₅₂: Loss of electrical continuity between Proximity Sensor 2 and Remote Data Concentrator 2
- *FC*₆₂: Position information provided by Proximity Sensor 2 is incorrectly processed by Remote Data Concentrator 2
- *FC*₇₂: Feedback of door position on side 2 does not correspond to real door position

6.3.4. Dispatch Conditions

In the example, let's consider the dispatch conditions:

- DC_{10} : The landing gear system cannot determine the real door position on side 1.
- DC_{20} : The landing gear system cannot determine the real door position on side 2.
- DC_{30} : The landing gear system cannot determine the real door position on side 2.

From the Minimum Equipment List, the dispatch condition DC_{30} has a NO DISPATCH status, i.e. the airline is not authorized to fly the aircraft with this condition.

6.3.5. Observations

In the example, the possible observations are:

- *OBS*₁₁: LOSS OF LANDING GEAR CONTROL 1 (ECAM Message)
- *OBS*₂₁: Conversion of Proximity Sensor 1 current by Remote Data Concentrator 1 is not plausible. (Built-In Test Report From Side 1)
- *OBS*₃₁: The Proximity Sensor 1 is disconnected from Remote Data Concentrator 1 (Human Observation)
- *OBS*₄₁: The Proximity Sensor 1 is disconnected from Remote Data Concentrator 2 (Human Observation)
- *OBS*₁₂: LOSS OF LANDING GEAR CONTROL 2 (ECAM Message)
- *OBS*₂₂: Conversion of Proximity Sensor 2 current by Remote Data Concentrator 2 is not plausible. (Built-In Test Report From Side 2)
- *OBS*₃₂: The Proximity Sensor 2 is disconnected from Remote Data Concentrator 1 (Human Observation)
- *OBS*₄₂: The Proximity Sensor 2 is disconnected from Remote Data Concentrator 2 (Human Observation)
- *OBS*₅₀: ACMF Parameter LG_CTL_1=FAILED and ACMF Parameter LG_CTL_2=FAILED
- *OBS*₆₀: LOSS OF LANDING GEAR CONTROL 1+2 (ECAM Message)

6.3.6. Oriented Graph of the Aircraft

The corresponding oriented graph for the example is given on Figure 4.



Figure 4. Oriented Graph of the Example

6.3.7. Aircraft Diagnosis

On the example, let's assume that R is the set of following reported Observations:

$$R = \{Reported(OBS_{21}), Reported(OBS_{11})\}$$

Then the diagnosis Δ for the aircraft (*SP*, *AO*, *DM*) with given reported Observations R, is:

$$\Delta = \{Ab(AO_{21})\}$$

The Figure 5 illustrates the propagation path that stands for all entailments from $Ab(AO_{21})$ to $Reported(OBS_{11})$ and $Reported(OBS_{21})$.

This figure illustrates that the graphical representation is an easy way to understand and follow how failure can propagate. When engineers design new aircraft, it is a powerful mean to share knowledge and to brainstorm on failure scenarios.

For diagnostic tool, it is a convenient representation to display details in deep troubleshooting mode. Indeed, graph is a familiar way to figure out the path from one point to another point.



Figure 5. Nodes involved in the propagation path (highlighted in yellow)

6.3.8. Aircraft Preventive Diagnosis

On the example, let consider the Dispatch Condition DC_{30} that has a NO DISPATCH status. The Aircraft Preventive Diagnoses preventing from DC_{30} for the aircraft (*SP*, *AO*, *DM*) with given reported Observations R are:

- $\Delta_P^1 = \{Ab(AO_{21}) \land Ab(AO_{12})\}$
- $\Delta_P^2 = \{Ab(AO_{21}) \land Ab(AO_{32})\}$
- $\Delta_P^3 = \{Ab(AO_{21}) \land Ab(AO_{62})\}$
- $\Delta_P^4 = \{Ab(AO_{21}) \land Ab(AO_{22})\}$
- $\Delta_P^5 = \{Ab(AO_{21}) \land Ab(AO_{42})\}$

6.3.9. Remaining Margins and Distances

From the Aircraft Diagnoses and Preventive Aircraft Diagnoses previously determined, let's give the corresponding remaining margins and distances:

- For Δ_P^1 , the Remaining Margin is $\mu_P^1 = \{AO_{12}\}$ and $d_{\mu_P^1} = 1$.
- For Δ_P^2 , the Remaining Margin is $\mu_P^2 = \{AO_{32}\}$ and $d_{\mu_P^2} = 1$.
- For Δ_P^3 , the Remaining Margin is $\mu_P^3 = \{AO_{62}\}$ and $d_{\mu_P^3} = 1$.
- For Δ_P^4 , the Remaining Margin is $\mu_P^4 = \{AO_{22}\}$ and $d_{\mu_P^4} = 1$.
- For Δ_P^5 , the Remaining Margin is $\mu_P^5 = \{AO_{42}\}$ and $d_{\mu_P^5} = 1$.

6.3.10. Remaining Risk Rate

If we suppose that each accusable object AO_i is attached with a respective failure rate λ_i , then the remaining risk rates for the remaining margins in the example are respectively:

Let λ₁₂ be the failure rate of AO₁₂. Given the remaining margin μ¹_P, let's apply the equation (15) of the Definition 14. (Remaining Risk Rate). It yields to:
 ρ_{μ¹_P} = λ₁₂

Likewise, we get the other remaining risk rates:

- $\rho_{\mu_P^2} = \lambda_{32}$
- $\rho_{\mu_P^3} = \lambda_{62}$
- $\rho_{\mu_P^4} = \lambda_{22}$
- $\rho_{\mu_P^5} = \lambda_{42}$

This enables to assess the risk that DC_{30} occurs in the next flights, and to decide to do preventive maintenance on AO_{21} , in order to keep an acceptable risk rate.

By this way, the risk of NO DISPATCH can be managed optimally according to the operational conditions of the airline.

For instance, let's suppose that:

 $\max(\lambda_{12},\lambda_{32},\lambda_{62},\lambda_{22},\lambda_{42}) > R$

where *R* is the maximum threshold accepted by the airline before triggering preventive maintenance. Then it is worth to repair the accusable object AO_{21} in order to gain tolerance margins against the dispatch condition DC_{30} .

The aircraft will continue its flight operations, being allowed to fly without any operational interruption, complying with airline (and passengers) expectations.

7. APPLICATION ON A380 AND LESSONS LEARNT

This approach was applied on Airbus A380 aircraft to model several systems and a real-time diagnostic algorithm enables to compute the Aircraft Diagnosis and Aircraft Preventive Diagnosis based on the aircraft model and the real-time observations collected from aircraft in real-time.

The Figure 6 depicts the principle of this real-time application.





The integrated aircraft graph includes more than 170,000 nodes.

Observations are automatically downloaded from aircraft to Airbus ground segment, even if the aircraft is still in-flight. These observations are the ones automatically detected by on-board systems: Continuous Built-In Tests reports, Flight Warning ECAM (Electronic Centralized Aircraft Monitor) messages, but also Aircraft Condition Monitoring Parameters that can be requested from Aircraft upon demand by the Human Operator. The Aircraft Diagnosis and the associated Aircraft Preventive Diagnosis are computed by a Diagnostic Engine reasoning on the oriented graph model.

This experience enabled to identify the following lessons learnt:

- This approach enables to get a very accurate diagnosis taking benefit from in-service experience. Indeed, the graph model can be updated on ground segment according to best in-service feedbacks.
- This Preventive Diagnosis enables to identify the risky upcoming Dispatch Conditions, so that Airbus is able to advice the airline about the best preventive maintenance to perform in order to avoid any delay, flight cancellation or high unscheduled maintenance costs.
- Nevertheless, the experience showed that Preventive Diagnosis results need to be handled by Airbus

Operators with very good overall knowledge of the aircraft and very high knowledge of the in-service experience, in order them to trigger the advice to Airline at the best time.

The fundamental problem is about predicting the time of next Dispatch Condition occurrence.

That is why it is needed to take benefit from Prognostics in order to provide indication about remaining lifetime before the Dispatch Condition occurs. This remaining lifetime can be used to organize the preventive maintenance from logistics (spare procurement, tools...) to operations (in the best conditions when the aircraft is back at its main base for instance).

8. INTEGRATION WITH PROGNOSIS

A way to solve this problem is to integrate the present preventive diagnosis approach with Prognostics that brings the capability to determine the remaining useful life before the occurrence of faults on accusable objects that are in the Remaining Margin.

For this, let's introduce additional logics.

8.1. Definition 15. (Degradation Condition)

A Degradation Condition is a logical constant that designates a condition that is an intermediate step on the way to a Failure Condition.

8.2. Definition 16. (Additional Production Rules in the Detection Mapping)

Let's extend the Detection Mapping defined in paragraph 4.8 with the following production rules:

Let O_i be an Observation and DeC_i be a Degradation Condition

$$DM_i = (DeC_i \vDash Reported(O_i))$$
 (16)

$$DM_i = (\neg DeC_i \vDash Reported(O_i))$$
 (17)

8.3. Definition 17. (Additional Production Rules in the System Pattern)

Let's extend the System Pattern defined in paragraph 4.9 with the following production rules.

Let AO_i be some Accusable Objects. Let DeC_i , DeC_j , DeC_k be some Degradation Conditions.

$$SP_i = (Ab(AO_i) \models DeC_i)$$
 (18)

$$SP_i = \left(DeC_i \vDash DeC_j \right) \tag{19}$$

$$SP_i = \left(DeC_i \land DeC_j \vDash DeC_k \right) \qquad (20)$$

$$SP_i = \left(\neg DeC_i \land DeC_j \vDash DeC_k\right) \qquad (21)$$

8.4. Definition 18. (Remaining Useful Life Before Failure Condition)

Let's define the following logical relation between Degradation Condition and Failure Condition using modal S5 logics (where \diamond means possibility).

Let's extend production rules of the System Pattern defined in paragraph 4.9 with the following one:

Let DeC_i *be a Degradation Condition and* FC_n *be a Failure Condition.*

$$SP_i = \mathcal{O}(DeC_i \models FC_n)_{RUL} \tag{22}$$

Meaning that it is possible that the Degradation Condition DeC_i entails the Failure Condition FC_n after the time duration RUL (Remaining Useful Life) has elapsed.

Then we can use the set of Kripke S5-structures where all *possible* worlds *after* RUL time has elapsed are such that

$$(DeC_i \models FC_n) \tag{23}$$

These worlds are accessible by worlds modeled by Eq. (22) before RUL time has elapsed.

Depending on the amount of different RULs expressed in the System Pattern, the number of accessible worlds increases. In other words, Prognostics enables to identify the future accessible worlds that model the aircraft.

8.5. Definition 19. (Remaining Useful Life Before Dispatch Condition)

Let DC be a set of Dispatch Conditions.

Let *R* be a set of reported Observations.

 $R = \{Reported(o_i)/o_i \text{ is an Observation}\}.$

Let's consider a preventive diagnosis Δ_P preventing from *DC* for an aircraft (*SP*, *AO*, *DM*) with given reported Observations R, as defined in paragraph 5.2.

Let's μ be a Remaining Margin for Δ_P , as defined in paragraph 5.4.

Let's *O* be an accusable object included in μ .

From the System Pattern, let D_0 be the set of Dispatch Conditions such that:

$$D_{0} = \begin{cases} DeC \text{ such that:} \\ \forall DC_{i} \in DC, (Ab(0) \models DeC) \text{and} (\Diamond (DeC \models DC_{i})_{RUL_{i}}) \end{cases}$$

 D_0 may be empty.

If D_0 is not empty, it enables to point out a subset of $\{RUL_i\}$.

The Remaining Useful Life Before Dispatch Condition is defined as:

Undefined if
$$D_0 = \emptyset$$

Min(RUL_i), $\forall i$, otherwise (24)

8.6. Graph representation

The Oriented Graph will be extended with new nodes standing for Degradation Conditions and new edges representing the entailments and possibilities added in paragraphs 8.2, 8.3, and 8.4.

8.7. Illustration of RUL on the example

Let's take the landing gear example again.

And let enrich the System Pattern with the Degradation Condition:

• *DeC*₁: Degraded Contact between Proximity Sensor 2 and its target

And with the following knowledge:

- $Ab(AO_{12}) \vDash DeC_1$
- $\Diamond (DeC_1 \vDash FC_{12})_{RUL_1}$

The Figure 7 presents the enriched graph.



Figure 7. Oriented Graph of the Example, with the Degradation Condition DeC_1 (*in green bottom left on* Figure 7)

Taking the same hypotheses as paragraph 6.3.8, the Aircraft Preventive Diagnosis preventing from DC_{30} for the aircraft (*SP*, *AO*, *DM*) with given reported Observations R will be:

- $\Delta_P^1 = \{Ab(AO_{21}) \land Ab(AO_{12})\}$
- $\Delta_P^2 = \{Ab(AO_{21}) \land Ab(AO_{32})\}$
- $\Delta_P^3 = \{Ab(AO_{21}) \land Ab(AO_{62})\}$

•
$$\Delta_P^4 = \{Ab(AO_{21}) \land Ab(AO_{22})\}$$

•
$$\Delta_P^5 = \{Ab(AO_{21}) \land Ab(AO_{42})\}$$

As well for Δ_P^1 , the Remaining Margin is $\mu_P^1 = \{AO_{12}\}$ and $d_{\mu_P^1} = 1$.

And it yields to $D_{AO_{12}} = \{RUL_1\}.$

The Remaining Useful Life Before Dispatch Condition is equal to RUL_1 . This enables to project the remaining time that is available to do preventive maintenance.

9. CONCLUSION AND PERSPECTIVES

Starting from a logical framework to formalize the problem of preventive diagnosis for airlines, the present paper proposed to define the Aircraft Diagnosis and Aircraft Preventive Diagnosis. Then the useful concepts of Remaining Margin, Remaining Distance and Remaining Risk Rate were defined. This paper proposed a graph representation of the logical aircraft model. These concepts were applied by Airbus on A380 aircraft successfully. The experience enabled to identify the need of integrating Aircraft Diagnosis, Aircraft Preventive Diagnosis with information coming from Prognostics. To do this, the logical framework was extended with concepts enabling to introduce the concept of Remaining Useful Life and to do an integrated and consistent logical reasoning with it.

This work could be followed by an extension to concepts of confidence depending on the uncertainty attached with the RUL value that is up to interest for the human decision to order preventive maintenance. Indeed, Modal Logics and validity could help to define a confident diagnosis that would be a true diagnosis in all possible worlds identified by Prognostics.

Moreover, the Graph theory and its applications in Neuroscience and Biology could help to figure out further concepts and algorithms for preventing from future Dispatch Conditions. Indeed, shall we imagine that an Aircraft System Pattern is in fact a very big molecule (of nodes) and that Degradations are in fact chemical reactions changing the composition of this big molecule in time?

REFERENCES

- R. Reiter (1987). A Theory of Diagnosis from First Principles, Artificial Intelligence, 32:57-95, 1987.
- J. de Kleer and A. K. Mackworth and R. Reiter(1992). Characterizing Diagnoses and Systems. *Artificial Intelligence*, 56:197–222, 1992.
- J. de Kleer and B. C. Williams. (1987) Diagnosing Multiple Faults. *Artificial Intelligence*, 32, 1987.
- K. D. Forbus and J. de Kleer. (1993) *Building Problem Solvers*, M.I.T. University, Press, 1993.
- Y. Shoham (1988) *Reasoning about Change: Time and Causation from the Standpoint of Artificial Intelligence*, Cambridge, Massachussets, The MIT Press.
- P. Ribot, Y. Pencolé, M. Combacau. (2008) Prognostics for the maintenance of distributed systems, *PHM'08*, *International Conference on Prognostics and Health Management*, October 6-10, 2008, Denver, USA, 2008.
- P. Ribot, Y. Pencolé, M. Combacau. (2009) Diagnosis and prognosis for the maintenance of complex systems. In

Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC). San Antonio, USA. Doi: 10.1109/ICSMC.2009.5346718.

- N. Belard (2012) Reasoning about Models: Detecting and Isolating Abnormalities in Diagnostic Systems, PhD Thesis, Toulouse, France, 2012.
- N. Belard, Y. Pencolé, M. Combacau. (2011) A Theory of Meta-Diagnosis: Reasoning about Diagnostic Systems, *Twenty-Second International Joint Conference on Artificial Intelligence*, 2011.
- I. Roychoudhury & M. Daigle (2011): An Integrated Model-Based Diagnostic and Prognostic Framework. 22nd International Workshop on Principle of Diagnosis, Murnau, Germany.
- W. Hodges (2001) Classical Logic I: First-Order Logic, in Guide to Philosophical Logic, ed. Louis Goble, Blackwell, Malden Mass. 2001.
- J-C. Laprie (1995) Dependable Computing: Concepts, Limits, Challenges, Invited paper to FTCS-25, the 25th IEEE International Symposium on Fault-Tolerant Computing, Pasadena, California, USA, June 27-30, 1995, Special Issue, pp. 42-54.
- J. de Kleer, J. Kurien (2003) Fundamentals of model-based diagnosis, 5th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, 2003.
- V. Chérière, C. Abelin, J. Roger, L. Vilalta-Estrada (2010) Procédé, dispositif et programme d'ordinateur d'aide au diagnostic d'un système d'un aéronef, utilisant des graphes d'événements redoutés, Institut National de la Propriété Industrielle, Brevet 2966616, Enregistrement 1004161.
- V. Chérière, J. Roger, V. Debray, B. Fabre, P. Chantal (2012) Procédé, dispositif et programme d'ordinateur d'aide au diagnostic préventif d'un système d'un aéronef, utilisant des graphes d'événements redoutés, Institut National de la Propriété Industrielle, Brevet 2989499, Enregistrement 1253383.
- V. Chérière, J. Roger, L. Vilalta-Estrada, I. Geanta (2012) Procédé, dispositif et programme d'ordinateur d'aide à l'analyse de la tolérance aux pannes d'un système d'un aéronef, utilisant des graphes d'événements redoutés, Institut National de la Propriété Industrielle, Brevet 2989500, Enregistrement 1253384.

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Placement of alert thresholds on abnormality scores

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ABSTRACT

The "s or more threshold trespassings out of N consecutive watch periods" detection verification strategy is known to offer advantages in terms of threshold value not too extreme under the constraint of low false alert rate, PFA. Typically PFA < 5%. The definition of PFA here considered is P(No degradation Alert). It means the probability that there is no degradation given that degradation has been detected. The alert threshold placement has previously been addressed in the case where the abnormality score with no degradation has a stationary distribution and may be approached with a continuous non parametric Parzen distribution. This is illustrated on an abnormality score of the daily lubricant consumption estimation of an aircraft engine. The watch period is a day. The N consecutive watch periods are seven consecutive service days. The s or more trespassings are six or more trespassings out of seven consecutive days. In such configuration, the threshold is 0.21 l/h, which is inside the observed distribution. With an abnormality alert strategy with no verification, i.e. s = N = 1, the threshold is a more extreme value of 0.31 l/h which is outside the observed distribution. Two steps were considered. Step 1: Learning of the abnormality score distribution with no degradation by a non parametric Parzen fit. Step 2: Threshold set by quintile interpolation on the adjustment. This is extended to the case where the abnormality score with no degradation has a discrete distribution close to a Dirac distribution. This is typically the case for abnormality scores based on "out of range" counts for measurement chains along M clock increments of a watch period, corresponding to a flight cycle. With no degradation, most of the counts during a

flight, but not all, are zero. Another example is an abnormality score based on a rough quantification of the time, "t SAV open", between the open command and the start of movement of a starter air valve, during a watch period corresponding to a start sequence. With no degradation, most of the t SAV open of a start sequence are reported "zero". Only a few start sequences trespass the few first quantification times. In these discrete cases close to Dirac the Parzen adjustment is no longer acceptable. A discrete degradation detection threshold, l, is set as a "l events or more count out of M" clock increments of a watch period, at each watch period for an "s out of N watch periods" confirmation strategy under the same constraint of P(No degradation | Alert) < PFA. This is done according to a binomial as well as a Poisson distribution on the number of events. Like in the continuous case two steps are considered. Step 1: Estimation of the ratio of discrete events with α confidence level based on the number, r, of events during a learning phase of I time increments over watch periods with no degradation. Step 2: Alert threshold set as the limit, l, on a watch period of size M for a "s out of N limit trespassings" detection strategy.

1. INTRODUCTION

This paper concerns PHM, Prognostics and health management (Sheppard, Kaufman, Wilmer, 2009). Embedded airframe systems are considered. In this area, prognosis usually starts with the detection of degradations which are precursors of "no go" conditions. It is classical to extract, each watch period, corresponding typically to a flight cycle or a flight day, a set of health indicators. These indicators may be then normalized on ground as differences between expected values, according to the recorded context parameters, and observed values (Lacaille, 2009).

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Abnormality scores are built from a set of different health indicators or as the value of a single health indicator.

Degradation detection thresholds on the abnormality scores are set, in a learning mode on a dataset of flight cycles with given hardware and software with no degradation. A concern for alert threshold choice is to find a compromise between not too many false alerts and sufficient detection. Typically, the probability of false alert (PFA) should be less than 5%. The definition of PFA here considered is P(No degradation|Alert). This is the probability of the considered embarked system to have no degradation given that a degradation alert has been emitted. PFA expresses the needs of the airlines' line maintenance seeking to limit unfounded component removals leading to "No fault found". False alert is different from the popular false positive detection (Wickens, 2002). Probability of false positive detection (PFP) is P(Alert|No degradation). This is the probability of the considered embarked system to have a degradation alert given that it has no degradation. A link between PFP and PFA can be expressed using Bayes rule (Hmad et al., 2011).

 $PFP = \frac{PFA}{1-PFA} \cdot P(Alert|Degradation) \cdot \frac{P(Degradation)}{1-P(Degradation)}$ (1) where:

- P(Degradation) is the probability per watch period of the considered degradation to occur. A watch period is typically a flight cycle or a flight day. A typical value for such probability is 10⁻⁶.
- P(Alert|Degradation), called "probability of detection" or probability of "true positive", is the probability of the considered embarked system to have a degradation alert given that it has a degradation. This probability is expected to be close to 100 %, under the constraint of PFA being small enough, typically 5 %.

Consequently, in such typical aeronautical environment, the operational requirement of PFA < 5% induces the requirement of PFP < 5 . 10^{-8} . This induced requirement is orders of magnitude less than the usual academic considerations for false positive ratio upper limit.

The matter of this study is to set alert thresholds on the abnormality scores. It is supposed that the distributions of the abnormality scores are stationary when there is no degradation. The purpose is to base the alert thresholds on a change of the distribution. Such change of distribution is considered as degradation. The constraint on PFA or PFP explained above is applied. Two situations are considered. In the first situation, the distribution of the abnormality score with no degradation may be approached with a continuous non parametric Parzen distribution (Silverman, 1986). This is illustrated by an abnormality score based on an estimation of the daily lubricant consumption. In the second situation, the distribution of the abnormality score with no degradation is close to a Dirac distribution. Most of the values are the same, in general zero. Only a few values are different. This is illustrated by abnormality scores based on "out of range" counts for measurement chains during a flight cycle. With no degradation, most of the counts during a flight, but not all, are zero. Another example is an abnormality score based on a rough quantification of the time, "t SAV open", between the open command and the start of movement of a starter air valve, during a start sequence. With no degradation, most of the t SAV open of a start sequence are reported "zero". When there are no SAV degradations, only a few start sequences trespass the few first quantification times. In these discrete cases close to Dirac the Parzen adjustment is no longer acceptable. The distributions are binomial considered or Poisson distributions on the number of events count during a watch period.

2. "S OUT OF N" VERIFICATION STRATEGY

In order to come back to more academic considerations than PFP upper limit of 5 . 10⁻⁸, an "s out of N" verification strategy is set. This means that an alert is emitted only if there are s trespassings of a given threshold on the abnormality score out of N consecutive watch periods. Such verification strategy is used in aeronautics (Pipe, 2011). It is considered to "not invoke this compromise" between PFP and probability of detection requirements.

N consecutive watch periods are considered under the hypothesis, H_0 , of a stationary distribution of the abnormality score with no degradation. An elementary threshold is set on this abnormality score such as the probability to trespass this threshold under H_0 is Pe. Then, the probability to trespass this threshold s times out of N may be calculated under H_0 according to a binomial distribution of parameters N and Pe. Conversely, Pe may be adjusted such that under H_0 the probability to trespass the threshold s times out of N is less than the required PFP. The value for Pe may be calculated as

$$Pe = B_{(s,N-s+1)}^{-1}(PFP)$$
(2)

where $B_{(s,n-s+1)}^{-1}$ is the inverse beta cumulative distribution function with parameters s and (N-s+1). This is a consequence of the well known property of eulerian functions (Coullet 1988) that $B_{(s,N-s+1)}^{-1}$ (PFP) is also {p| 1 - F_{N,p}(s - 1) = PFP} where F_{N,p} is the binomial cumulative distribution function with parameters N and p.

It appears that for N and s > 1 Pe is orders of magnitude higher than PFP. Typically, with a "s out of N", N=9 and s=7 verification strategy, according to equation (2), Pe = $B_{(s,N-s+1)}^{-1}(5.10^{-8}) = \{p|1 - F_{s-1,N}(p) = 5.10^{-8}\} \approx 5.5$. 10^{-2} .

For consistency, $B_{(1,1)}^{-1}$ being the identity function, it can be noticed that when s=1 and N =1, the "1 out of 1" alert is the basic alert with no verification.

Other examples are developed further. Two situations are considered.

3. FIRST SITUATION: CONTINUOUSLY ADJUSTABLE ABNORMALITY SCORE DISTRIBUTION.

In the first situation, the distribution of the abnormality score with no degradation may be approached with a continuous non parametric Parzen distribution (Hmad et al., 2011). This is illustrated by an abnormality score based on an estimation of the daily lubricant consumption (Figure 1).



Figure 1. Daily lubricant consumption estimation with no degradation.

The concern of alert threshold set for continuously adjustable abnormality score distributions has been addressed by the authors in several papers (Masse, Hmad, Boulet, 2012, Massé, Hmad, Grall, Beauseroy, 2013; Hmad, et al., 2013). In these contributions, the observed CDF of the abnormality score with no degradation may be fit with a Parzen non parametric continuous CDF.

A Parzen fit (Hmad et al., 2013) is appropriate for continuous abnormality scores such as engine lubricant consumption (Demaison, Flandrois, 2010). This is confirmed on the example of figure 1 by the p-value of the Kolmogorov Sirnov test which is much higher than the usual limit of 5 %. (Figure 2).



Daily consumption (1/h)



The abnormality detection threshold is then the quantile of 1-PFP with no verification strategy or 1-Pe with a verification strategy.

Figure 2 shows two abnormality score thresholds:

- 0.31 l/h for a "one shot" with no verification abnormality alert strategy with $PFP = 5.10^{-8}$
- 0,21 l/h for a "6 out of 7" alert verification strategy with $Pe = 4.4.10^{-2} \approx B_{(6,7-6+1)}^{-1}$ (PFP).

In the first case, with no verification strategy, the threshold is outside the observed distribution. In the second, with verification strategy, the threshold is inside the observed distribution. This is better in terms of threshold accuracy.

In terms of probability of detection, P(Alert|Degradation), the other side of the requirements, it can only been imagined at that stage what would be the consumption distributions at a level with impact on operations (Figure 3). Translations in mean have just been applied to the initial observed distribution with no overconsumption. These over consumptions are stated in the maintenance manual.



Figure 3. Histograms of the daily consumptions with no over consumptions and alert thresholds of figures 1 and 2 to be compared to imagined over consumption histograms.

With the no verification threshold, 90% of the mean over consumption (0.38 l/h) are alerted and 100% of strong over consumptions (0.76 l/h) are alerted. With the "6 out of 7" verification threshold, 97 % of the mean over consumptions are alerted and 100% of strong over consumptions are alerted.

Using formula 1, a posterior evaluation of PFA may be estimated, close to 5% in all cases, due to the high levels of probabilities of alerts.

4. SECOND SITUATION: ABNORMALITY SCORE DISTRIBUTION CLOSE TO A DIRAC DISTRIBUTION

4.1. Use cases

The novelty of the present study is when the abnormality score distribution is close to a Dirac distribution.

Such situation is encountered with an embedded redundant sensing system monitored by an abnormality score based on SST (Selection status) counting (Foiret, 2013). At each clock increment the status, "regular" or "out of range" is issued. The abnormality score, extracted at each flight is the number k of transitions from "regular" to "out of range" or from "out of range" to "out of range". In the case with no degradation, most of the flights have k = 0 such transitions among m clock increments. In the example of figure 2 among 750 flights, only one has k=1 and one has k=18. All the others have k=0. It is not appropriate to adjust a Parzen non-parametric distribution to an observed distribution on only three values with one prominent.



Figure 4. Example of a "close to Dirac" abnormality score distribution with no degradation.

Such situation of a distribution of the abnormality score close to a Dirac distribution may also be encountered with a continuous abnormality score with a rough sampling.





This is the case with a starter air valve (SAV) where the health indicator, "t SAV open" is the time between the open command and the start of movement. When there is no degradation of the SAV, t SAV open is mainly reported 0 seconds. In fact, the time increment is 0.125 second. Consequently, a "0" report means that t SAV open is less than 0.125 second, which is often the case with no degradation. For instance, considering 50 starts with no SAV degradation, 43 were reported "0" for t SAV open, 5 were reported between 0.125 and 0.25 second, one between 0.375 and 0.5 s and one between 0.5 s and 0.625 s (Figure 5).

A Parzen fit is no longer appropriate for such continuous abnormality scores with rough sampling. This is confirmed by the p-value of the Kolmogorov Sirnov test which is much lower than the usual limit of 5 %.

4.2. Principle

It is more appropriate to consider, rather than a threshold on a continuous score value, the number of times, k, out of M clock increments, during a flight that an undesirable event has occurred. In the example of figure 4, the undesirable events considered are

- The shift from the status "0k" to the status "out of range value" on one channel or "out of range gap" between two channels
- The confirmation of the status "out of range value" on one channel or "out of range gap" between two channels.

In the example of figure 5, the undesirable event considered is a t SAV open increment of 0.125 s.

Therefore, it is referred to a binomial or a Poisson distribution. Two steps are established: Estimation and threshold set.

- Estimation of the undesirable event ratio, \hat{p} , or $\hat{\lambda}$ on a dataset of flights with no degradation with given hardware and software.
- Threshold, *l*, set on the number, *k*, of events out of M trials where the ratio of undesirable events is higher than \hat{p} or $\hat{\lambda}$ with a probability of error
 - < PFP, where PFP is defined by formula 0 (1) for a "one shot" abnormality alert strategy
 - < Pe, where Pe is defined by formula (2) 0 for a "s out of N" trespassing alert verification strategy.

4.3. Estimation

Estimation, \hat{p}_{α} , with a confidence level α , typically $\alpha = 50\%$ or 90 %, of p, the ratio of unexpected events, in accordance with a binomial distribution of the number of unexpected events among the I cumulated time increments on a dataset of flights with no degradation with given hardware and software:

$$\hat{p}_{\alpha} = \{p|1 - F_{\mathrm{I},p}(r) = \alpha\} = B_{r+1,\mathrm{I}-r}^{-1}(\alpha)$$
(3)

where:

- $F_{I,p}$ is the binomial CDF of parameters I and p $B_{r+1,I-r}^{-1}$ is the inverse beta CDF of parameters r+1and I-r
- r is the number of unexpected events observed during the I time increments.

On figure 4, I = 750 flights x 1200 time increments in transient phase = 900000 increments. The unexpected event occurrence number is r = 1 + 18 = 19. With these data, $\hat{p}_{90\%} = 2,88 \ 10^{-5}, \ \hat{p}_{50\%} = 2,19 \ 10^{-5}$. The maximum likelihood estimation is $\hat{p}_{ML} = \frac{r}{I} \approx \hat{p}_{44\%} = 2,11 \ 10^{-5}$.

Estimation, $\hat{\lambda}_{\alpha}$, with a confidence level α , typically $\alpha = 50\%$ or 90 %, of λ , the occurrence rate of unexpected events, in accordance with a Poisson distribution of the number of unexpected events among the t_c cumulated time increments on a dataset of flights with no degradation with given hardware and software:

$$\widehat{\lambda}_{\alpha} = \left\{ \lambda \middle| 1 - F_{\lambda \cdot \mathbf{t}_{c}}(r) = \alpha \right\} = \Gamma_{r+1,t_{c}}^{-1}(\alpha) = \frac{\chi_{2\cdot r+2}^{2}(\alpha)^{-1}}{2 \cdot t_{c}} \quad (4)$$

where:

- $F_{\lambda \cdot t_c}$ is the Binomial CDF of parameter $\lambda \cdot t_c$ Γ_{r+1,t_c}^{-1} is the gamma CDF of parameters r+1 and t_c $\chi_{2\cdot r+2}^{2}$ is the inverse chi-square CDF with 2.r + 2 degrees of freedom
- r is the number of unexpected events occurrence during the t_c cumulated time increments.

On figure 4, the t_c cumulated time increments = 750 flights x 1200 time increments in transient phase = 900000. The unexpected event occurrence number is r = 1 + 18 = 19. With these data, $\hat{\lambda}_{90\%} = 2,88 \ 10^{-5}, \hat{\lambda}_{50\%} = 2,19 \ 10^{-5}$. The maximum likelihood estimation is $\hat{\lambda}_{ML} = \frac{r}{t_c} \approx \hat{\lambda}_{44\%} = 2,11$ 10-5.

On this example \hat{p} and $\hat{\lambda}$ are equal.

4.4. Threshold set

Set of a threshold, *l*, on the number k, of unexpected events, out of M time increments, during a flight cycle for which it may be considered that the ratio of unexpected events is higher than \hat{p} or $\hat{\lambda}$ with a probability of error lower than:

- Pa defined by formula (1) for a "one flight" trespassing detection strategy or
- Pe defined by formula (2) for a "s out of N flights" trespassing detection verification strategy.

Set of a threshold according to a binomial reference. The threshold l, out of N clock increments for a flight for detection of a increase of p in reference to \hat{p} is set such as P(No degradation | Detection) < PFA, typically, PFA = 5 %.

$$l = Min\{k | 1 - F_{M,\hat{p}}(k-1) \le PFP \text{ or } Pe\} =$$

$$Min\{k | B_{k, M-k+1}(\hat{p}) \le PFP \text{ or } Pe\}$$
(5)

where:

- $F_{M,\hat{p}}$ is the binomial CDF with parameters M and \hat{p}
- $B_{k, M-k+1}$ is the beta CDF with parameters k and M-*k*+1.

In other words, l is the limit on the number of occurrences of the unexpected event out of M clock increments for rejecting the hypothesis that the true ratio of unexpected events, p, is equal or more than \hat{p} with a probability of error less than PFP or Pe.

In the previous example, for M = 6000 observation increments per flight and $\hat{p}=2,19 \ 10^{-5}$ per increment

If $Pa = 5.10^{-8}$ for a "one flight" abnormality detection strategy then l = 6 unexpected events out of 6000 observation increments per flight.

If Pe ≈ 5.5 . 10⁻² for a "7 trespassing of *l* out of 9 flights" for detection then l = 2 unexpected events out of 6000 observation increments per flight.

Set of a threshold according to a Poisson reference. The threshold *l* on the number, k, of unexpected events during a flight of duration t, for detection of a increase of λ in reference to $\hat{\lambda}$ is set such as P(No degradation|Detection) < PFP, typically, PFP = 5 %. may also be set according to a Poisson reference:

$$l = Min\{k|1 - F_{\lambda t}(k-1) \le PFP \text{ or } Pe\}$$

= $Min\{k|\Gamma_{k,t}(\hat{\lambda}) \le PFP \text{ or } Pe\}$
= $Min\{k|\chi^{2}_{2,k}(2 \cdot \hat{\lambda} \cdot t) \le PFP \text{ or } Pe\}$ (6)

where:

- $F_{\hat{\lambda},t}$ is the Poisson CDF of parameter $\hat{\lambda} \cdot t$
- $\Gamma_{k, t}$ is the gamma CDF of parameters k and t $\chi^2_{2\cdot k}$ is the chi square CDF with 2 · k degrees of freedon

In the previous example, for a flight duration t = 6000 time increments, and $\hat{\lambda}=2,19\ 10^{-5}$ per time increment

If $PFP = 5.10^{-8}$ for a 'one flight' abnormality detection strategy then l = 6 unexpected events per flight.

If Pe ≈ 5.5 . 10⁻² for a "7 trespassing of *l* out of 9 flights" for detection then l = 2 unexpected events per flight.

On this example both approaches lead to the same thresholds.

4.5. Operational illustration

This is illustrated on the example of figure 5 concerning the abnormality score based on t SAV open, the time between open command and start of movement of a starter air valve. Annovingly, the 50 starts with no degradation represented on figure 5 have been followed twice by a SAV removal for reason of no opening. The t SAV open are reported on figure 6. Both estimation windows with no degradation conclude on a negative Parzen fit as on figure 5. Therefore a close to Dirac distribution estimation is set according to § 4.3 "Estimation". The first estimation is run on 50 starts with no degradation, represented on figure 5 and figure 6. The input parameters are:

• I = 50 flights x 130 time increments per flight = 6500 time increments.

• r = 5 x 1 time increment + 1 x 3 time increments + 1 x 4 time increments = 12 undesirable events



Figure 6. Example of figure 5 continued twice to SAV removal foreseen by degradation detection and affirmation.

According to formula (3) or (4) of § 4.3 "Estimation", the frequency of occurrence of undesirable event may be approached by $\hat{p}_{50\%} \approx \hat{\lambda}_{50\%} \approx 1.95 \cdot 10^{-3}$.

Two alerts are set:

- A detection alert based on a 4 trespassings out of 5 consecutive flights
- An affirmation alert based on a 7 trespassings ot of 9 consecutive flights.

According to formula (2) of § 2. "s out of N verification strategy", $Pe \approx 10^{-2}$ for 4 out of 5 detection alert verification strategy and $Pe \approx 5.51 \cdot 10^{-2}$ for 7 out of 9 affirmation alert verification strategy. According to formula (6) of § 4.4 "Threshold set", the thresholds are 3 and 1 t SAV open increments.

With these parameters, both SAV removals are foreseen (Figure 6).

The profiles of distribution change before SAV removal are different. In the first case, it may be explained by an electromechanical intermittent contact. In the second case, by a mechanical seize root cause.



Figure 7. t SAV open observed on several engines. Degradations leading to removals were reported on engine A only.

Except the outstanding case with two SAV removals of engine A, all the other cases represented on figure 7 did not lead to SAV removal. Consequently, it is expected that the detection and affirmation strategy does not alert for possible degradation. Watching the profiles, a doubt is possible with engines C and E, which scatter the values of t SAV open.



Figure 8. Parzen adjustment of the observed CDF of t SAV open on the 50 first flights.

The Parzen Kolmogorov fit test allows continuous adjustment on engine C (Figure 8).



Figure 9. t SAV open through 700 starts of engine C. No detection or affirmation are alerted.

Fortunately, no detection or affirmation are alerted (Figure 9).

Engine E, unfortunately, presents an occurrence ratio change after the estimation window. This leads to detection and affirmation alerts.



Figure 10. t SAV open through 900 starts of engine E. Even though no SAV is reported, there is obviously an occurrence ratio change after the estimation window.

5. CONCLUSION

Many PHM solutions may be killed at entry into service for two reasons:

- The first alarm is not appropriate (thresholds too low)
- The first "no go" condition is not predicted (thresholds too high).

The process presented in this paper avoids such inappropriate thresholds.

The Kolmogorov Smirnof test of a non parametric continuous Parzen fit of the abnormality score distribution allows discriminating continuous distributions from distributions close to a Dirac distribution.

This second situation is processed in two steps: Occurrence ratio estimation and alert threshold set. Both are based on the count of unexpected events during watch periods such as flights or flight days. Both refer to a binomial distribution or a Poisson distribution.

The process is completely manageable in terms of maximal false positive detection of the distribution change. The process is generic and may be used as in-service fleet follow up of a set of abnormality scores. Only the abnormality scores which have a change in distribution are highlighted. Two levels of alert were set: Detection alert, based on a 4 out of 5 threshold trespass verification and affirmation alert based on a 7 out of 9 verification.

The operational deployment however is based on two assumptions:

- The abnormality scores distributions are stationary with no degradation
- A change of the abnormality score distribution means degradation up to operational event to be predicted.

The operational illustration demonstrated a counter example of the assumptions. A starter air valve had a change in distribution which meant not degradation up to valve stuck.

REFERENCES

- Coullet J. (1988). Méthode de calcul des fonctions de répartition des lois usuelles de probabilité par le calcul direct des intégrales. *Revue de statistique appliquée*, tome 36, pages 5-18
- Demaison F., Flandrois X., Massé J.R., Massot G., Hmad O. & Ricordeau J. (2010). Méthode de suivi de la consommation d'huile dans un système de lubrification de turbomachine. Patent # 1H105790 1093FR, WO 2011131892 (A1).
- Beauseroy P., Boulet X., Grall-Maes E., Hmad O., Massé J.R. Procédé de surveillance d'une dégradation d'un dispositif embarqué d'un aéronef avec détermination automatique d'un seuil de décision (2013) Patent # FR 2990725 (A1).
- Foiret G. (2013) Système de surveillance d'une chaine de mesure d'un turboréacteur, Patent # WO 2013038091 (A1)
- Hmad O., Grall E., Beauseroy P., Masse J.R. & Mathevet A., (2011). A comparison of distribution estimators used to determine a degradation decision threshold for very low first order error. *ESREL conference*, September 18-22, Troyes, France.
- Hmad O., Masse J.R, Beauseroy P., Grall-Maës E., & Mathevet (2013). A. Maturation of Detection Functions by Performances Benchmark. Application to a PHM Algorithm. *Prognostics and System Health Management Conference*, September 9-11, Milan. *Chemical Engineering Transactions*, Vol. 33.
- Lacaille J (2009) Standardized Failure Signature for a Turbofan Engine. *IEEE Aerospace Conference*, March 7-19, Big Sky, Montana, USA.
- Masse J.R., Hmad O., & Boulet X. (2012) System PHM algorithm maturation, *First European Conference of the Prognostics and Health Management Society*, July 3-5, Dresden, Germany.
- Massé J.R., Hmad O., Grall E., Beauseroy P. (2013). System PHM Algorithm Maturation. *Prognostics and System Health Management Conference*, September 9-11, Milan. *Chemical Engineering Transactions*, Vol. 33.
- Pipe, K., & Culkin, B., (2011). Dynamic alert generation technology for condition monitoring systems. *The Eighth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies*, June 20-22, Cardiff, UK.
- Sheppard, J.W., M.A. Kaufman, and T.J. Wilmer. "IEEE Standards for Prognostics and Health Management." *Aerospace and Electronic Systems Magazine* 24, no. 9 (2009): 34–41.
- Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. London: Chapman and Hall.
- Wickens, T.D. (2002). *Elementary Signal Detection Theory* USA: Oxford University Press.

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Investigation of an Indicator for On-line Diagnosis of Polymer Electrolyte Membrane (PEM) Fuel Cell Flooding using Model Based Techniques

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ABSTRACT

The durability and reliability of producing high quality power for long periods of time have the potential to be the leading marketing factors for future hydrogen and fuel cell power sources. In the past few decades, several researchers have been devoted to investigating diagnostic techniques for fuel cell systems. However, in commercial fuel cell applications, on-line diagnosis is urgently required so that fuel cell degradation can be detected at its early stage, and mitigation strategies can be performed to recover fuel cell performance. In this paper, on-line diagnosis of fuel cell flooding is investigated. For this purpose, a generalised fuel cell stack model is developed, and water mass balance equations are used to study water balance inside the fuel cell stack. Moreover, with these equations, the flooding indicator is proposed and its relationship with liquid water inside the stack is evaluated. Results demonstrate that the proposed indicator is sensitive to the liquid water in the stack, thus can be used for flooding diagnosis. Furthermore, the expectation of the proposed indication in the cell flooding case is also presented. The advantage of this method is that parameters in the flooding indicator can be determined with measurements from tests, thus quick diagnosis can be made during the practical fuel cell operation.

1. INTRODUCTION

In the last few decades, hydrogen and fuel cells have emerged as potential initiatives that could serve as alternative energy sources, with characteristics of being zero-emission energy conversion and power generation devices. They are currently being engineered for a range of applications including automotive, stationary power, aerospace and customer electronics.

However, fuel cell reliability and durability is one of the barriers which block the wider application of fuel cell systems. A possible solution for this problem is effective diagnostic techniques. In the past few years, several studies Lei Mao et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

have been devoted to the diagnosis of fuel cell systems using both model and non-model based techniques (Fouquet et al. 2006, Giurgea et al. 2013, Hernndez et al. 2010, Onanena et al. 2013, Steiner et al. 2011, Zheng, 2013), and most of them have been verified with numerical or experimental studies. Meanwhile, there is only limited investigation about successful application of on-line diagnostic methods for commercial fuel cell systems (Ingimundarson et al. 2008, Narjiss et al. 2008, Li et al. 2013). Narjiss, et al. presented a method of using an isolated DC/DC power converter and digital signal processor to measure fuel cell harmonic impedance, thus fuel cell degradation related to gas feeding and membrane humidification could be detected by monitoring the measured impedance. Ingimundarson, et al. used hydrogen mass balance equations to detect the leak of hydrogen based on measurements from tests directly. Li, et al. employed a combination of Fisher discrimination analysis and a Gaussian mixture model to distinguish normal and faulty fuel cells using individual cell voltage measurements. With these techniques, fuel cell degradation can be detected and isolated during its operation, thus strategies can be taken to maximise fuel cell lifecycle performance. However, it should be noted that as processing of measurement data is required in these studies, with designed signal processors in the test configuration or signal processing techniques after collecting the measurements, these processings may be time-consuming in the real application, and can not give instant alert for the fuel cell degradation. Therefore, further studies are still required to investigate the on-line diagnostic techniques for fuel cell systems.

In this study, the on-line diagnosis of fuel cell flooding is investigated. The proposed indicator can give instant information about accumulated liquid water during the stack operation, and location of excess water can also be indicated. Therefore, the proposed indicator can not only detect the fuel cell stack flooding, but also show the amount of accumulate water inside the fuel cell stack, which can be used to quantify the level of flooding. As water management is one of the key points for fuel cell performance, enough water should be kept in the membrane for the passage of hydrogen ions, but too much water will block the reaction sites, thus preventing reactant gases within the fuel cell (Knowles et al. 2010, Schmittinger et al. 2008, Wu et al. 2008). Moreover, flooding is an aging factor for fuel cell, that is, its performance will be reduced gradually. However, if flooding is not detected and mitigated at its early stage, it will lead to irreversible damage to the membrane, causing failure of the fuel cell (Ous and Arcoumanis, 2013, Rama et al. 2008).

In the paper, the water balance equations at the anode and cathode will be presented, these equations are commonly used in fuel cell system models (Khan and Lqbal, 2005, Pukrushpan, 2003, Mann et al. 2000), discussed in section 2. With these equations, water accumulation rates are calculated to study the water balance inside the fuel cell with a numerical study described in Section 3. Furthermore, section 4 proposes a flooding indicator, which can be used in practical fuel cell applications as it can be easily obtained using measurements during fuel cell operation. Numerical results show that the indicator can represent the liquid water condition inside the fuel cell, and sensitivity of the indicator is also studied. Section 5 predicts the performance of the proposed flooding indicator under the fuel cell flooding case, based on its performance under normal fuel cell operation. Finally, conclusions are given and further work is suggested.

2. FUEL CELL STACK MODEL

The Proton Exchange Membrane (PEM) fuel cell typically includes two porous electrodes separated by a proton conducting membrane, which is impermeable to gases but can allow proton to pass through it. Catalyst is commonly used to separate electrodes from the membrane.

During fuel cell operation, hydrogen enters the cell on anode side while air enters on the cathode side. A catalyst on the anode side splits hydrogen atoms into electrons and positive charge hydrogen protons. The protons can pass through the membrane while electrons pass the electrical circuit to reach the other side. Voltage is created across the cell by passed protons. A catalyst on the cathode side will react passed protons, electrons, and oxygen to form water and also product heat.

According to previous studies (Khan and Lqbal, 2005, Pukrushpan, 2003), a fuel cell model can be developed to express the behaviour of the fuel cell. In the fuel cell model, the water condition inside the cell should be considered, and the water balance equations are usually used for this purpose. Based on these investigations, the water balance equations at the cathode and anode sides should be expressed separately (Eqs. 1 and 2 respectively):

$$\frac{dm_{w,ca}}{dt} = W_{v,in,ca} + W_{l,in,ca} + W_{v,gen} + W_{v,membr} - W_{v,out,ca} - W_{l,out,ca}$$
(1)

$$\frac{dm_{w,an}}{dt} = W_{v,in,an} + W_{l,in,an} - W_{v,membr} - W_{v,out,an} - W_{l,out,an}$$
(2)

Where m is the gas mass (kg), W is the gas mass flow rate (kg/s). Subscripts used in the equations have different meanings, 'ca' and 'an' mean cathode and anode, respectively, 'in' represents inlet flow terms, 'out' represents outlet flows, 'reacted' means reacted gas, 'l' represents liquid water, while 'v' means water vapour, and 'membr' represents water vapour across the membrane. From Eqs.(1) and (2), the water accumulation rates at the cathode and anode can be calculated. It should be noted that inlet water vapour, inlet liquid water, generated water product can be measured directly, outlet water vapour and liquid water can be obtained using measurements during fuel cell operation, and water across the membrane should be determined with the model.

3. INVESTIGATION OF WATER ACCUMULATION INSIDE THE FUEL CELL USING THE WATER BALANCE EQUATIONS PUBLICATION BY THE ANNUAL SOCIETY OF THE PROGNOSTICS AND HEALTH MANAGEMENT SOCIETY

3.1. Development of the Fuel Cell Model

With the water balance equations in section 2, water balance inside the fuel cell can be investigated. In this study, a generalised fuel cell model is developed, which includes modules determining anode and cathode flows, a module which evaluates membrane condition, and a module calculating fuel cell voltage. Fig. 1 shows the block diagram of the developed fuel cell model, details of the model, such as detailed differential equations, and determination of model parameters, can be found in other studies (Ous and Arcoumanis, 2013, Rama et al. 2008, Khan and Lqbal, 2005).



Figure 1 Fuel cell model block diagram

3.2. Verification of Developed Fuel Cell Model

Before using the developed model for analysis, its performance is verified with polarisation curves from previous studies (Khan and Lqbal, 2005). Table 1 lists the input parameters from tests in the reference paper, and Fig. 2 depicts the comparison of the polarisation curves from test data in the reference and the data from the developed model. It can be observed that the polarisation curves match well,

which indicates the developed model can express the fuel cell stack behaviour with good quality.

Table 1 Input parameters for fuel cell model from Khan and Lqbal, (2005)

indicated in the figure reflecting the warm up stage and the stable state of the fuel cell stack (shown by the bold vertical line). The reason for this is that the fuel cell stack requires some time to reach the balanced state.

Parameter	Value
Number of fuel cells	54
Active electrode area of	46.5cm ²
single cell	
Hydrogen flow rate	1.15 stoich
Air flow rate	2.0 stoich
Hydrogen pressure	3.5 bar
Air pressure	3.5 bar



Figure 2 Comparison of polarisation curves from the model and test in Khan and Lqbal, (2005)

3.3. Investigation of Water Accumulation Inside the Fuel Cell

With the developed fuel cell stack model, the water balance at the cathode and anode can be evaluated with Eqs. (1) and (2). It should be mentioned that as the performance of the developed model has only been verified under normal operations, its performance under degradation conditions needs further verification, thus in this study, only the normal operation condition is used for analysis. Moreover, a constant current value of 20A is employed in the analysis, this value can give high cell voltage and low parasitic power demand, leading to about 50% system efficiency at full load, which is commonly used in practical fuel cell systems.

Fig. 3 depicts the cell voltage, and water accumulation rates at the anode and cathode with a cathode relative humidity (ratio of the partial pressure of water vapour in the mixture to the saturated water vapour pressure at same temperature and pressure) of 1, which can give optimal fuel cell performance. It can be observed that without fuel cell degradation, the individual cell voltage will reach a stable value, and the water accumulation rate approaches zero. However, unbalanced water content and increasing trend of cell voltage can be found at the beginning, which is



Figure 3 Cell voltage and water accumulation rates under normal cell condition

By increasing the cathode relative humidity to 2 (under this condition, water will be accumulated inside the fuel cell stack, but the stack voltage will not decrease, this can be seen from Fig. 4a), more water may be kept at the cathode side, the performance of the cell model is analysed and results are shown in Fig. 4. From the results, the same value of cell voltage at the steady state stage can be seen, which indicates no degradation exists in the fuel cell. In this case, the water accumulation rates are still zero, meaning balanced water at the anode and cathode, even with liquid

water inside the cell. However, it should be noted that in this case, the fuel cell system requires a longer time to reach the stable state, which means the fuel cell system does not work under the optimum operation condition due to the increased cathode relative humidity.



Figure 4 Cell voltage and water accumulation rates under normal cell condition with increased current

According to the results, it can be concluded that under fuel cell normal operation, water balance at the anode and cathode can be observed and water accumulation rates are zero. From these results, the flooding indicator is proposed for on-line diagnosis (as all parameters can be acquired directly and indirectly during operation, which is described in section 2), and its sensitivity to liquid water inside the fuel cell stack will be studied in following sections.

4. PROPOSED FLOODING INDICATOR AND ITS RELATIONSHIP WITH LIQUID WATER INSIDE THE FUEL CELL

As described in section 2, all terms in Eqs. (1) and (2) can be determined with measurements during fuel cell operation except water across the membrane, thus in order to use the water balance equations for on-line diagnosis, water across the membrane should not be used.

According to results in section 3, under normal operation conditions, Eqs. (1) and (2) should be zero, meaning zero water accumulation rates at anode and cathode. Therefore, the water accumulation rates can be used in this study to determine excess water inside the fuel cell stack, and the flooding indicator is proposed as the difference between the inlet and outlet water amount, which can be expressed by modifying Eqs. (1) and (2).

$$FL_{ca} = W_{v,in,ca} + W_{l,in,ca} + W_{v,gen} - W_{v,out,ca} - W_{l,out,ca}$$
(3)

$$FL_{an} = W_{v,in,an} + W_{l,in,an} - W_{v,out,an} - W_{l,out,an}$$
(4)

Where FL_ca, and FL_an are the flooding indicators for the cathode and anode sides, respectively. All other variables are as described in Eqs. (1) and (2).

Fig. 5 depicts the flooding indicator using Eqs. (3) and (4), and liquid water inside the anode and cathode with cathode relative humidity of 1. Results demonstrate that under normal conditions, flooding indicators from Eqs. (3) and (4) are the same, meaning balanced water condition inside fuel cell stack. Moreover, in this case, liquid water can not be found inside the cell, although at stack warm up stage, liquid water inside fuel cell stack can be observed.





Figure 5 Flooding indicators and liquid water at anode and cathode

The sensitivity of the flooding indicator with liquid water inside fuel cell stack is investigated by increasing the cathode relative humidity to 2, flooding indicators are calculated and shown in Fig. 6, and liquid water at anode and cathode are also depicted.





Figure 6 Flooding indicators and liquid water at anode and cathode with increased relative humidity

From figure 6(a) and 6(b), flooding indicators are about 10 times larger than that from the lower cathode relative humidity, but values from the anode and cathode are still the same, meaning water balance inside cell. Moreover, from Fig. 6(d), liquid water can be observed inside the cathode at stack steady state stage, although this does not cause a voltage drop and cell degradation, this further confirm that the fuel cell stack system does not work in the optimum operation condition. It should be noted that in this case, only the cathode relative humidity is increased, thus accumulated liquid water at anode is not found as shown in Fig. 6(c).

Moreover, with further increased cathode relative humidity, liquid water inside the cathode and corresponding flooding indicator are determined, and their relationship is depicted in Fig. 7. It should be mentioned that in these cases, the water accumulation rate is still zero, which means no degradation within the fuel cell stack.



Figure 7 Relationship between liquid water inside cathode and flooding indicator

From figure 7, the flooding indicator will increase clearly with increased liquid water inside the cathode side, which further confirms the possibility of using the proposed indicator for evaluating liquid water inside the fuel cell stack, when the accumulated liquid water inside the fuel cell stack reach a certain level, fuel cell stack begins degradation. It should be noted that when the indicator is employed for flooding diagnosis, its threshold value should be determined to define the amount of liquid water causing fuel cell stack flooding, this value may change for different fuel cell stack systems. Moreover, it will be mentioned in the next section that the proposed indicator will give different values at anode and cathode sides in flooding case due to unbalanced water condition inside the fuel cell stack.

The results can also be explained from a theoretical point of view. Under normal operation condition, water accumulation rates at the anode and cathode are zero, thus the flooding indicator is actually the water across the membrane based on Eqs. (1) and (2). Based on previous studies (Ous and Arcoumanis, 2013, Wang et al. 2013), with an increase of reactant relative humidity, the water activity of the membrane will be increased, which will lead to a higher rate of water flux across the membrane.

Based on these results, it can be concluded that the proposed flooding indicator is sensitive to liquid water inside the fuel cell stack and can be used to indicate the liquid water condition. With increased liquid water inside fuel cell stack, flooding indicator will increase significantly. Moreover, as the required parameters in Eqs. (3) and (4) can be monitored continuously during fuel cell stack operation, the indicator can provide instant information about the accumulated liquid water inside the stack.

5. EXPECTATION OF PERFORMANCE OF PROPOSED FLOODING INDICATOR IN THE FUEL CELL FLOODING CASE

According to the results in sections 3 and 4, water accumulation rates at the anode and cathode are zero, and the flooding indicator equals the water across the membrane, thus cathode and anode flooding indicators should be the same under normal fuel cell stack operation, indicating the balanced water condition within fuel cell stack.

However, with fuel cell stack flooding, excess water will be kept inside the fuel cell stack, leading to an unbalanced water condition. In this case, the water accumulation rate should be increased, and by comparison of Eqs, (1)-(4), the flooding indicator should include water across the membrane and the water accumulation rate, thus its value will not follow the trend shown in Fig. 7 and should be increased significantly.

As described before, the flow rates of inlet water vapour and liquid water can be measured directly during fuel cell stack operation, and flow rates of outlet water vapour and liquid water, and generated water product inside fuel cell stack, can be determined using measurements from tests, including anode and cathode pressures, and current. Therefore, during fuel cell stack operation, the proposed flooding indicator can be monitored continuously, and a sudden increase of the flooding indicator value indicates excess water inside the fuel cell stack, thus flooding can be diagnosed.

Further, as the flooding indicator can be calculated at the anode and cathode using Eqs. (3), (4), respectively, the location of the fuel cell stack flooding can also be determined, since flooding can cause a higher value of indicator due to a faster water accumulation rate.

The performance of proposed indicator in on-line fuel cell stack flooding diagnosis is currently being investigated with measurements from a practical fuel cell stack system, and the results can be used to further validate the effectiveness of the flooding indicator.

6. CONCLUSION

In this paper, the mass balance equations at the anode and cathode are employed to indicate the water condition inside fuel cell stack, and the flooding indicator is proposed as online method to detect excess liquid water in the fuel cell stack, which can be used for diagnosis of fuel cell stack flooding.

Under normal operation conditions, the water accumulation rates at the anode and cathode are observed to be zero with a numerical study. Based on this, the flooding indicator is proposed as the difference between inlet and outlet water amounts to express the liquid water condition at the anode and cathode. Under the normal operation condition, the proposed flooding indicator equals water across the membrane, and its performance is investigated using numerical studies by changing the cathode relative humidity. From the results, the flooding indicator is sensitive to the liquid water condition, it will be increased significantly with an increase of liquid water inside fuel cell stack.

Moreover, the performance of the proposed indicator in fuel cell stack flooding is predicted. Under the flooding condition, the flooding indicator includes water across the membrane and water accumulation rate, and excess water inside fuel cell stack will cause sudden increase of proposed indicator. By monitoring the flooding indicator during fuel cell stack operation, it is possible to detect the existence of stack flooding, and location of flooding can also be determined.

Further work will be performed to verify the effectiveness of this flooding indicator using test data from a practical fuel cell stack system, and the flooding indicator will be studied with a fuel cell stack model, which will be modified to express the fuel cell stack flooding scenario. It should be mentioned that in the practical application, the measurements will contain noises, thus before applying proposed indicator for diagnosis, signal processing techniques may be required to minimize the noise effect. Moreover, as in the practical fuel cell stack system tests, multiple degradation factors may occur simultaneously, thus a more robust flooding indicator will be investigated in order to work under more complex conditions.

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REFERENCES

- Fouquet, N., Doulet, C., Nouillant, C., Tanguy, G.D., Bouamama, B.O. (2006). Model based PEM fuel cell state-of-health monitoring via ac impedance measurements. *Journal of Power Sources*, 159(2), 905-913.
- Giurgea, S., Tirnovan, R., Hissel, D., Outbib, R. (2013). An analysis of fluidic voltage statistical correlation for a diagnosis of PEM fuel cell flooding. *International Journal of Hydrogen Energy*, 38(11), 4689-4696.
- Hernndez, A., Hissel, D., Outbib, R. (2010). Modeling and fault diagnosis of a polymer electrolyte fuel cell using electrical equivalent analysis. *IEEE Transactions on Energy Conversion*, 25(1), 148-160.

- Onanena, R., Oukhellou, L., Come, E., Jemei, S., Candusso, D., Hissel, D., Aknin, P. (2013). Fuel cell health monitoring using self organizing maps. *Chemical Engineering Transactions*, 33, 1021-1026.
- Steiner, N.Y., Hissel, D., Mocoteguy, P., Candusso, D. (2011). Diagnosis of polymer electrolyte fuel cells failure modes (flooding & drying out) by neural networks modeling. *International Journal of Hydrogen Energy*, 36(4), 3067-3075.
- Steiner, N.Y., Hissel, D., Mocoteguy, P., Candusso, D. (2011). Non intrusive diagnosis of polymer electrolyte fuel cells by wavelet packet transform. *International Journal of Hydrogen Energy*, 36(1), 740-746.
- Zheng, Z., Petrone, R., Pera, M.C., Hissel, D., Becherif, M., Pianese, C. (2013). Diagnosis of a commercial PEM fuel cell stack via incomplete spectra and fuzzy clustering. *IECON – 39th Annual Conference of IEEE*, Vienna, November 10-13, 2013.
- Ingimundarson, A., Stefanopoulou, A.G., McKay, D.A. (2008). Model-based detection of hydrogen leaks in a fuel cell stack. *IEEE Transactions on Control and System Technology*, 16(5), 1004-1012.
- Narjiss, A., Depernet, D., Candusso, D., Custin, F., Hissel, D. (2008). Online diagnosis of PEM fuel cell. 13th Power Electronics and Motion Control Conference, 2008, Poznan, Poland.
- Li Z., Outbib, R., Hissel, D., Giurgea, S. (2013). Online diagnosis of PEMFC by analysing individual cell voltages. 2013 European Control Conference, Zurich, Switzerland, July 17-19, 2013.
- Knowles, M., Baglee, D., Morris, A., Ren, Q. (2010). The state of art in fuel cell condition monitoring and maintenance. 25th World Electric Vehicle Symposium and Exposition, Shenzhen, China, November 5-9, 2010.
- Schmittinger, W., Vahidi, A. (2008). A review of the main parameters influencing long-term performance and durability of PEM fuel cells. *Journal of Power Sources*, *180(1)*, 1-14.
- Wu, J., Yuan, X.Z., Martin, J.J., Wang, H., Zhang, J., Shen, J., Wu, S., Merida, W. (2008). A review of PEM fuel cell durability: Degradation mechanisms and mitigation strategies. *Journal of Power Sources*, 184(1), 104-119.
- Ous, T., Arcoumanis, C. (2013). Degradation aspects of water formation and transport in proton exchange membrane fuel cell: A review. *Journal of Power Sources*, 240(15), 558-582.
- Rama, P., Chen, R., Andrews, J. (2008). A review of performance degradation and failure modes for hydrogen-fuelled polymer electrolyte fuel cells. *Proc.IMechE Part A: Power and Energy*, 222, 421-441.
- Khan, M.J., Lqbal, M.T. (2005). Modelling and analysis of electro-chemical, thermal, and reactant flow dynamics for a PEM fuel cell system. *Fuel Cells*, 5(4), 463-475.
- Pukrushpan, J.T. (2003). *Modeling and control of fuel cell* systems and fuel processors. Doctoral dessertation, The University of Michigan, USA.
- Mann, R.F., Amphlett, J.C., Hooper, M.A.I., Jensen, H.M., Peppley, B.A., Roberge, P.R. (2000). Development and application of a generalised steady-state electrochemical model for a PEM fuel cell. *Journal of Power Sources*, 86(1-2), 173-180.
- Wang, H., Li, H., Yuan, X.Z. (2011). *PEM fuel cell failure* mode analysis. CRC Press

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Derivation of Fuzzy Diagnosis Rules for Multifunctional Fuel Cell Systems

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ABSTRACT

This paper presents a model-based approach for the derivation of fuzzy diagnosis rules. These are used to classify data of faulty system behavior in order to identify root causes. The data is gained from an extended simulation model of a multifunctional fuel cell system for aircraft use. Faulty behavior is implemented into each component and a bottom up simulation is carried out. The data gained is classified according to root causes. This means that each data vector is assigned to a class representing one type of simulated fault. The classified data is then fed into an evolutionary optimization procedure. There it is weighted and separated into training and validation data.

Inside the optimization procedure, the structure of the fuzzy diagnosis rule is represented by a chromosome that has a discrete and a real valued part. The discrete part describes the selection of a signal and the real valued part states parameters of the membership function for each signal. Based on training data, a genetic algorithm optimizes both parts and a set of optimal binary and real valued parameters is gained. By that, one fuzzy diagnosis rule at a time is identified that best fits a set of fitness functions. On basis of this rule, weights of the training data are updated afterwards. This is done in order to guide the genetic algorithm in the next run to data vectors that are not covered effectively yet. Each run of the algorithm gives a new fuzzy diagnosis rule. The performance of the set of all rules that are gained so far is evaluated by use of validation data. Subsequently, a new run is started. This process continues until a stop criterion is reached. A set of optimal fuzzy diagnosis rules is gained in the end.

1. INTRODUCTION

The increasing scarcity of resources and growing demands on the European aviation's social, economical and environmental impact have led to the formation of scenarios and goals for the years 2020 (European Commission, 2001) and 2050 (European Commission, 2011). Besides a drastic reduction of greenhouse gases and noise, low door-to-door travel times, low accident rates, and a reliable transport function at low operating costs are demanded. In more detail, all European flights should arrive within one minute of the planned arrival time. Comparing this goal with data of the year 2012 (European Organisation for the Safety of Air Navigation, 2013b), 16.7% of all European flights had a delay of more than fifteen minutes. This was mainly due to technical issues (European Organisation for the Safety of Air Navigation, 2013a), which caused maintenance actions to happen and high cost to arise. The fulfillment of the future goals for European air traffic is thus far from being reached. This is even intensified with respect to new complex technologies to be integrated into the system's architecture of future aircraft.

An approach of current research deals with the integration of fuel cells (FC) on board of short range aircraft. FC enable the generation of electrical power without the emission of greenhouse gases and noise. In order to use these ecological benefits, a current concept consists in the replacement of the Auxiliary Power Unit (APU). The APU is a combustion engine that is mainly used to deliver electrical power during ground phase. However, the provision of the same amount of power using FC results in a highly increased system weight. Hence, in order to make sure, that the use of FC is not only ecologically beneficial, but also economically feasible, the integration of FC has to be done in a multifunctional way. This means that all products of the FC have to be used. By that, FC do not only deliver electrical power, but also oxygen depleted air for tank inerting and fire suppression, as well as process water (Enzinger, 2010).

A simplified integration of FC into an aircraft architecture on basis of an Airbus A320 is shown in Figure 1. In this concept, FC are used to provide electrical power during ground operation for the conventional on-board systems as well as for an electrical taxiing system. Another product of the elec-

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trochemical process is humid oxygen depleted air. This is cooled down, dried and used for kerosene tank inerting. The resulting heat flow is conducted to the wing's leading edge for anti-icing and the water is fed to the on board water system. A complex system architecture and many challenges arise thereby.



Figure 1. Integration of fuel cell technology into the overall aircraft systems architecture.

Summarizing the current status, FC on board of future aircraft can drastically reduce the emission of greenhouse gases and noise, and contribute to the fulfillment of future goals of European air traffic. This is achieved beneficially by a multifunctional integration strategy. However, the complex system architecture and the ambitious operational goals for the year 2050 lead to many challenges. Without proving that a multifunctional fuel cell system (MFFCS) can be operated and maintained beneficially there will be no chance to bring it on board of future aircraft. Hence, efficient health management functions are required. Tasks to be performed are reasoning about causes and effects, and early failure detection amongst others. This leads to challenges like optimal sensor placement, and the definition of built-in-test procedures. Handling these issues in a manual way is laborious, cost intensive and prone to human errors. A systematic and model-based development process is therefore needed. This is addressed in this paper in terms of fuzzy diagnosis rules. These are used for inferring causes of detected failures and malfunctions as a new type of a built-in-test procedure.

This paper is organized as follows. In Section 2, the concept of fuzzy diagnosis rules is introduced and motivated. A model-based approach to gain an optimized set of rules is shown in Section 3. Results of a study on a multifunctional fuel cell system are depicted in Section 4. The content of the paper is summarized in Section 5 and an outlook on open topics is given.

2. MOTIVATION

A multifunctional fuel cell system has to function efficiently, but also to be operated economically. Hence, a poor availability of operation can be a major drawback for a successful integration on board of future aircraft. Due to that, there is a distinct need to detect failures and malfunctions as early as possible, and identify root causes to an adequate level, so that economic damage can be avoided. These actions can be supported by means of a diagnosis function that works with diagnosis rules (Modest & Thielecke, 2012). These consist of a premise holding an indicator, and a conclusion suspecting or clearing candidates of root causes. In order to clarify this concept, basics are explained in the following.

An indicator of a diagnosis rule can have the discrete values $\{-1, 0, 1\}$ representing the colors $\{Low, Nominal, High\}$. An example is given in Figure 2 where two signals are shown. E001 represents a measurement of fuel cell current, and TX3A represents a measurement of air temperature. At the instant of time t_F a failure at the component level is simulated. A change in system behavior can be observed afterwards. This change is evaluated with respect to thresholds and persistence times. By that, at the instant of time $t_{D,1}$ the indicator E001 gets the color Low, and at the instant of time $t_{D,2}$ the indicator TX3A gets the color High.



Figure 2. Measurements of faulty behavior and indicators with discrete values.

The indicators are used to match premises of two types of discrete diagnosis rules. These are *suspect* and *clear* rules where the first one has the following form:

if
$$E001 = Low$$
 then suspect {LRU A,.., LRU K}. (1)

Suspect rules are used as starting point of the reasoning process. By means of this type of rule a set of potential root causes, e.g. a line replaceable unit (LRU) or a specific failure mode on the component level, is generated and hypotheses are gained. These hypotheses can fully explain the indicator color. In order to test the necessary condition for the particular hypothesis, further indicators and clear rules are used. These have the following form:

if TX3A = High then clear {LRU C, LRU D, LRU E}. (2)

By means of several clear rules the necessary condition for all the suspected candidates is tested so that the final diagnosis is inferred. According to the required level of detail, this can be a set of components including the real root cause. However, requiring a very detailed level of isolation, e.g. having a final diagnosis of only one suspect, could lead to a high amount of indicators needed and by that to many sensors to be integrated into the system. An approach for avoiding this necessity can consist in using indicators having not only discrete but *fuzzy* values. By that, not only exceeding of a threshold is taken into account but also the level of exceedance. An example for that is shown in Figure 3.

Threshold



Figure 3. Taking into account the level of exceedance of a threshold for discrimination between failures. a) Failure A. b) Failure B.

In the example, there are two failures simulated. These lead to the same indicator color which is E001 = Low. Based only on this information, the root cause can't be inferred exactly. However, taking into account the level of exceeding of the threshold, now offers the possibility to discriminate between the failures. The level of absolute exceeding of the threshold for Failure A is smaller than for Failure B. These levels are used to derive several fuzzy sets that are then used as the premise of a diagnosis rule whose conclusion is a suspected component. This states a fuzzy diagnosis rule. An example looks like follows:

if E001 = Low with Exceeding =
$$a_{E001}^{1}$$
 (3)
then suspect LRU A with certainty ϵ_{LRUA} .

In Equation 3, the term a_{E001}^1 is a fuzzy set that is related to the exceeding of a threshold. With respect to the pattern, that matches the premise, the rule's conclusion is the suspect LRU_A with certainty degree ϵ_{LRUA} . Compared to Equation 1 only one suspect is left. Clear rules are omitted in this new concept. In the next section, a model-based approach to derive the required fuzzy sets in an optimized way and gain a set of fuzzy diagnosis rules is presented.

3. FUZZY DIAGNOSIS RULES

Fuzzy diagnosis rules are used to match and classify faulty system behavior during operation. Knowledge about this behavior is gained on basis of an extended system model. This enables the simulation of failures at component level. Effects at system level are gained through different types of sensors and are structured in a matrix format. This is shown in Section 3.1. The effects are evaluated by using fuzzy inference. The basics are presented in Section 3.2. There, matching degree and membership function are explained and it is shown which parameters have to be determined for the derivation of fuzzy diagnosis rules. These parameters are gained in an optimized way on basis of an evolutionary optimization procedure. This is introduced in Section 3.3. The entire process for the derivation of fuzzy diagnosis rules is shown in Section 3.4.

In general, a fuzzy diagnosis rule should have the following structure:

if
$$f_i^v = A_i$$
 with Exceeding = a_i
and ... and $f_j^v = A_j$ with Exceeding = a_j (4)
then suspect FM_x with certainty ϵ_{FM_x} .

The premise of the rule makes use of features f_i^v of the *i*th dimension of the feature vector f^v . These are matched to colors A_i that belong to a predefined color space, and fuzzy sets a_i . Both are conjunct for a set of features. Each of the fuzzy sets is characterized by a membership function that determines the degree of each input f_i^v belonging to the specific fuzzy set a_i . This structure is used to assign features to a class FM_x that belongs to the set of all the failures FM that are taken into account. This is done with certainty ϵ_{FM_r} .

In order to determine the required features f_i^v and the parameters of the fuzzy sets a_i , data about faulty behavior is required. This is gained on basis of an extended system model which is shown in the next section.

3.1. Extended system model

In order to derive fuzzy diagnosis rules, data about faulty system behavior is required. This data is gained from an extended simulation model which is based on a dynamic nominal system model (Grymlas & Thielecke, 2013). This has been derived by using the *Matlab* toolbox *Simscape*. This allows for an a-causal modeling of physical behavior using equations. An overview of the model is given in Figure 4.

Compressor Pipe Air-Valve Air data Environment H2-Tank H2-Valve H2-Valve H2-Valve FC-Stack B

Figure 4. Extended system model of a MFFCS.

The system model consists of two fuel cell stacks that are supplied with pressurized air by a compressor and with hydrogen by a H_2 tank. Different pipes and valves are used for transportation and control. The oxygen depleted air of both fuel cell stacks is merged, transported and separated for further tasks. This could be kerosene tank inerting and cargo fire suppression. Processing the air is done by using pipes and valves. The hydrogen that has not been used in the electrochemical process inside the fuel cells is fed back to the hydrogen supply. Pumps, valves and pipes are used therefore.

The nominal system model is extended with faulty behavior on the component level. Examples are leakages of pipes, jamming of valves and dedicated failure modes of fuel cells. An example of a failure model of a pipe of the air supply is shown in Figure 5.



Figure 5. Failure model of a pipe.

The failure model of the pipe consists of a block representing the pipe's capacity and a valve that is connected to the environment. The integration into the overall model is done by using three ports. Two of them are physical conserving and bidirectional whereas the failure mode port is directional. By means of a time controlled failure signal, the valve can be opened in order to simulate a leakage. This is done by adapting the specific flow coefficient k_v that is influencing the mass flow \dot{m}_{air} through the valve (Herwig, 2006). This is shown in Equation 5.

$$\dot{m}_{air} = k_v \cdot \sqrt{\frac{\rho_{air,in} \cdot p_{air,out}}{T_{air,in}}} \cdot (p_{air,in} - p_{air,out}).$$
(5)

After implementing all failure modes in the overall model, a bottom up simulation is carried out. The respective effects of each failure are observed by using sensors, that have been placed at several positions inside the model. An example is shown in Figure 4. By means of air data sensors, information about mass flow, pressure, temperature as well as 0_2 and H_20 fractions are gained. These values are evaluated with respect to thresholds like it is shown in Equation 6. This approach is used in order to increase the distance between the data sets of all the failure modes which facilitates the classification in later steps.

$$p_{FC1,in} * = \frac{p_{FC1,in} - \text{thresh.}_{p_{FC1,in}}}{\text{thresh.}_{p_{FC1,in}}}.$$
 (6)

An example of how the evaluated effects of different failure modes look like is depicted in Figure 6. There, data is shown for 12 failures of the air supply system of both the fuel cell stacks. Only 7 data lines can be seen. This is due to the fact of overlapping failure modes showing the same effect. This is the case for different levels of friction of air pipes for this particular feature.



Figure 6. Data of faulty system behavior.

Each line in Figure 6 represents one failure mode that has been simulated. This will be explained in more detail in Section 4.1. In the next steps, it will be worked with the respective failure data. Therefore, the data is transferred into a

matrix format which is shown in Table 1.

All available data is sampled at fixed instances of time by using a unique time vector for all failure modes. At each step of sampling, all features f_i^v , e.g. $p_{FC1,in}*$ and $T_{FC1,in}*$, are aggregated in a row of the matrix. Hence, a row always holds a vector of features f^v for a specific failure mode. The type of failure mode is represented by the *Class* variable in the last column. This procedure is done for all sampling points and repeated for all failure modes. The respective data is concatenated in the end.

The class variable c has a range from one to 12 which represents 12 failure modes that are taken into account in this study. The task of the fuzzy diagnosis rule is to classify the data vectors f^v so that the correct conclusion, meaning the correct class c can be inferred. This is done by using fuzzy inference which is explained in the next section.

Index	$p_{FC1,in}*$	 $T_{FC1,in}*$	Class c
1	14.8043	 57.7561	1
2	14.8043	 57.7561	1
3	14.8042	 57.7561	1
543	26.1362	 11.0998	2
544	26.1362	 11.0998	2
545	26.1362	 11.0999	2
4000	-12.6088	 11.0999	12

Table 1. Classified data of faulty system behavior.

3.2. Fuzzy Inference

Fuzzy inference is used by a set of fuzzy diagnosis rules in order to match features and derive conclusions. It is based on fuzzy sets in the rule's premise. These sets can be formulated by using two different approaches. The first one is descriptive with a linguistic variable from a color space. This means that each rule uses the same color for a given feature if it is in a certain range. An example would be a range of [0.1..0.4] for feature f_1^v which could be assigned to the color *Low*. A drawback is that the range is fixed and holds for all rules. Hence, the second approach is approximative where each rule is allowed to define its own fuzzy sets rather than using predefined colors. This means that each rule can work with its own range of feature values. Although this shows a lack of interpretability, it offers more granularity and by that leads to better results. This approach is used in this study.

The matching degree $\mu_n(f^v)$ of a fuzzy diagnosis rule n and feature vector f^v states the compatibility between f^v and the premise. It is defined as follows (Cox, 1994):

$$\mu_n(f^v) = \prod_{i=1}^N \mu_i^n(f_i^v).$$
(7)

In Equation 7, the term $\mu_i^n(f_i^v)$ is the membership grade of rule n in dimension i of the feature vector f^v . This is im-

plemented as a double sided *Gaussian* membership function having the form (Cox, 1994):

$$\mu_{i}^{n}(f_{i}^{v}) = \begin{cases} \exp\{\frac{-(f_{i}^{v} - m_{l}^{n,i})^{2}}{(\sigma_{l}^{n,i})^{2}}\}, & f_{i}^{v} < m_{l}^{n,i}, \\ 1, & m_{l}^{n,i} \leq f_{i}^{v} \leq m_{r}^{n,i}, \\ \exp\{\frac{-(f_{i}^{v} - m_{r}^{n,i})^{2}}{(\sigma_{r}^{n,i})^{2}}\}, & f_{i}^{v} > m_{r}^{n,i}. \end{cases}$$
(8)

In Equation 8, the terms $m_l^{n,i}$ and $m_r^{n,i}$ are the centers of the left and right Gaussian functions with widths $\sigma_l^{n,i}$ and $\sigma_r^{n,i}$. This applies for rule n and feature i.

During derivation of the fuzzy rule base, the rule consequent c_n of rule n has to be determined. This is done by calculation of the dominating class c of all the classes F among all instances f^v with class label c^f which are covered by the rule's premise:

$$c_n = \arg\max_{c=1:F} \sum_{f^v, c^f = c} \mu_n(f^v).$$
 (9)

The approach of Equation 9 is called maximum voting scheme. It uses overlapping and cooperating fuzzy sets rather than only maximum matching.

After having fixed all rule consequents c_n and having derived the entire rule base, Equation 9 is adapted to have the form:

$$c_{max} = \arg\max_{c=1:c_n} \sum_{n,c_n=c} \mu_n(f^v).$$
 (10)

Based on Equation 10, inferring a solution to the classification problem by using the derived rule base is again done by using maximum voting. This time however, the decision is made by summing up the matching degrees $\mu_n(f^v)$ for one given feature vector f^v and the conclusion c_n of rule n. The maximum argument then gives the overall conclusion c_{max} .

The degree of certainty ϵ of correct classification of class c is calculated as the ratio of the sum of matching degrees $\mu_n(f^v)$ for $c = c_{max}$ and all available feature vectors f^v referred to the overall matching degree, irrespective of the rule's consequent:

$$\epsilon_c = \frac{\sum_{f^v, c = c_{max}} \mu_n(f^v)}{\sum_{f^v} \mu_n(f^v)}, \ \mu_n(f^v) > 0.$$
(11)

In order to identify those parameters of the fuzzy inference so that the desired behavior of correct classification with a high degree of certainty is achieved during operation, fuzzy modeling is used. This can be done manually but is complex and prone to failure. The use of automatic approaches for the derivation of membership functions and rule base is motivated thereby.

In literature there are mostly non technical but medical and geographical approaches that use evolutionary algorithms to automatically and optimally construct rule base and membership functions (Herrera, Lozano, & Verdegay, 1995) (Andres Pena-Reyes & Sipper, 1999) (Gonzles & Francisco, 1997) (Stavrakoudis, Theocharis, & Zalidis, 2009). An overview is given in the next section and one approach is chosen.

3.3. Optimization Procedure

As a form of an evolutionary algorithm, the genetic algorithm (GA) is used in this study. The GA is an iterative procedure that uses a population of individuals where each individual is represented by a genome. This encodes a solution inside a given problem space that comprises all feasible solutions to the problem under study (Coello, Lamont, & van Veldhuizen, 2007). In general, the GA always starts with an initial population of individuals and evolves towards optimized individuals by using genetic operators inspired by nature. For details please refer to (Coello et al., 2007).

In literature there are basically three approaches for using genetic algorithms to derive parameters of membership functions and fuzzy rules (Michalewicz, 1996) (Gonzles & Francisco, 1997). These are explained briefly in the following.

The Michigan Approach In the Michigan approach, each individual of the GA represents a single rule and respective membership functions. The fuzzy inference system is represented by the entire population of individuals. Due to the fact that several rules participate in the inference process the active rules are in constant competition for the best action to be proposed and cooperate to form an efficient fuzzy rule-based system. The cooperative-competitive nature of this approach is one drawback as it complicates the decisions on which of the rules are ultimately responsible for an optimal behavior. By that an effective policy to build adequate fitness values is necessary (Michalewicz, 1996).

The Pittsburgh Approach In the Pittsburgh approach, each individual of the GA represents a candidate for the entire fuzzy rule-based system. This means that it holds a predefined number of rules with respective membership functions. Genetic operators are used to generate new generations of the entire system. A benefit of this approach is that an evaluation is easily possible as the entire system is encoded in one individual. A major drawback though is a high computational cost as well as the fact that the number of rules has to be defined in advance.

The Iterative Rule Learning Approach In the Iterative Rule Learning approach each individual represents a single rule of the rule base to be derived. The GA is used sequentially to determine a single optimal rule in each run. This is a partial solution to the entire problem. In order to solve that, the GA is used in an iterative manner in order to discover new

rules and check each time if all cost and performance criteria are already fulfilled. If this is the case the process stops. In order to prevent the discovery of redundant rules there are approaches to remove covered data sets as well as to penalize covered data sets (Gonzles & Francisco, 1997). The benefit of this approach is that it combines the benefits of the Michigan and the Pittsburgh approaches which is the speed and the simplicity of defining and applying optimization criteria.

The iterative rule learning approach is chosen in this study. This generates one rule at a time in an iterative manner. The rule is represented by a genome. This is a finite set of symbols which is split into a real valued part representing parameters of the membership function and a binary valued part representing the features that are chosen. An example is depicted in Equation 12.

$$\begin{bmatrix} | \underbrace{0 \mid 1}_{\text{Binary part}} & || \underbrace{m_l^1 \mid \Delta m^1 \mid \sigma_l^1 \mid \sigma_r^1 \mid m_l^2 \mid \Delta m^2 \mid \sigma_l^2 \mid \sigma_r^2 \mid \sigma_r^2 \end{bmatrix} \quad (12)$$

Real-valued part

In Equation 12, a genome is shown that represents a fuzzy diagnosis rule. There are two features available where the first one is not active in the current case. Each binary value is related to four real valued parameters. These are part of the membership function and have been introduced previously. The parameter Δm^1 is the difference between the left and right center of the Gaussian membership function:

$$\Delta m^1 = m_r^1 - m_l^1, m_r^1 > m_l^1.$$

An important aspect of the iterative rule learning approach is the penalization of covered data sets. The approach of *Boosting* is applied for that, as proposed in (Stavrakoudis et al., 2009). Basically this means, that initially all data sets are weighted with a single factor w^{f_v} . This can be a value of one. After each run of the GA, the rule error of the current rule is determined for each feature vector f^v . Features that are classified correctly are reduced in their weight whereas misclassified features keep their former weight. For more details please refer to (Hastie, Tibshirani, & Friedman, 2009).

The weights w_{f_v} are included in the fitness function of the GA where the overall fitness function consists of three sub functions. These are introduced in the following.

The set of fuzzy diagnosis rules should exhibit a low rate of misclassification. This is taken into account using the factors ω^+ and ω^- .

$$\omega^+ = \sum w_{f_v} \cdot \mu_n(f^v), \forall f^v \exists c_{f^v} = c^n.$$
(13)

$$\omega^{-} = \sum w_{f_v} \cdot \mu_n(f^v), \forall f^v \exists c_{f^v} \neq c^n.$$
 (14)

By means of Equation 13, a weighted sum of membership grades is gained for those features that are classified correctly. Misclassified features are taken into account by means of Equation 14. Using ω^+ , the class coverage is defined as first factor f_1 of the overall fitness function:

$$f_1 = \frac{\omega^+}{\sum w_{f_v}}, \forall f^v \exists c_{f^v} = c^n.$$
(15)

Using Equation 15, correctly classified features are taken into account. In order to have a rule that supports a high amount of feature vectors f^v , factor n is defined as the ratio of ω^+ related to the sum of the weights of all features covered by the rule, independent of the class label:

$$n = \frac{\omega^+}{w_{f_v}}.$$
 (16)

By means of Equation 16 the class support f_2 is defined as follows:

$$f_2 = \begin{cases} 1, & \text{if } n > k_{cov} \\ n/f_{cov}, & \text{otherwise.} \end{cases}$$
(17)

By using the factor f_2 the generality of the rule is enforced. Depending on the number of classes, a value of $f_{cov} \in [0.2, 0.5]$ is proposed in (Stavrakoudis et al., 2009). As a last factor the rule consistency is introduced. This means that the rule should not only possess a high number of correct classification but likewise a low number of misclassification. This is addressed by means of factor f_3 :

$$f_3 = \begin{cases} 0, & \text{if } k_c \cdot \omega^+ < \omega^- \\ (\omega^+ - \omega^- / k_c) / \omega^+, & \text{otherwise.} \end{cases}$$
(18)

A value of $f_c \in [0, 1]$ is proposed in (Stavrakoudis et al., 2009). All factors are normalized so that the overall fitness function is defined as the product of f_1 , f_2 and f_3 :

$$f = f_1 \cdot f_2 \cdot f_3. \tag{19}$$

3.4. Fuzzy Diagnosis Rule Generation Algorithm

The previous sections introduced basics of fuzzy inference and an optimization procedure that is used to train fuzzy diagnosis rules. These tasks are integrated into an algorithm that is explained in the following. An overview is given by Figure 7.

A model of a MFFCS is used to gain data of faulty system behavior. This is split into training data (TD) and validation data (VD), where TD is used for training of rules and VD for testing the current performance of classification. The rule base is initially empty. According to the iterative rule learning approach, one fuzzy diagnosis rule is trained at a time by using the fitness function from Equation 19 for evaluation. In a post processing step, the binary part of the genome is analyzed further. All non zero entries are sequentially set to zero and it is checked if the fitness value remains constant. If this is the case, there is no need for the related feature. Hence, the total number of required features and sensors can be re-



Figure 7. Process for the derivation of optimized fuzzy diagnosis rules.

duced. By means of VD, the current performance is tested. If it is above an initial threshold and higher than the previous performance, the rule is accepted and added to the rule base. In a *boosting* step, the current rule error is calculated on basis of the misclassified data, and the weights of TD are updated. The process continues in a loop until a stop criterion is reached. In the current case this is the number of runs of the algorithm. In the future, this can also be coupled to the performance. If the process stops, all genomes are transformed into the structure of Equation 4 and a fuzzy diagnosis rule base is gained.

4. RESULTS

This section depicts the results that are obtained by applying the algorithm from Section 3.4 to a MFFCS. In Subsection 4.1, failure modes that have been taken into account are highlighted and sensors are shown that provide data about faulty system behavior. Afterwards, in Subsection 4.2 results of the optimization procedure are discussed and examples of the derived rule base are presented.

4.1. Failure modes

In the current study, 12 different failure modes have been taken into account. These are given by six components where each component contains two failure modes. These components are part of the air supply of both the fuel cell stacks as it is shown in Figure 8. An overview of the failure modes is depicted in Table 2.

Component	Failure Mode	Class. c
Compressor	Increased friction	1
compressor	Jamming	2
Pine A	Increased leakage	3
T IPC A	Highly increased leakage	4
Pipe B	Increased leakage	5
т пре в	Highly increased leakage	6
Pipe C	Increased leakage	7
T Ipe C	Highly increased leakage	8
Air Volvo A	Jamming in closed position	9
All- valve A	Jamming in half opened position	10
Air-Valve A	Jamming in closed position	11
All- valve A	Jamming in half opened position	12

Table 2. Failure modes that have been taken into account.

In order to detect the failure modes and classify the related data, 10 sensors Si have been placed in the system. These provide 12 measurements as shown in Figure 8. Measurements range from pressure p of air and hydrogen, mass flow \dot{m} , electrical current I to the fraction of oxygen x_{02} and gaseous water x_{H20} in the air. By means of the optimization procedure, those features are identified that are really needed for data classification.

4.2. Fuzzy diagnosis rule base

In total, 250 runs of the fuzzy diagnosis rule generation algorithm have been performed and a classification performance of 99.2% has been reached. This is achieved by 15 rules. These are split into three rules that are used for inference of classification 3, two rules for classification 4 and one rule for every other classification. Measurements of current by means of sensors S3 and S7 as well as measurement of mass flow \dot{m} by means of sensor S9 are not required to achieve the result. After termination of the algorithm all rules are transformed into the format shown in Equation 4. In order to clarify the result, an example is given in the following.

Two rules are used for inferring a highly increased leakage of pipe A which is class 4. These are the rules 8 and 11 of the rule base. Rule 8 uses three features. These are provided by sensors 4, 6 and 9. Rule 11 uses one feature which is provided by sensor 9. The structure of rule 8 is shown in Equation 20 and the structure of rule 11 in Equation 21.

Rule 8: if
$$S4 : x_{H20}* = High$$
 with Exceeding = a_4^8
and $S6 : p* = Low$ with Exceeding = a_6^8
and $S9 : p* = Low$ with Exceeding = a_9^8
then suspect $c = 4$ with certainty ϵ_4 . (20)

In a cooperative manner, rule 11 supports the inference of the conclusion of rule 8.

Rule 11: if
$$S9: p* = Low$$
 with Exceeding $= a_9^{11}$
then suspect $c = 4$ with certainty ϵ_4 . (21)

Both the rules use the feature S9 : p* which is shown in Figure 9. There are depicted effects which are based on a simulation of an increased leakage and a highly increased leakage of pipe A. At an instant of time $t_F = 30s$ those failures are activated. Based on that, a decrease of S9 : p* can be observed that is followed by an increase which is based on control action.



Figure 9. Effects of increased and highly increased leakage of pipe A.

At time t_D both the failures are detected by means of indicator color S9 : p* = Low. Inferring the root cause starts at this moment. For this task, only a small part of the data range is used by the fuzzy sets a_9^8 and a_9^{11} . This is shown in Figure 10 where a detailed view of Figure 9 is given.



Figure 10. Detailed view of effects increased and highly increased leakage of pipe A.



Figure 8. Sensor locations and components with faulty behavior that have been taken into account in the study.

Rule 8 uses a data range that covers data for both classes 3 and 4. The result that can be inferred is not sufficient so that rule 11 is used for support. The respective data range covers a part of the data range of rule 8 but only the part that is unique for class 4.

An interesting aspect of rules 8 and 11 is that both use data of the hydrogen supply in terms of S9 : p* in order to infer failures of the air supply. They don't use the feature S2 : p*that has been shown in Figure 6 as an illustrative example of raw data of faulty behavior. Based on only S2 : p* it was obvious that both the classes 3 and 4 could not be inferred as the effects overlap. By means of the rule generation algorithm this result is confirmed and optimal features are gained for separation. Instead of using S2 : p* the feature S9 : p* is more valuable although not a part of the air supply. If the rules would have been created in a manual way, this feature would therefore probably not be used although giving good results. Furthermore, a manual generation of the fuzzy sets in an optimized way would have been hardly possible.

5. CONCLUSION

Multifunctional system concepts and ambitious goals for the future of European air traffic require powerful health management technologies to ensure a safe operation and a high availability. This paper introduced a model-based approach for the derivation of fuzzy diagnosis rules for multifunctional fuel cell systems. These rules are used for the inference of root causes of detected failures and malfunctions. A fast and reliable troubleshooting is gained by that. In order to clarify the background of the paper, the concept of a multifunctional fuel cell system has been explained in detail in the beginning. The importance of dealing with health management functions has been emphasized and the general concept of fuzzy diagnosis rules has been introduced afterwards. Subsequently, a novel approach to derive a fuzzy rule base was depicted. An extended system model has been used to gain knowledge about effects of failures and malfunctions. These effects have been allocated a unique class label which represents the underlying root cause. Data of faulty system behavior was gained and stored in a matrix. In an evolutionary optimization procedure, fuzzy sets have been trained on basis of the matrix data so that the correct class label can be inferred. Based on a case study, a rule base of 15 rules has been derived in the end. An example illustrated two rules and showed that the novel approach gives valuable results. Compared to other classification procedures, a traceable and human interpretable approach has been introduced.

The case study of this paper dealt with the air supply system of two fuel cell stacks. The approach has also been applied to the entire multifunctional fuel cell system including the fuel cell stacks. However, in order to clarify the basic approach and the general procedure to derive the rule base, only a small part of all failure modes and malfunctions has been dealt with in the case study. A further paper on the application of the approach on specific fuel cell failures is in progress and will come in future. Furthermore, in future work, the proposed approach could be extended to also deal with early failure detection as a first step of prognosis. Degraded behavior can be simulated therefore in different levels up to failures and malfunctions. The respective data can then be dealt with by using the approach described in this paper.

NOMENCLATURE

- A color variable
- I current
- N Number of rules
- R Rule
- a fuzzy set
- m mass
- m_l left center of Gaussian function
- m_r right center of Gaussian function
- T temperature
- c class variable
- *p* pressure
- f^v feature vector
- f fitness function
- h height
- *i* dimension
- k_v specific flow coefficient
- x fraction
- ϵ certainty factor
- μ_n matching degree of rule n
- ρ density
- σ width
- ω classification factor

REFERENCES

- Andres Pena-Reyes, C., & Sipper, M. (1999). A Fuzzy-Genetic Approach to Breast Cancer Diagnosis. *Artificial Intelligence in Medicine*, *17*(2), 131–155.
- Coello, C. A. C., Lamont, G. B., & van Veldhuizen, D. A. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems* (2nd ed.). Boston and MA: Springer Science+Business Media, LLC.
- Cox, E. (1994). The Fuzzy Systems Handbook: A Practitioner's Guide to Building, Using, and Maintaining Fuzzy Systems. San Diego, CA, USA: Academic Press Professional, Inc.
- Enzinger, M. (2010). Technology Programmes-Multifunctional Fuel Cell Application. Hamburg.
- European Organisation for the Safety of Air Navigation.

(2013a, March). *Coda Digest - Delays to Air Transport in Europe - Annual 2012* (Tech. Rep.). Brussels, Belgium: Eurocontrol-Central Office for Delay Analysis.

- European Organisation for the Safety of Air Navigation. (2013b, May). Performance Review Report - An Assessment of Air Traffic Management in Europe during the Calender Year 2012 (Tech. Rep.). Brussels, Belgium: Eurocontrol-Performance Review Commission.
- European Commission. (2001, January). European Aeronautics: A Vision for 2020. *Report of the group of personalities*.
- European Commission. (2011). Flightpath 2050 Europe's Vision for Aviation. *Report of the high level group on aviation research*.
- Gonzles, A., & Francisco, H. (1997). Multi-Stage Genetic Fuzzy Systems based on the Iterative Rule Learning Approach. *Mathware and Soft Computing*, 4(3), 233– 249.
- Grymlas, J., & Thielecke, F. (2013). Virtual Integration and Testing of Multifunctional Fuel Cell Systems in Commercial Aircraft. SAE International Journal of Aerospace, 6(2), 746–760.
- Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd ed.). New York: Springer.
- Herrera, F., Lozano, M., & Verdegay, J. L. (1995). Generating Fuzzy Rules from Examples using Genetic Algorithms. *Fuzzy Logic and Soft Computing*, *4*, 11–20.
- Herwig, H. (2006). *Strömungsmechanik: Eine Einführung in die Physik und die mathematische Modellierung von Strömungen* (2nd ed.). Berlin: Springer.
- Michalewicz, Z. (1996). *Genetic Algorithms* + *Data Structures* = *Evolution Programs* (3rd ed.). Berlin: Springer.
- Modest, C., & Thielecke, F. (2012). A Design Methodology of Optimized Diagnosis Functions for High Lift Actuation Systems. In I. Roychoudhury, J. R. Celaya, & A. Saxena (Eds.), *Proceedings of the Annual Conference of the Prognostics and Health Management Society 2012* (pp. 233–248). PHM Society.
- Stavrakoudis, D., Theocharis, J., & Zalidis, G. (2009). Genetic Fuzzy Rule-based Classifiers for Land Cover Classification from Multispectral Images. In S. G. Tzafestas & K. P. Valavanis (Eds.), *Applications* of Intelligent Control to Engineering Systems (Vol. 39, p. 195-221). Dordrecht: Springer Netherlands.

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Towards the Industrial Application of PHM: Challenges and Methodological Approach

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ABSTRACT

The diagnosis and prognosis capabilities are the key points of PHM (Prognosis Health Management) research. Most of the endeavor and investment are being oriented to get and improve these capabilities: new sensors, measurement techniques, communication/data solutions, detection algorithms, decision algorithms and reliability calculate tools. Nowadays it is actually possible take advantage of these capabilities to improve systems operation and maintenance. In spite of this, massive industrial application is still far away. Many of industrial sectors barely have heard about of PHM and its potential, or only have introduced classical CBM (Condition Based Maintenance) tools -vibration analysis, ultrasound, thermography- to specific and local maintenance applications.

In this paper a comprehensive understanding of the problem of transferring PHM into industrial environments and its relevance is introduced. It's also argued the need of develop a methodological approach as a key point for getting a broad applying of PHM-based solutions. To do this, the main challenges to be addressed are listed and analyzed..

1. INTRODUCTION

Nowadays it is actually possible to take advantage of the capabilities of ICT (Information and Communications Technology) to improve systems operation and maintenance. Among others, a most accurate description of the degradation processes is now available. How deep can we characterize the system states? Is it possible to take maintenance decision based on objective knowledge about these current and future states? PHM goes lot further than other maintenance management tools to answering these questions.

A PHM solution (PHM-based solution), in a first approach, can be defined as the process of determining the current state of a system in terms of reliability and prediction of its future state. Generally it combines sensing and interpretation of environmental, operational, and performance parameters to assess the health of a product and predict RUL (Remaining Useful life) (Zio et. al, 2010). But owing to its relevance and development, PHM has become a new engineering discipline. This is strongly defended by different authors and institution, especially the PHM Society. Attending to this approach, PHM is a discipline that relies on the use of in-situ monitoring and advance methods of analysis (include fault detection, diagnostics, prognostics, and health management) to assess system degradation trends, and determine remaining useful life, allowing system to be evaluated in its actual life cycle conditions and mitigate the system-level risk (Sun et al 2012).

PHM is considered by the different authors as the key factor to definitely promote a qualitative jump toward intelligent maintenance. Lee *et. al* (2006), give to PHM and emaintenance a fundamental role in maintenance development, where maintenance actions are synchronized with the overall operation of the system as well as the necessary maintenance resources and spare parts. Ly *et. al.* (2009), explain how to develop solutions for PHM effectively and efficiently will take a tremendous effort to coordinate all levels of managements from engineers to the top corporate level (maintenance managers, project officers, program managers,...). The entire enterprise must be coordinated in order to make PHM effective over the lifecycle operation of any system from the design, manufacturing, operational and logistical domains.

So, why these powerful improvements are not being applied extensively? Despite the great advances achieved in the last decade in the technologies included within the PHM topic,

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massive industrial application is still far away. In every CBM/PHM solution (as it is referenced by Vatchevanos el al. 2006), high technological fields have to be combined and adapted. A successful implementation required a deep knowledge of involved technology, methods and algorithms, besides great expertise in the particular application field. It possible to conclude that there are two general challenges in this development process: the coordination between corporate levels (alignment of technology uses with the business model and with profit generation) and the design of methodologies and frameworks support to its implementation efficiently (complex application scenarios by signals number, technologies, process dynamic or human interferences)

In parallel to this, the maintenance strategies evolution has to be considered. From "run to fail" or corrective maintenance to a new strategies with high level of proactiveness, that take advantage of technologies to prevent the failures and avoid their effects. In this shift, two aspects have to be considered: the improvement of the maintenance engineering and its tools and, on the other hand, the very development of the systems to maintain. Jardine et al. (2006) explain how preventive maintenance has become a major expense of many industrial companies. They argue how the rapid development of modern technology has made that products have become more and more complex while better quality and higher reliability are required. And this makes the cost of preventive maintenance higher and higher. Because of this, more efficient maintenance approaches such as CBM are being implemented to handle the situation. In this point, it is necessary to clarify that actually two different views about the CBM can be considered. One is the classical CBM, comprising the well-known use of techniques as vibration, thermography, ultra-sound, etc., which has a great implantation in the industry. On the other hand, new concepts have been introduced, as CBM+ (Ly et al 2009) or PdM (Predictive Maintenance) (Gupta et al. 2012), trying to introduce a more comprehensive view of condition and health system management, which includes the understanding and employ of prognosis technological capabilities. Condition based maintenance referred by Jardine is closer to the last one, and it also point out to the proactive maintenance approach introduce by other authors.

The concept of "proactiveness" or "proactive maintenance" is driving the evolution of maintenance (Lopez-Campos et al. 2013). PHM and "e-maintenance" are the levers of this development (Lee 2006). This approach is also included in the definition of e-maintenance introduced by Muller et al. (2009) when they talk about "Maintenance support includes the resources, services and management Necessary to enable proactive decision process execution".

Following this introduction, Section 2 outlines the main factors of industrial application of PHM-based solutions,

making an introduction of the benefits that it can provide in contrast with the complexity of its implementation. In Section 3 it is argue the necessity of methodological approaches for optimize and assurance the results of this solution. A review of interested standards is included and principal aspects for building a practical methodology are listed. Finally, in Section 4 the conclusions of this paper are summarized.

2. CHALLENGES AND BENEFITS OF PHM INDUSTRIAL APPLICATIONS

Crucial questions when introducing these advances within an organization/system-for asset management, maintenance or equipment design tasks- are the follows: true benefits of the introduction of these tools are obtained? Is it worth it for the company drives their development in terms of competitiveness and profitability through these types of improvements?

Clearly, the application of any new maintenance development is based on the fact it provides a cost reduction and/or improved system reliability to, in last term, optimize the system life cycle cost (Crespo2006).Now, it is not sufficient to justify the industrial use of PHM. PHM-based solutions imply complex technological developments, so it is necessary to be more precise making it clear to the company how these improvements are achieved and where they will have to work (assets, human resources formation, technology investment, etc). In this sense, it is important the expected results of the implementation of these improvements are aligned with the strategic objectives and according with the capabilities and resources of the company. The concept of e-maintenance, when it is analyzed from the view of its contribution with the ebusiness management strategies, play an important role in connecting the capabilities provided by the PHM-based solutions with business strategies (Figure.1)



Figure 1. An enterprise view of e-maintenance (Lee 2004)

It seems then necessary, in order to promote a more extended use of PHM techniques, extract and show in a sorted way the positive results of the incorporation of these advancements in the industry. In order to do this, in this paper two different but complementary perspectives have been used: new capabilities/improvements for maintenance task execution and potential specific benefits that can be provided by PHM applications along system life cycle.

2.1. Improvement and Benefits of PHM Applications

2.1.1. New capabilities/improvements

PHM is related to the effective introduction of new capabilities at the service of maintenance management among others life cycle product stages. This approach helps us to understand the scope in maintenance evolution provided by these technologies. Muller et al. (2008), analyzing the potential improvements in the e-maintenance concept application context (we have exposed above, the close relation between PHM-solutions and e-maintenance), introduce the following references to the maintenance tasks evolution:

- Remote and on-line maintenance:
- Cooperative/collaborative maintenance:
- Maintenance documentation/record and knowledge capitalization and management
- Fault/failure analysis and predictive maintenance

<u>Remote and on-line maintenance</u>: here we introduce the capability to remotely link to a factory's equipment allowing remote maintenance actions as diagnosis, through data collection and analysis. This reduces the manpower cost and introduces tools to diagnose the faults and to improve the preventive maintenance thanks to the machine performance monitoring. The connection of field monitoring with decision centers adds value to the top line, trim expenses, and reduce waste (Crespo and Gupta, 2006).

Cooperative/collaborative maintenance: the opportunity to implement an information infrastructure connecting dispersed subsystems and actors. In many cases, very few technicians manage the key information of the system. As a result the company doesn't really control some critical aspect of their facilities. There is also a lack of information exchange between different actors. Implementing these strategies allows a strong cooperation between different human actors, different enterprise areas (production, maintenance, purchasing, etc.) and also external stakeholders (suppliers, customers, machine manufacturers, etc.).It provides maintenance management with a transparent, seamless, and automated information exchange process to access all the documentation in a unified way, independently of its origin (equipment manufacturer, integrator, and end-user) Information exchange process within the company is formalized, making the technical

knowledge of the system is documented in the company (performance, maintenance, reliability) and not only in the hands of some good technicians. It also improve transparency and efficiency levels into the entire company and it can be an adequate support of business process integration (Hausladen and Bechheim, 2004), contributing to the acceleration of total processes, to an easier design, and to synchronize maintenance with production, maximizing process throughput, and minimizing downtime costs

<u>Maintenance</u> documentation/record and knowledge <u>capitalization and management</u>: One of the most urgent industrial problems is how to realize knowledge-based operation and maintenance of plants. It has to collect, record, and store information regarding degradation modes, degradation sections of the machine, degradation frequency, degradation time and place, time required preventing, cost required to prevent, suggested and/or applied maintenance practices, etc. This knowledge capitalization aims at creating a corporate memory (i.e. a structured set of knowledge related to the firm experience in a field domain) of enterprise (Rasovka et al 2005)PHM solutions give as a result accurate and wide information about systems condition and, at the same time, it implies a great knowledge of the system and its behavior.

Fault/failure analysis and predictive maintenance: This is the aspect more directly related to PHM. In order to properly analyze it, in the following paragraphs we are going to delve in the prognosis and PHM capabilities and its benefits.

2.1.2. Benefits of PHM

Gupta et a. (2012) argue that this techniques or solutions deepens the benefits of condition-based maintenance: (1) increasing the availability (avoid operational interruptions thanks to early detection capabilities reduce maintenance times by a better scheduling with less unscheduled maintenance); (2) reduction of direct maintenance cost (optimization of the use of each component, replacing it when it has reached almost all its full potential and better control on the maintenance scheduling: at the right place, at the right moment with associated resources to conduct the maintenance actions)

Ly et al. (2009) talking about differences between reactive, preventive and proactive maintenance, point out the main problems of schedule maintenance, which is the most extended practice in the industry: high cost, labor intensive; unnecessary maintenance operations performed when really not needed; does not prevent catastrophic failure. They also include high rates for false diagnostic indicators, and present some indicators such as: ReTest OK (RTOK), Could Not Duplicate (CND), No Evidence Of Failure (NEOF), No Fault Found (NFF). Finally argue that news approaches mitigate many of these problems and offer benefits including: decrease false alarms; increase operational availability and mission reliability; reduce logistics footprint; maximize return on capital invested, as measured by quantitative and non-quantitative benefits.

A more exhaustive analysis of the benefits of the prognosis is presented by Sun et al. (2012). They argue that prognosis can bring benefits in all stages of the system life-cycle process: (a) benefits for system design and development; (b) benefits in production; (c) benefits for system operations; (d) benefits in logistics support and maintenance; (e) benefits in phase-out and disposal (f); benefits in reducing Life-Cycle Costs (LCC). In general the approach given by Sun is very close to the principles of LCC analysis and it is in the line of other interesting work as Takata et al. (2004). In this sense is important remind the relevance of the first life cycle steps, since it is estimated that around 65% of improvement margins, the opportunities to create value, are decisions that can be taken during the early stages of the life cycle of the system (Crespo, 2006)

- (a) In the system design, engineers can improve and optimize the design from the collected and stored useful historical information provide by an effective prognosis (system usage patterns, operating conditions, environmental conditions, known failure modes, and possible deficiencies). This information also could optimize test design and execution. These tasks consume a lot of resources (time and cost). In addition, prognostics can assist in constructing a logistics support system.
- (b) In production phases, prognosis is a powerful tool for quality control process. The monitoring and prognostics of manufacturing equipment status can provide more information about equipment itself than traditional quality control, thus promoting the quality control process and quality assurance. In this phase is also analyzed the role of suppliers and OEMs (original equipment manufacturers) working with system manufacturers in the sense of "collaborative maintenance" explained above, provide componentlevel prognostics solutions.
- (c) System operation: Getting an advance time of even a few minutes before failure could be very significant, and could enhance system safety, especially for systems whose failure might cause a disastrous accident. Prognosis also provides active control of system reliability. Actual operating conditions may be quite different from what the system was designed for, and will affect the life consumption and operational reliability of the system. The monitoring capability of PHM makes it possible to take active control actions regarding environmental and operational conditions. With PHM, operators can determine the remaining life and extended life, and develop replacement plans for systems and their sub-systems and reduce the

occurrence of No Fault Found (NFF). Intermittent failures are impossible to assess using traditional prediction methods, resulting in the supply and maintenance chains suffering NFF problems, and prognosis is the most suitable approach to mitigate NFF risk. Finally warranty management and service is also a field where PHM and e-maintenance can have great influence, as is also discussed by Gonzalez-Prida et al. (2012)

- (d) Regarding benefits in logistic support and maintenance, prognosis provides a foundation for PdM (predictive maintenance) or CBM, more powerful than traditional predictive plans (an interesting discussion can be consulted on Gupta et a. 2012). That results in minimized unscheduled maintenance, eliminated redundant inspections, reduced scheduled regular maintenance, extended maintenance cycles, improved maintenance effectiveness, decreased ground test equipment requirements, and reduced maintenance costs. Regarding to logistic issues, predictive logistics is expected to optimize the performance measures of a system, and improve the planning, scheduling, and control of activities in the supply chain. Others interesting benefits are: reduce maintenance and inspection and repair-induced failures, avoid costs in direct and indirect maintenance manpower and increase maintenance effectiveness. These benefits can be followed and assessed using graphical tools as presented by Barberá et al (2012)
- (e) Phase Out and disposal: With PHM, a system's fulllife-cycle data, including installation, operation, and maintenance, can be managed and used to optimize end-of-life processing operations. Parts removed can be classified for treatment according to their life history and RUL. Here is included the consideration about that a system with prognostics capability can meet the requirements of modern society: energy saving, emission reduction, and a green environment.
- (f) Reducing Life-Cycle Costs. As it is said above the approach used by Sun et al. (2012) is very close to LCC analysis. Here, in this point, it is specifically dedicated to the direct life-cycle cost reduction. Prognosis provide cost avoidance opportunities, especially for total ownership cost of critical system (reduce regular inspection costs, unnecessary replacement of components with remaining life)
- (g) Replacement cost: The product/system useful life optimization has a great impact in replacement cost. This could be one of the most quantitative important benefits, with a best ROI (Return of Investment), depending on the company sectors. The cost benefit analysis indicates that investments in this area are likely to have large payoffs.

2.2. Introduction to PHM-application complexity

Industrial maintenance management has always been a complex activity that involves handling a large amount of information. Furthermore, in maintenance evolution new capabilities have been incorporated at the service of reliability and maintenance engineering. And manage more capabilities means more complexity. Tools like RCM and other significant efforts to develop frameworks, standards and methodologies (Lopez-Campos, 2011), have allowed enormous improvements through a better understanding of the maintenance task and the development of the maintenance management itself. However, better maintenance does not mean simpler maintenance. Actually, these techniques involve many resources and knowledge.

Likewise, the application of computerized tools and technologies of information and communication (ICT) - always present in the history of the maintenance function since the first personal computers in the 50s (Kans 2009) - has become in the essential support for modern maintenance, but it also introduces more level of complexity. And this is a great problem that companies have to deal.

The conclusion is that PHM-based solutions implementing is a very complex task. So, despite the benefits that can be achieved, this complexity imposes significant entry barriers, technical and economical. In Figure 2 main complexity factors that every PHM-based solution has to integrate are presented.



Figure 2. Complexity factors of industrial PHM-applications

Data treatment, communication and interfaces: An integral software / hardware solution has to be designed to bear the full cycle of information flow (Lopez-Campos et al, 2013): sensors, signal digitization, data capture and communications field level, processing basic detection algorithms, data storage, controls interfaces / alarm analysis

interfaces. Furthermore, we must add the relation with others hardware/software present in the systems and the relation with information systems for the management process as CMMS (Computerized Maintenance Management System) or ERP (Enterprise Resource Planning).

High specific technological knowledge: it is necessary to combine and adapt different high-technology fields. We have just mentioned above the specific area of knowledge of software/hardware/communications. To this must be added areas of technology equipment, measurement the techniques, mathematical methods for fault detection, reliability engineering and finally the analysis of economic controls and ROI. A deep knowledge in every technology, method or algorithm is essential for a successful implementation, in addition of the knowledge in the application field (Cheng, Azarian, &Pecht, 2010). This is why it is required the effective implementation of a cooperative/collaborative open framework, in the sense it has been discussed in the previous section. This has to be support and interface for the necessary interrelation between different areas and technicians

Strategic and holistic view and business value: Finally, it is necessary to make the results of the investment in PHMbased solutions visible to the organization, assuring they responsive to management strategies. This is not a simple task. Especially if you consider that implementation times can be high and the design and development of these solutions combine multiple resources, implies high direct costs and interfere with the normal operation of the production process (Crespo 2006). All of this requires the management commitment and a deep knowledge of the process and its objectives by the involved staff. Although this is a well-known aspect to consider when an improvement process is implemented (as in the processes

All this requires the commitment of the management and the knowledge of the process and its objectives by the staff. This is a well known aspect in the implementation of improvement process as international quality standards.

3. JUSTIFICATION OF THE NEED OF METHODOLOGICAL APPROACH

The massive introduction of PHM techniques (within "emaintenance" concept) in the industry, as mentioned above, implies the companies to know the utility of these tools and the benefits they provided, for the business, in last term. In addition the company has to incorporate the required knowledge by these new techniques and translate it into new skills of its staff. The other important aspect is the integration with business and production management, which includes the integration with other management tools and software. PHM can be use in a specific solution for a particular case. It can provide great benefits in the short/medium term, especially when it deal with critical system or failure. But most ambitious approaches must include the design and implementation of a general strategy that combines different PHM-based solutions with more conventional maintenance options into a proactive maintenance plan (Lopez-Campos et al, 2013) It means that PHM applications have to be linked to the maintenance plan. In this sense Vachtsevanos et. al (2006) introduce a final module of its proposal of integrated system architecture for machine diagnosis and prognosis for CBM, a maintenance scheduler module. Other hand, different authors have proposed frameworks and methodologies to organize maintenance management in an industry, facility or system (Moubray 1997, Crespo 2006, Waeyenbergh & Pintelon 2009). These are practical approaches that try to help to engineers to schedule maintenance in real cases, giving a sequential process to use the different maintenance engineer tools and defined the set of various maintenance interventions (corrective, preventive, condition based, etc.) Other relevant aspect that is present in these methodological references is the role they give to the maintenance plan as main objective of the process and point where every decision is integrated within the overall maintenance strategy according to the company resources constrains. Taken these frameworks as reference of how industry treats the maintenance management process, we might conclude that it is necessary to link PHM result with the design and re-adaptation of maintenance plan and how integrate PHM with the rest of maintenance interventions within the overall maintenance strategy. It is also important point out the value of methodological approaches in the industry to develop an efficient and effective maintenance.

Standards are also references to consider that can be used to support PHM applications. Although few standards exist of direct relevance to prognostic systems and PHM system (Sheppard et al 2008) the close ties between PHM and traditional diagnostic and maintenance systems, several standards for the maintenance and diagnostic communities can be applied to PHM. Standards provide users with some guidelines to help them to accomplish their expected missions. In this sense, two main important approaches o standards groups could be distinguish:

- Information flow structure.
- Requirements and advices to assurance a good solution and the confidence of the results.

In relation with the first group, Ly et al. (2009) argue that CBM/PHM systems must have open systems architecture in order to maximizing the investment and remark the international institutions that are working to develop standards are key enablers to the architecture: Institute of Electronic and Electrical Engineers (IEEE), Society of Automotive Engineers (SAE), Machinery Information

Management of Open Standards (MIMOSA), International Organization for Standardization (ISO). Here we can highlight the reference to ISO17334 and MIMOSA (CBM-OSA). An example of a practical interpretation and use of these standards is presented by Lopez-Campos et al. (2013). Other interesting references that we must also consider are specialized standards in hardware/software solutions as ISO 18435, IEC 62264 or some most specific ISO and IEEE standards.

In the second group it could be included standards as ISO 17359, ISO 13381 or even PAS 55 and ISO 14224. The ISO 17359 reference focuses on the general procedures and requirements to be considered when setting up a condition monitoring based program. It has to be highlight the fact this standard, like others standard referenced in it (ISO 17359 include an exhaustive list of condition monitoring standards), rely on traditional CBM approaches and they will must be adapted for support PHM based approaches in a most suitable way. The standard ISO 13381-1 defines failure prognostics, details the steps of the prognostics process, gives indications on the monitoring system and on how to estimate the confidence interval associated with the calculated RUL and proposes some mathematical tools which can be used to model the degradation (Tobon-Mejía et al, 2010). The rest of the mentioned standards in this paragraph introduce methodologies, aims and requirements to be included in a development of a overall solution, from the point of view of the general system performance and strategic or business approach.

Finally, there are a lot of references in the PHM specialized literature of frameworks to help PHM system developers and integrators for faster system development and deployment (Kunche et al. 2012). These frameworks address the problem of implementing a PHM solution from a technical point of view, but not the maintenance management issues.

We can conclude that there is a lot of background information and references. The problem is that it is difficult to access and manage this all these references in an orderly manner. This complicates in some way the industrial application of certain techniques, especially linked to the most advanced PHM. The problem is even bigger when working with complex systems with multiple signals and information systems. General methodological approaches have to be proposed to guide industry in the design process of new maintenance strategies where PHM potential has more relevance. In these proposals it is necessary to address how PHM is integrated with the maintenance strategies and the complete implementation process, from a need of a PHM solution is identified to maintenance plan execution.

What is presented below in this section is not the methodology itself, which will be subject to next research works. It is presented, preliminarily, the relevant aspects to be considered to implementing a PHM solution. They are

presented providing an initial order to link these tasks in the following figure:



Figure 3.Relevant aspect include in a methodology construction

<u>Preparatory task and implementation plan</u>: It is necessary to request the relevant information over the facilities to be analyzed and the management systems that assist them. Also is necessary to create the work team. One of the most important constraints of this kind of approaches is related don't get an appropriated working team. This problem is well describing in references about RCM application (Crespo 2006). In fact much of the success of the process is precisely at this stage. Within these tasks may be included team formation. It is essential to establish a planning and allocation of resources to the project, including participation of required technical profiles. Also you have to make it very clear project phases, from design of the solution until the maturation phase after implantation.

Determination of asset hierarchy: The first point of this step is the analysis of operational context and the environment in which the system is integrated. You need to understand as clearly as possible the relation of the systems with the environment in which they are integrated. Issues such as the relation of the system with the overall productive process are valued. Describing the application environment it is also defined whether the PHM-based solution is used for product /system design (product/system design improvements) for the operation phases of the assets (process performance/control improvements) or both. After that, to establish the asset hierarchy, a criticality analysis is performed. It includes determination of criteria for evaluating the systems according to their severity. This approach introduces in the process of generate a PHM-based solution a link with strategic criteria. Finally, the analysis of CMMS systems is included, since they are necessary to obtain reliability data to evaluate the systems criticality.

RCM Analysis Critical equipment: In order to obtain all the benefits that PHM offers, it is necessary to implement it in an appropriated manner, selecting the most adequate items and the frontiers of the system to be maintained using this policy. Reliability Centered Maintenance (RCM) can be useful in this sense (Lopez-Campos et al 2013). The RCM approach contains a variety of methodologies such as: FMEA (Failure Mode and Effect Analysis), RBD (Reliability Block Diagram), RP (Reliability Prediction), FTA (Fault Tree Analysis) and ETA (Event Tree Analysis). As pointed out by several authors, the use of RCM technique is necessary for the proper selection of the CBM processes and technologies. This conclusion must be translated to PHM applications (Sun 2012, Cheng 2010, Gomez 2012, Vachtsevanos 2006) RCM analysis helps in selecting the optimal maintenance policy for every maintainable item: diagram Input-Process-Output determination of operating standards for each of the systems / functions, functional loss, failure modes and failure mode criticality

Signals and detection methods assignment for critical failure modes. From the information generated above, the possibilities to follow and detect each critical failure mode are analyzed. This includes the analysis of signals presents in the system, the analysis of the possible symptoms associated with each failure, the introduction of measurements technologies employed in classical CBM approaches and the use of advanced detection strategies, i.e., PHM detection tools. It is in this section where the contributions of the research on PHM detection methods will be discussed. From this point, with the support of information and advices from the standards, the platform software/hardware for running the PHM solution is designed (Lopez-Campos 2013). This platform can combine commercial solutions with ad hoc developments, both hardware and software.

<u>Algorithms to support making-decision</u>: This section includes the choice of models for calculating RUL, the economical estimation risk and comparison based on these data from different maintenance strategies. The calculation or estimation of the RUL is, jointly with detection algorithms, the main PHM solutions contribution. When PHM tools are used, is necessary to distinguish those that are used in each case. The methodology has to help to know what tools we have available, how they are used, when it is used and how the different results are related within the general system to be developed.

<u>Transferring results to the maintenance plan and business</u> <u>indicators</u>. A key module of the platform that will have the responsibility of PdM decisions, which will be integrated into the maintenance plans. Based on the results, the specific actions for being incorporated into the maintenance plan will be proposed and included in the CMMS. Finally a set of KPI's to control the process of improvements and its impact over the operation and business performance is also necessary.

Following the efficiency and effectiveness of maintenance. One of the key aspects of effective proactiveness is the ability to interpret the results of the actions and maintenance policies. So, in this section a practical performance control of the implemented actions is proposed. In this sense, one possibility is programming graphical tools supporting decision-making process. This achieves an accurate and efficient management of assets and resources in an organization, even when there is a large number of elements with functional configuration that is highly complex (Barbera et al 2012). To obtain actual applications of analytical models, practical, functional, innovative, and simple tools can be generated. Figure 4 present and example of GAMM method (Graphical Analysis for Maintenance Management) proposed by these authors, where they used two graphics to present jointly maintenance operation data and level of system reliability at the moment maintenance intervention. This will help to make tactical and operational decisions easier. New graphical tool on the basis of data related to the interventions sequence performed to a piece of equipment in during a time horizon. It must provides easy access to certain variables patterns showing useful information for maintenance management and decision making in the short, medium, and long term.





4. CONCLUSIONS

In this paper the general context of PHM industrial application has been presented, summarizing benefits and challenges. Finally the main factors that have to be considered for designing a practical methodology for implementing a PHM-based solution have proposed. The issues exposed in this paper are a first step in a much larger investigation, that will be focused, necessarily, on analyzes of PHM implementation in real cases. This will help to verify the practical utility of these solutions in different sectors and situations andit will let incorporate to the analysis the real constraints that these processes can incorporate.

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ACRONYMS

- ALS Autonomic Logistic System
- *CBA* Cost-benefit Analysis
- CBM Condition-based Maintenance
- CND Could Not Duplicate
- *ETA* Event Tree Analysis
- FMEA Failure Modes and Effects Analysis
- *FTA* Fault Tree Analysis
- GAMM Graphical Analysis for Maintenance Management
- *ICT* Information and communications technology
- *KPI* Key Point Indicator
- LCC Life-cycle Costs
- MTTR Mean Time to Repair
- NEOF No Evidence Of Failure
- *NFF* No Fault Found
- *PdM* Predictive Maintenace
- PHM Prognostics and Health Management
- *PM* Preventive Maintenance
- *RBD* Reliability Block Diagram
- *ROI* Return on Investment
- *RP* Reliability Prediction
- RTOK Re-test Ok
- *RUL* Remaining Useful Life

References

Barberá L., Crespo A., Viveros P., Arata A., (2012). The Graphical Analysis for Maintenance Management Method: A Quantitative Graphical Analysis to Support Maintenance Management Decision Making, *Quality* and Reliability Engineering International 2012. DOI: 10.1002/qre.1296

- Cheng S., Azarian M., Pecht M. (2010), Sensor Systems for Prognostics and Health Management, *Sensors*, 10, 5774-5797; doi:10.3390/s100605774.
- Crespo A, Gupta, J. (2006) Contemporary maintenance management: process, framework and supporting pillars. *Omega*, vol. 34(3), pp. 313–26.
- Gómez, J.F., Crespo, A. (2012), Maintenance Management in Network Utilities, frame-work and practical implementation, Springer-Verlag, London
- Gonzalez-Prida, V., Crespo, A., Barberá, L. (2012).New Services Generated by the E-Technology Applied on the Warranty Management.*International Journal of E-Business Development*, vol. 2, 1, pp. 16-22
- Guillén A.J., Gómez J., Crespo A., Guerrero A., Sola A. (2013), Advances in PHM application frameworks: Processing Methods, Prognosis Models, Decision Making, *Chemical Engineering Transactions*, vol 33, 2013.
- Gupta, J., Trinquier, C., Lorton, A., Feuillard, V. (2012), Characterization of prognosis methods: an industrial approach. *European Conference of the Prognostics and Health Management Society 2012.*
- Hausladen, I., Bechheim, C. (2004) E-maintenance platform as a basis for business process integration. *Proceedings* of *INDIN04*, second *IEEE international conference on industrial informatics*, Berlin, Germany, 2004. p. 46– 51.
- International Standards Organization (ISO) (2004). Condition Monitoring and Diagnostics of Machines -Prognostics part 1: General Guidelines. In ISO, *ISO13381-1:2004.* Genève, Switzerland: International Standards Organization.
- Industrial automation Systems and integration (ISO).Diagnostics, capability assessment and applications maintenance integration. Part I: overviewand general requirements. In ISO, ISO 18435-1:2009. Genève, Switzerland: International Standards Organization.
- Industrial automation Systems and integration (ISO). Condition monitoring and diagnostics of machines: General guidelines. In ISO, *ISO 17359:2011*.Genève, Switzerland: International Standards Organization.
- Industrial automation Systems and integration (ISO). Petroleum, petrochemical and natural gas industries: Collection and exchange of reliability and maintenance data for equipment. In ISO, *ISO/DIS 14224:2004*.Genève, Switzerland: International StandardsOrganization.
- Jardine, A., Lin, D., Banjevic, D., (2006). A review onmachinery diagnostics and prognostics implementing condition based maintenance. *MechSyst Signal Process*, vol. 20, pp.1483–1510.
- Kans M., (2009). The advancement of maintenance information technology.A literature review.*Journal of Quality in Maintenance Engineering*, vol. 15 (1), pp. 5– 16.

- Lee, J, Ni, J. (2004). Infotronics-based intelligent maintenance system and its impacts to closed-loop product life cycle systems. *Invited keynote paper for IMS'2004—International conference on intelligent maintenance systems, Arles, France, 2004.*
- Lee, J., Ni, J., Djurdjanovic, D., Qiu, H., Liao, H (2006), Intelligent prognostics tools and emaintenance. *Computers in Industry*, vol 57, pp. 476– 489
- López-Campos, M., Crespo, A., Gómez, J.F. (2013), Modelling using UML and BPMN the integration of open reliability, maintenance and condition monitoring management systems. *Computers in Industry*, vol. 64, p.p. 524–542.
- López-Campos, M., Crespo, A. (2011), Modelling a maintenance management framework based on PAS 55 standard, *Quality and Reliability Engineering International*, vol. 27 (6), pp. 805–820.
- Ly, C., Tom, K, Byington, C.S., Patrick, R., Vatchsevanos, G. J. (2009). Fault Diagnosis an Failure Prognosis on Engeneering System: a Global Perspective. 5th Annual IEEE Conference on Automation Science and Engineering Bangalore, India,
- Moubray J, (1997), *RCM II: Reliability-centred Maintenance*. New York: Industrial Press Inc.
- Muller, A., Crespo, A., Iung, B. (2008). On the concept of e-maintenance: Review and current research, *Reliability Engineering and System Safety*, vol. 93, pp. 1165–1187
- Pecth, M., Rubyca, J. (2010). A prognostics and health management roadmap for information and electronics-rich systems, *Microelectronics Reliability*, vol. 50, pp. 317–323.
- Rasovska, I, Chebel-Morello, B., Zerhouni, N. (2005). Process of s-maintenance: decision support system for maintenance intervention. *In: Proceedings of the 10th IEEE conference on emerging technologies and factory automation*, vol. 2, pp. 679–86
- Waeyenbergh, G., Pintelon, L., 2009. CIBOCOF: a framework for industrial maintenance concept development. *International Journal of Production Economics*, 121, 633–640 2009.
- Takata S, Kimura F, Van Houten FJAM, Westkämper E, Shpitalni M, Ceglarek D, Lee J. (2004), Maintenance: Changing Role in Life Cycle Management, *Annals of the CIRP*, 53/2, 643 – 656.
- Sheppard J, Kaufman M, Wilmering T (2008), IEEE Standards for Prognostics and Health Management, IEEE AUTOTESTCON 2008.
- Sun, B., Zeng S., Kang, R., Pecht, M., (2012), Benefits and Challenges of System Prognostics, *IEEE Transactions* on *Reliabilty*,vol 61(2), pp 323-335
- Kunche S., Chen Ch., Pecht M. (2012), A review of PHM system's architectural frameworks *MFPT 2012: The Prognostics and Health Management Solutions Conference*, 24-26 April, Dayton, OH, 2012

- Tobon-Mejia, D., Medjaher, K., Zerhouni N. (2010). The ISO 13381-1 Standard's Failure Prognostics Process Through an Example. *IEEE Prognostics & System Health Management Conference, PHM'2010., Macau* (China)
- Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent fault diagnosis and prognosis for engineering system*. Hoboken, NJ: John Wiley & Sons, Inc.
- Zio E., Di Maio F. (2010). A data-driven fuzzy approach for predicting the remaining useful life in dynamic failure scenarios of a nuclear system, Reliability Engineering and System Safety 95, 49–57

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Closed-loop Control System for the Reliability of Intelligent Mechatronic Systems

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ABSTRACT

So-called reliability adaptive systems are able to adapt their system behavior based on the current reliability of the system. This allows them to react to changed operating conditions or faults within the system that change the degradation behavior. To implement such reliability adaptation, self-optimization can be used. A self-optimizing system pursues objectives, of which the priorities can be changed at runtime, in turn changing the system behavior.

When including system reliability as an objective of the system, it becomes possible to change the system based on the current reliability as well. This capability can be used to control the reliability of the system throughout its operation period in order to achieve a pre-defined or user-selectable system lifetime. This way, optimal planning of maintenance intervals is possible while also using the system capabilities to their full extent.

Our proposed control system makes it possible to react to changed degradation behavior by selecting objectives of the self-optimizing system and in turn changing the operating parameters in a closed loop. A two-stage controller is designed which is used to select the currently required priorities of the objectives in order to fulfill the desired usable lifetime.

Investigations using a model of an automotive clutch system serve to demonstrate the feasibility of our controller. It is shown that the desired lifetime can be achieved reliably.

1. INTRODUCTION

Self-optimizing mechatronic systems are a class of intelligent technical systems that are able to autonomously adapt their behavior if user requirements or operating conditions change (Gausemeier, Rammig, Schäfer, & Sextro, 2014). To this end, the current situation is monitored and the objectives of the system are determined. Using model based multiobjective optimization, for which a model of the dynamical behavior of the system is used, optimal system configurations are calculated before operation of the system. To adapt the system behavior during operation, the self-optimizing system selects among these optimal system configurations.

In order to use self-optimization to ensure that the requirements regarding reliability of the system are met, a suitable selection process has to be implemented. To adapt the system behavior advantageously with regard to system reliability, it has to be possible to lower work load or wear on critical components by selecting appropriate optimal system configurations. Thus it is also necessary to include system degradation in the objective functions used for the multiobjective optimization.

To control the remaining useful lifetime, the whole system history has to be taken into account as well. This could not be achieved by directly including remaining useful lifetime in the model used for multiobjective optimization, as then each objective function evaluation would require a simulation of the whole system lifetime. Such a simulation requires a lot of computing effort, rendering this approach impossible. Thus a process to take the system history into account separately during operation is required. For this, our presented selfoptimization based remaining useful lifetime controller can be used.

2. MAINTENANCE PLANNING

The big advantage of actively controlling the reliability of a system becomes apparent if the whole life-cycle including maintenance is considered. Within the scope of this section, it is assumed that after maintenance, a system is as-good-asnew. Traditionally, maintenance was conducted as either corrective of preventive maintenance (Birolini, 2007). In corrective maintenance, system functionality is reestablished once a failure occurs. This strategy is cheap at first, but once a failure occurs and the system is unavailable, maintenance has to be conducted as soon as possible, making the repair expensive. It

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Figure 1. Maintenance planning techniques and their effect on usable lifetime.

also comes with the risk of catastrophic failures which make it unsuitable for many systems. This approach maximizes the usable lifetime, as can be seen in Fig. 1. Availability, however, is limited due to unnecessarily long unscheduled maintenance.

Preventive maintenance, on the other hand, allows a high availability of the system by retaining system functionality. This is achieved by conducting maintenance before a failure occurs, making the maintenance schedulable and thus highly efficient. Usually, suitable maintenance intervals are determined using stochastic models for large fleets of systems (Joo, Levary, & Ferris, 1997). This approach has the advantage of achieving high availability with planned maintenance intervals, but usable lifetime until maintenance is lower than usable lifetime until failure. This increases the cost of operation due to earlier maintenance than necessary. Also it is best suited for large fleets of identical systems and can hardly be implemented for unique machinery.

In order to overcome these drawbacks, condition based maintenance can be used. According to (Jardine, Lin, & Banjevic, 2006), a condition based maintenance program consists of three steps: Data acquisition, data processing and maintenance decision making. In the first two steps, the current state of the system is assessed. After evaluation, efficient maintenance policies are recommended. A condition based maintenance program is comprised of two important aspects: Diagnostics and prognostics. In diagnostics, existing faults are detected, isolated and identified before they



Figure 2. Basic structure of clutch system.

lead to a failure. Prognostics, on the other hand, deals with the prediction of future faults. The main objective is to estimate the time until a fault occurs or the probability of it occuring. Using this information, the system can be operated without wasting usable lifetime for overly cautious maintenance intervals and also without requiring unscheduled maintenance. While this is advantageous over corrective and preventive maintenance, it remains a reactive method in which the system degradation drives the scheduling of maintenance operations and which makes planning of inspection and maintenance complex (Chena & Trivedi, 2005).

By combining information about the current system reliability with a feedback to system operation, it becomes possible to adjust system behavior according to its current reliability. This allows reversal of the usual approach. It now becomes possible to schedule maintenance operations with the system adapting its behavior and its degradation accordingly. The proposed closed loop control allows for such operation.

3. APPLICATION EXAMPLE

A single plate dry clutch has already been introduced as application example in (Meyer, Sondermann-Wölke, Kimotho, & Sextro, 2013) and is used again in this contribution. This type of clutch is commonly utilized in passenger vehicles to connect an internal combustion engine to the drivetrain. The basic outline of the clutch system is shown in Fig. 2. It consists of two friction plates with coefficient of friction μ , of which the input plate is connected to the engine while the output plate is connected to the driven system, e.g. a gearbox. The input and the output plates are rotating at speeds $\omega_1 = 1 \frac{\text{rad}}{\text{s}}$ and ω_2 respectively. To engage the clutch, both plates are pressed against each other by the force F_N , thus transmitting torque T_f from the input plate to the output plate and in turn applying this torque to the driven system.

The system dynamics can be modelled with

$$T_f(t) = F_N(t) \cdot \mu(\Delta\omega(t)) \cdot r_{eff}, \qquad (1)$$

$$\dot{\omega}_2(t) = \frac{1}{\Theta_2} \cdot \left(T_f(t) - d_2 \cdot \omega_2(t) \right), \tag{2}$$

$$\mu\left(\Delta\omega\right) = \mu_0 \cdot \frac{2}{\pi} \cdot \arctan\left(\frac{\Delta\omega}{\hat{\omega}}\right) \tag{3}$$



Figure 3. Pareto front of clutch system with two objective functions: f_1 : minimize wear and f_2 : Minimize accelerations, i.e. maximize comfort. Note that the duration of an actuation cycle t_r has a great effect on both objectives.

where $\mu_0 = 1$ is the nominal coefficient of friction, $\Delta \omega = \omega_2 - \omega_1$ is the difference in revolutionary speed of the plates, $\hat{\omega} = 0.1 \frac{\text{rad}}{\text{s}}$ is the accuracy parameter, $r_{eff} = 1 \text{ m}$ is the effective radius of the plates, $\Theta_2 = 1 \frac{\text{kg}}{\text{m}^2}$ is the moment of inertia of driven system, $d_2 = 1 \frac{\text{N} \cdot \text{m} \cdot \text{s}}{\text{rad}}$ is the damping factor of the driven system. Arbitrary values, which do not model a particular system, were chosen to demonstrate the proposed control method.

Also in (Meyer et al., 2013) it was shown that using multiobjective optimization techniques, a control trajectory for the actuation force $F_N(t)$ can be computed to actuate the clutch system. Multiobjective optimization techniques attempt to minimize user defined objective functions by adapting system parameters. Typically, it is not possible to minimize multiple objective functions at once, but instead as one objective function value is lowered, another objective function value rises. This leads to the so-called Pareto front, which consists of all optimal compromises between multiple objective functions. To each point on the Pareto front, system parameters are given in the Pareto set. To compute Pareto front and Pareto set, a genetic algorithm which comes with the Matlab global optimization toolbox has been used.

The required objective functions are included in a full model of the system dynamics. For our system, the objective functions are f_1 , which represents the power loss in the clutch P_f and in turn corresponds to the wear rate of the clutch plates, and f_2 , which represents e.g. comfort of vehicle passengers:

$$f_{1} = \int_{t_{0}}^{t_{0}+t_{r}} (P_{f}(t))^{2} dt = \int_{t_{0}}^{t_{0}+t_{r}} (T_{F}(t) \cdot \Delta \omega(t))^{2} dt,$$

$$f_{2} = \int_{t_{0}}^{t_{0}+t_{r}} (\dot{\omega}_{2}(t))^{2} dt.$$



Figure 4. Pareto set of clutch system with 84 possible actuation trajectories $F_N(t)$.

To compute the values of these objective functions, the dynamical model of the system is simulated over the period $t = t_0 \dots t_0 + t_r$ using trajectories for $F_N(t)$ as simulation input.

The duration of the actuation cycle and the shape of the trajectory are the optimization parameters. To include these in the optimization procedure, the trajectory was subdivided into 16 sections with equal durations. For the trajectory to begin with a completely disengaged clutch and end with a completely engaged clutch, $F_N(t_0) = 0$ N and $F_N(t_0 + t_r) = 100$ N are assumed. The optimization parameters are then the total duration of the actuation cycle t_r and the shape computed by using 15 intermediate values $F_N\left(t_0 + \frac{1}{16} \cdot i \cdot t_r\right), i = 1 \dots 15.$ Linear interpolation is used between these values. This way, the Pareto front shown in Fig. 3 with the corresponding Pareto set shown in Fig. 4 is obtained. A short total duration of the actuation cycle yields low energy losses but high accelerations, as opposed to a long duration, which yields inverse results. Each trajectory is a trade-off between these two objectives.

4. CONTROLLING THE RELIABILITY

In prior works (Meyer et al., 2013), a basic controller for the reliability of the clutch system was presented. However, the approach outlined therein was limited in its effectiveness since it did not take the inherent non-linearities and deviations between multiobjective optimization model and real system into account. It was not capable of handling deviations that required a great change from the nominal working point. The approach presented in the remainder of this contribution overcomes these drawbacks and offers better generalizability to other engineering problems.

A two-stage controller design has been favored for the possiblity to be designed separately for high-frequency perturba-



Figure 5. Full two-stage control loop.

tions on the inner loop and for low-frequency perturbations on the outer loop.

While priorities of objectives of a self-optimizing system may be selected arbitrarily, the system behavior does not necessarily reflect this immediately. On the one hand, an adaptation usually takes some time to take full effect; on the other hand the system model used for multiobjective optimization and the real system might deviate from one another, thus if a working point is chosen based an pre-calculated optimal system configurations, which are based on the system model, the actual system might behave differently. This leads to differences between desired objectives and achieved objectives.

To overcome these shortcomings, Krüger et al. developed a closed loop control for the objectives of a self-optimizing system (see (Krüger, Remirez, Kessler, & Trächtler, 2013)), colloquially called "Pareto controller". The purpose of this controller is to ascertain a pre-selected system configuration is actually being used, despite of perturbations or deviations between optimization model and actual system. To this end, the desired system configuration is selected with a so-called α -parameterization, which can be defined individually for each system. Suggestions are made, e.g. to use a Simplex-based method or to calculate the ratio among two objectives. In the course of this paper, we define the α -parameterization as follows, it is also included in Fig. 3:

$$\alpha = \frac{f_1}{f_2}.$$

The desired parameterization value α_{des} is used as controller input. The current value of the α -parameterization, α_{cur} is required for the controller to calculate the used value α_{used} according to the difference between α_{cur} and α_{des} . Once α_{used} has been calculated, the parameters of the system are determined by the so-called *s*-transform and set in the system. After *a certain time*, the resulting system behavior is evaluated to determine the current value α_{cur} of the α -parameterization. It is assumed that the behavior adaptation and evaluation of the actual system behavior takes some time to take full effect. For this reason, the Pareto controller works in discrete time on a *slow* time scale, where one discrete time step is the constant time period required for the full behavior adaptation and evaluation process. For this reason, in the abstract model of the system, the output is delayed by the unit delay $\frac{1}{2}$.

This Pareto controller is used as inner loop of the full control loop. It is not able to take the full lifetime information into account and serves the purpose of reliably achieving the desired system behavior.

The outer loop, on the other hand, is responsible for controlling the remaining useful lifetime. For this, an abstract model of the system adaptation process is required. As the inner loop already controls the desired behavior, the outer loop does not need to take actual system parameters into account but instead relies on using the α -parameterization as system input. System output and controlled variable is the remaining useful lifetime *RUL*. The reference input is denoted by *RUL_{des}*. However, the relationship between α and *RUL* is highly nonlinear. The difference in remaining useful lifetime $\Delta RUL(\alpha)$ over a single actuation cycle *i* can, however, be approximated using the system model. This is called the *r*-transform:

$$\Delta RUL(\alpha) = r(s(\alpha))$$

To obtain the current remaining useful lifetime, an integral element $\frac{z}{z-1}$ in the dynamic system, and a unit delay $\frac{1}{z}$ for the evaluation of the current remaining useful lifetime are added, as shown in Fig. 5.

As controller for the remaining useful lifetime, a P controller was chosen. An integral element is not required to correct for steady state errors due to the integrating properties of the wear process. It calculates the *r*-transformed desired α -parameterization $r(s(\alpha_{des}))$ according to:

$$G_{RUL} = \frac{r\left(s\left(\alpha_{des}\right)\right)}{RUL_{des} - RUL} = K_{p,RUL}$$
(4)

This discrete controller can be implemented in the same discrete time used for the Pareto controller. The controller output is then converted by the inverse *r*-transform $s^{-1}(r^{-1})$ to give α_{des} .

The reference input generated for the RUL-controller needs to be strictly monotonically decreasing. If it was not, an actuation cycle with no or even negative wear would be required, which is physically impossible. The chosen reference input begins with RUL_{des} (new system) = 100% and ends with RUL_{des} (end of specified lifetime) = 0%. Linear interpolation is chosen for intermediate cycles. The reference input can be altered during operation in case of changed requirements. An adaptation of system behavior is then conducted by means of the control loop.

5. SETUP OF THE CONTROLLER FOR THE APPLICATION EXAMPLE

When controlling the remaining useful lifetime, the system behavior is adapted by changing system objectives. However, it needs to be ascertained that these objectives are met. As was mentioned in the basic introduction of the control loop in section 4, a specifically designed closed loop control by Krüger et al. (Krüger et al., 2013) is used. This control loop as well as the RUL-controller that builds on it are working in discrete time, their stepsize is *big* compared to the system dynamics. Since the clutch system has discrete events, one step corresponds to one full actuation cycle. Due to this, the stepsize of both controllers is 1 cycle.

5.1. Pareto controller

The basic idea of the closed loop Pareto controller is to define the desired system behavior using a so-called α -parameterization. The value of this parameterization is used as reference input α_{des} for the controller. The actual current value α_{cur} is computed from signals or measured variables of the system.

At first, the α -parameterization needs to be defined. For the clutch system, which pursues two objectives only, the fraction of both objective values is used, i.e. $\alpha = \frac{f_1}{f_2}$. This approach has several advantages over more complex parameterizations, e.g. the Simplex-based parameterization suggested in (Krüger et al., 2013). First, it is very simple to calculate, thus requiring low computational time. Second, and more importantly, no knowledge about the Pareto front, such as an approximating function, number of known points or values at the edges, is required. This makes evaluating the currently achieved value α_{cur} independent of any assumptions about other possible working points.

The α -value needs to be transformed into a set of parameters to be used by the actual system. For this, the *s*-transform is used. It determines the desired Pareto point from the Pareto front and selects the Pareto set, which contains all system parameters, accordingly. For the clutch system, linear interpolation between pre-calculated Pareto points is used. This is done in three steps: At first, the two Pareto points closest to the desired α -parameterization α_{des} are searched. In the next step, the two sets of parameters are selected from the Pareto set P_{set} . Last, linear interpolation is used for each pair of parameters to obtain the final parameter.

To determine the closest Pareto point, the α -paramterization value for each pre-calculated Pareto point is calculated. For this, $k = 1 \dots n, k \in \mathbb{N}, n \in \mathbb{N}$ Pareto points are assumed:

$$\alpha_k = \frac{f_{1,k}}{f_{2,k}}.$$

The following two steps are conducted at runtime. At first, k closest to the currently desired value α_{des} is searched:

$$\min_{k} \left(\left| \alpha_k - \alpha_{des} \right| \right)$$

Once this is known, linear interpolation among two points with α -values closest to the desired value α_{des} is conducted to find system parameters W from the Pareto set P_{set} :

$$P\left(\alpha_{des}\right) = \begin{cases} \frac{\left(P_{set,k} + P_{set,k+1}\right) \cdot \alpha_{des}}{\alpha_k + \alpha_{k+1}}, & \text{if } 1 < k < n \text{ and} \\ \frac{\left(P_{set,k-1} + P_{set,k}\right) \cdot \alpha_{des}}{\alpha_{k-1} + \alpha_k}, & \text{if } 1 < k < n \text{ and} \\ \frac{\alpha_{k-1} + \alpha_k}{\alpha_{k-1} + \alpha_k}, & \alpha_{k-1} | > |\alpha_k - \alpha_{k+1}|, \\ P_{set,k}, & \text{else.} \end{cases}$$

The advantage of this approach is that even though a limited number of Pareto points is known from numerical multiobjective optimization, a *close* approximation for intermediate values can be found. This is important in subsequent steps, since all controllers developed herein have continuous output values and expect the system, i.e. *s*-transform, clutch system, objective evaluation, and s^{-1} -transform, to accept such and work continuously as well.

With linearly interpolating between Pareto points, it is assumed that all computed possible solutions P_{set} to the optimization problem are *similar*. Proof that this assumption holds is difficult, but clear indications can be seen in Fig. 4.

The s^{-1} -transform, on the other hand, is very simple once current values of the system objectives $f_{1,cur}$ and $f_{2,cur}$ are determined by evaluating measured variables or signals from the system:

$$\alpha_{cur} = \frac{f_{1,cur}}{f_{2,cur}}.$$

With these transformations all set, the actual controller can be parameterized. It was created according to (Krüger et al., 2013) without modifications. The controller parameters were chosen as $K_p = 0.05$ and $K_i = 0.05$.

The controller reference input is the desired α -parameterization α_{des} . It is set by the outer loop which controls the remaining useful lifetime of the system and induces a behavior adaptation by changing α_{des} .

5.2. RUL controller

The purpose of the outer control loop is to determine the currently required desired α -parameterization α_{des} from the desired remaining useful lifetime RUL_{des} and the current remaining useful lifetime RUL.

At first, the remaining useful lifetime RUL needs to be determined. This is highly application-specific. A model-based approach has been selected to estimate the remaining useful lifetime of the friction plates. It is based on the assumption that clutch plate wear is proportional to friction energy E_f (Fleischer, 1973). For each actuation cycle *i* with time span $t = t_{0,i} \dots t_{0,i} + t_r$, where t_r is the duration of the actuation cycle, the wear w(i) occuring during this cycle is:

$$w(i) = p_f \cdot \Delta E_f(i) = p_f \cdot \int_{t_{0,i}}^{t_{0,i}+t_r} P_f(t) \,\mathrm{d}t$$
$$= p_f \cdot \int_{t_{0,i}}^{t_{0,i}+t_r} T_F(t) \cdot \Delta \omega(t) \,\mathrm{d}t.$$
(5)

The proportionality factor is assumed to be $p_f = 1$ for normal wear behavior. Due to e.g. errors in manufacturing or materials, it might deviate, thus requiring a changed operating point in order to fulfill the specified lifetime.

To estimate the remaining useful lifetime, all actuation cycles need to be taken into account. To do so, the sum of the wear occuring in each cycle w(i) is summed over all prior m cycles, i.e. $i = 1 \dots m, i \in \mathbb{N}, m \in \mathbb{N}$. The remaining useful lifetime RUL for the next cycle m + 1 can then be estimated by taking the maximum amount of wear w_{max} of the clutch into account. This results in the following relation:

$$RUL(m+1) = 1 - \left(\frac{\sum_{i=1}^{m} w(i)}{w_{max}}\right).$$
 (6)

To convert the RUL-controller output to a desired value of the α -parameterization, the inverse *r*-transform $s^{-1}(r^{-1})$ needs to be defined next. Since $\Delta RUL(\alpha)$ can not easily be computed analytically, the main cause of wear needs to be determined. As was shown in eqns. 5 and 6, the remaining useful lifetime mainly depends on the friction energy ΔE_f , thus $\Delta RUL(\alpha) \sim \Delta E_f$.

To setup the inverse *r*-transform, the friction energy for each pre-calculated α -parameterization $\Delta E_f(\alpha)$ is computed by simulating the system model for one full clutch cycle. The resulting relationship between α -parameterization and ΔE_f is shown in Fig. 6.

Using a least-squares approach, an approximating function was fitted to obtain a computationally effective $s^{-1}(r^{-1})$ -



Figure 6. Compensation of nonlinear behavior.

transform. An exponential ansatz was chosen:

$$\alpha_{approx} = q_1 \cdot e^{q_2 \cdot \Delta E_f}$$

The parameterized approximating function $(q_1 = 0.3714, q_2 = 0.5536)$ is also shown in Fig. 6.

The objective-based controller for the remaining useful lifetime is implemented according to eq. 4. As proportional gain parameter, $K_{p,RUL} = 1000$ was chosen.

6. SIMULATION RESULTS

To evaluate the feasibility of the proposed approach, simulations that span the whole lifetime of the clutch system were conducted. For this, a model of the dynamic behavior of the clutch system according to eqns. 1, 2 and 3 was used.

An artifical fault was introduced into the system model: After 200 regular clutch cycles, the wear proportionality factor was changed from $p_f = 1$ to $p_f = 2$. This way, the simulated wearing process was accelerated; the plates wear twice as fast as they did previously. As can be seen in Fig. 7, the system behavior is adapted accordingly. At first, a slight deviation between desired and obtained RUL can be observed; however, the system lasts for the required 500 cycles.

In another test of the behavior adaptation process, the requirements for the system were changed at 200 cycles. The system is now required to last for 600 cycles instead of 500 cycles, as was the initial requirement. As can be seen in Fig. 8, the adaptation process enables the system to successfully adapt its behavior to changed requirements.

As was shown, an adaptation to either changed system degradation processes or to changed requirements is possible. The controlled system fulfills the desired properties regarding reliability.



Figure 7. System behavior if a fault occurs. At 200 cycles, the proportionality factor p_f was changed to simulate a clutch system wearing twice as fast as was anticipated for a normal system.

The adaptation to accelerated wear processes and changed user requirements comes at the expense of degrading performance of the system. In case of the clutch system, the value of the α -parameterization is lowered for both adaptations. This leads to lower, i.e. better values of the objective *minimize* wear and to higher, i.e. worse values of the objective minimize accelerations. As can be seen in Fig. 4, the main difference between different working points is the duration of the actuation trajectory. A system running in nominal operating mode, i.e. before 200 cycles are reached, has an actuation duration of approximately 9.5 s, giving a comfort value $f_2 = 0.039$. If changed user requirements are to be taken into account, the actuation duration is shortened to approximately 8.9 s, lowering the comfort value to $f_2 = 0.064$. In order to compensate accelerated wear processes, the selected working point requires an even faster actuation duration of approximately $6.9 \,\mathrm{s}$ at a comfort value $f_2 = 0.25$. These lower values signify a quicker and less comfortable acceleration maneuver, which is required to react on these great variations in system behavior or requirements. Even though the difference in comfort value suggests severely limited operating potential, the benefit of reaching pre-defined reliability goals will in most cases outweigh the loss in comfort.

7. CONCLUSION & OUTLOOK

The behavior adaptation process of an intelligent system is modelled abstractly. A two-stage control loop was designed with the inner loop controlling the desired system behavior whereas the outer loop controls the remaining useful lifetime. To this end, an existing controller for the inner system behavior is implemented. For the outer loop, a new controller is added. Simulation results show, that the adaptation of the



Figure 8. System behavior for changed requirements. At 200 cycles, the system requirements are changed; it is now expected to sustain 600 actuation cycles.

system behavior based on the remaining useful lifetime successfully adapts the behavior if either the system behavior or the requirements change. In both cases, the desired useful lifetime can be accomplished.

While simulations show that the system degrades as desired, experimental validation is still required. Since the behavior adaptation and experiments that span the whole system lifetime are complex, the setup of a dedicated test rig is currently being pursued.

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REFERENCES

- Birolini, A. (2007). *Reliability engineering* (5th ed.). Berlin Heidelberg: Springer.
- Chena, D., & Trivedi, K. S. (2005, October). Optimization for condition-based maintenance with semi-markov decision process. *Reliability Engineering & System Safety*, 90(1), 25-29. doi: 10.1016/j.ress.2004.11.001
- Fleischer, G. (1973). Energetische Methode der Bestimmung des Verschleißes. *Schmierungstechnik*, 4(9), 269-274.
- Gausemeier, J., Rammig, F. J., Schäfer, W., & Sextro, W. (Eds.). (2014). Dependability of self-optimizing mechatronic systems. Heidelberg New York Dordrecht London: Springer. doi: 10.1007/978-3-642-53742-4

- Jardine, A. K. S., Lin, D., & Banjevic, D. (2006, October). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483-1510. doi: 10.1016/j.ymssp.2005.09.012
- Joo, S. J., Levary, R. R., & Ferris, M. E. (1997, February). Planning preventive maintenance for a fleet of police vehicles using simulation. *SIMULATION*, 68(2), 93-99. doi: 10.1177/003754979706800202
- Krüger, M., Remirez, A., Kessler, J. H., & Trächtler, A. (2013, June). Discrete objective-based control for selfoptimizing systems. In *American control conference* (acc), 2013 (p. 3403-3408).
- Meyer, T., Sondermann-Wölke, C., Kimotho, J. K., & Sextro,
 W. (2013). Controlling the remaining useful lifetime using self-optimization. *Chemical Engineering Transactions*, 33, 625-630. doi: 10.3303/CET1333105

BIOGRAPHIES

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Networked Modular Technology for Integrated Aircraft Health Monitoring: Application to Rotary Structures

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ABSTRACT

The largest variable cost to aircraft's manufacturers and flying companies is unscheduled maintenance. Therefore, developing efficient and modular PHM system capable to scale different architectures topologies for in flight and on ground health monitoring could be cost effective, since it brings indication and warning prior to damage occurring.

In this paper, we propose an innovative diagnostic and prognostic health system based on a combination of modular acquisitions interfaces and processing units.

An embedded JTFA (Joined Time-Frequency Analysis) method based on STFT (Short-Time Fourier Transform) or Wigner-Ville transforms are used to extract a relevant signature. The proposed algorithms and PHM system technology are applied for diagnosis of mechanical flows in a high speed rotating gear of a demonstrator machine. A detailed description of data management and rooting from vibration sensors to the processing unit will be exposed.

Finally, a proof-of-concept experiment will be designed to demonstrate the integration of all the described system elements to detect any damage or anomaly into the monitored structure.

1. INTRODUCTION

Health management and damage assessment of rotary structures is one of the major issues that face Helicopter's and turbofan's manufacturers. In this context, PHM applications can actually provide a wide range of benefits for complex systems such as transmission gear boxes or jet engine turbine.

For the time being, main and engine accessories are systematically replaced either upon failure or after a pre calculated time of use. These maintenance procedures which are typified in many reports (FAA report DOR/FAA/CT-92/29) create huge cost of maintenance and materials (Cf. Figure 1).

Therefore, forecasting the remaining useful life of these subsystems can improve flight safety and reduce exploitation cost by reducing unscheduled events and regular maintenance (Heng et al 2009). Moreover, a constant monitoring of critical subsystems reduces preventive aircraft grounding which increase airplanes readiness.

Labor Cost Material Reparation Other



Figure 1. Maintenance, repair, and operations (MRO) cost distribution in (%) (PIPAME report)

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In aircraft industries, real time monitoring of vibration (Lastapis et al 2007, Dempsey et al. 2007) is systemically used to detect machine faults including structure flaws, impacts, cracked rotors or oil degradation. Due to the complex nature of the inspected systems, analytical studies based on predictive behavior models show their limit quite quickly. Additionally, it has been shown by Lewicki et al. 2010 and Bechhoefer et al. 2011 that there is no single condition indicator (CI) which is sensitive to every failure mode.

So, in most methods, the diagnostic is simply based on comparison of vibration amplitudes or frequencies to a baseline. However, in the case of some complex machines, such as helicopter blades or turbofan, the detection of abnormal behavior is in essence complicated by the fact that changes in operational conditions makes acquired vibration non stationary. Because of that, classical vibration based diagnostics techniques which focus either on time domain or frequency domain are not suitable. In such cases an efficient approach to monitor (CI) condition indicator may be based on (JTFA) Joined Time-Frequency Analysis (Klein 2013).

The current paper proposes an automated solution for feature extraction. Health indicators such as temperature, pressure or vibration are acquired using on board sensors through avionics buses or analog interfaces. Hence, there is no need to plug external non-qualified sensors. To inform operators of needed repairs, the system is capable through embedded processor to evaluate the global health using evaluative and dynamic thresholds.

For the purpose of this article, We focused our studies, on the joined time frequency analysis of abnormal vibration behavior thought the instrumentation of piezoelectric sensors. Using an embedded processor, an analysis algorithm based on smart comparisons between different signatures will be exposed. Damage assessment approach is in fact based on a smart differentiation between classified signatures acquired prior and after to the damage. The healthy signature, in the other hand is extracted using a statistical characterization of the studied machine.

Finally in the last section, we will demonstrate the flexibility that network embedded modular system architecture may bring to PHM in aerospace.

2. JOINED TIME-FREQUENCY ANALYSIS AND FEATURE EXTRACTION METHODS :

Based on JTF analysis, feature extraction methods can be computed using different techniques of signal processing. This section provides a short description of the considered methods:

1. Short-Time Fourier Transform: STFT is widely used for JTF analysis. It splits a time domain signal f(t) into small segments and applies a window function

W(t) to each one before computes a FFT (Fast Fourier Transform) of each segment :

$$STFT_f^u(t',\omega) = \int_f [f(t) \cdot W(t-t')] \cdot e^{-i\omega t} \cdot dt \quad (1)$$

Since it uses a typical Fourier transform, this method requires a stationary signal over each segment interval. So to analyze semi-transient signals, the required segments lengths could be adapted dynamically to the observed system. In this case, the major consideration is to correctly balance between time and frequency resolution (Qian et al 1999). In fact, due to Heisenberg-Gabor uncertainty principle, a wide window W(t) gives good frequency resolution and poor time resolution. In opposite a narrow time slice gives a good time resolution and poor frequency resolution. These two cases could be problematic for fast transient signals.

2. Wavelet Analysis is mostly used to localize the exact time of a specific vibration event. This approach is widely used as a JTFA technique for Lamb wave triangulation and feature extraction (Boukabache et al. 2013). Basically, Wavelet Transform (WT) contains informations similar to STFT. However due to the special proprieties of the used wavelet, the resolution in time is much higher at high frequencies. The resolution difference between STFT and Wavelet Transform is shown in Figure 2.



Figure 2. Time-Frequency sampling resolution representation of different JTF methods

3. **Bilinear Time-Frequency Distribution** using Cohen's Class Distribution Function: (CCDF) was firstly proposed in 1966 in the context of quantum mechanics (see Cohen 1966). It is a generalized timefrequency representation method that utilizes bilinear transformations thought the use of a kernel function :

$$C_x(t,f) = \iint_{-\infty}^{\infty} A_x(\eta,\tau) \Phi(\eta,\tau) e^{-i2\pi(\eta t - \tau f)} d\eta d\tau \quad (2)$$

Where $A_{\rm x}$ is the ambiguity function and Φ is the kernel function which could include **Choi-Williams** Distribution (Lazorenko 2006) Wigner-Ville Distribution (Boashash 1987) or Zhao-Atlas-Marks (Rajagopalan et al. 2006). The main primary advantage of CCDF is its capability to analysis non stationary signals. This technique could therefore be applied to transient vibration data collected through high speed transition conditions. However, the bilineartransformation needs a careful investigation of used window function otherwise it suffers from inherent cross-term contamination which degrades the clarity for most practical signals.

Therefore based on these points and the study of (Byington et al, 2011) the authors chose a STFT as a JTFA method. Compared to the other techniques, STFT offers the best compromise between resolution performance and embedded computational time. In fact, efficient FFT algorithms already exist for embedded CPU or FPGA which makes STFT time calculation quite efficient. In addition, small amount of data is needed to computes the algorithm which lighten aircraft data bus traffic.

3. THE PROPOSED PHM SYSTEM

In order to monitor several airplanes systems without overloading the weight with additional sensors, we developed new system architecture, capable to interact with existing embedded avionics and embedded sensing units (See Figure. 3).

The presented technology is built around harsh networked electronic modules (see Figure 3 and 4) where each one is dedicated to a specific task such as:

- Sensors instrumentation and acquisition (Temperature, Strain, Pressure, Acceleration and Deformation)
- Multiple avionics protocol communication interfaces (ARINC429, CAN, Ethernet, RS422) to connect the PHM system with on board calculators
- Waveform and signal generation (current, voltage, resistive load ...) to simulate avionics sensors behavior or to provide calibrated stimulus.

Based on embedded CPUs, each module has lightweight signal processing capabilities to execute basics algorithms such as filtering or buffering.



Figure 3. Synoptic of the proposed PHM modular system

Moreover using hot swap and reconfiguration capabilities, the modules can be plugged and unplugged freely without damaging the PHM System. The theoretical maximum number of plugged modules is in fact only limited by the internal network bus bandwidth. Hence, this architecture allows high level of scalability to manage aircraft life cycle.



Figure 4. Synoptic of the proposed PHM modular system



Figure 5. Experimentation setup

In addition, a central processing and control unit with advanced calculation capabilities manages the whole network scheduling and behavior. This command module is also responsible of sensors data collection, storage and processing as well as, the execution of JTFA diagnostic/prognostic algorithms. In fact, collected data could be exploited on ground with a post treatment for precise analysis or during flight using empiric thresholds for immediate alarm annunciations. The modular scalability of the proposed PHM architecture, allows immediate on flight installation to monitor in real time undesired events.

4. PROOF OF CONCEPT

4.1. Experimental setup

For the purpose of this article, we used as an experimental machine: a phonic wheel developed to characterize a turbojet engine rotating speed. During its operating, the produced vibration is measured using a PZT piezoelectric sensor of 5mm radius pasted directly onto the external frame of the demonstrator. In the meanwhile, rotating speed is acquired using an inductive sensor (See Figure 5).



Figure 6. Data acquisition chain

The phonic wheel is actually driven by an electric brushless motor capable to reach a realistic rotating speed of 10000RPM. When activated, the rotation of the wheel generates vibrations signature that produces local micro deformations. Hence, according to the applied strain, the piezoelectric sensor generates charges Q(t). To be exploitable, these charges are converted into a voltage signal using a simple charge converter (See Figure 6).



Figure 7. Photo of the experimental setup

Analog acquired values are digitalized using a Delta Sigma 24bits ADC inside the sensors module (See Figure 6), then buffered, eventually filtered using a low pass FIR filter and finally transmitted when the command module requests it. At the last stage of the process, the data is buffered into a hardware FIFO synthetized into an FPGA and finally handled by the processor to compute an STFT based JTFA analysis.

To synchronize the global system and schedule each task of the process, the command module controls the wheel speed using short time impulse orders and acquires the rotation speed using the inductive sensor. Hence, the command module applies to the mechanical system a strictly similar operating condition which allows the extraction of a relevant signature.

4.2. Experimental results

To demonstrate the detection capabilities of the described PHM system, in steady states conditions and pseudo stationary operational conditions, we performed two representatives' experiments.



Figure 8. Healthy vibration baseline at 1000RPM



Figure 9. Abnormal vibration signature at 1000RPM

4.2.1. Abnormal behavior in steady state operation mode

In this configuration, the command module stabilizes the phonic wheel around fixed speed and acquired generated vibrations using the PZT sensors after 5s.

Using equation (1) a simple spectrogram is computed through the calculation of the squared STFT magnitude.

Spectrogram
$$\{x(t)\}(t',\omega) = |STFT_f^u(t',\omega)|^2$$
 (3)

A relevant signature baseline (See Figure 8) is therefore extracted using Eq. 3 then compared to an abnormal signature acquired for the same operating conditions. For this experience, we simulated a machine degradation using a faulty contact with the shaft. In this case, data analysis shows a clear spectrogram response modification. Beside to the initial low frequencies (<500Hz) shown clearly in figure 8, the mechanical default add to the spectrogram higher spikes frequencies around 1kHz. In addition, it is interesting to notice that magnitudes of low frequencies are the same in the two figures 8 & 9.



Figure 10. Healthy baseline: Power Spectrogram Representation (dB/Hz) in 2D at 1000RPM



Figure 11. Abnormal signature: Power Spectrogram Representation (dB/Hz) in 2D at 1000RPM







Figure 13. Normalized damage response

In all the experimentations, we used a Hamming windowing to compute de DFT. The calculation of the power spectrogram representation presented in figures 10 & 11 shows the need to have same scaling. Actually, with this representation, the coloration map doesn't allow any thresholding. To solve this issue, we recalculate a common scale to both signatures using a simple normalization. The results are shown in figures 12 & 13. Using this simple algorithm, we are capable to detect any magnitude variation versus to the baseline (presented in figure 12) using a simple threshold fixed to 1.1.

4.2.2. Abnormal behavior in pseudo transient operation mode

In real operational condition, the speed or the load may vary with time. In this case, the previously presented algorithm does not suit. To simulate such behavior, the command module sends to the phonic wheel a series of orders to increment its speed by step of 2.5seconds to reach a maximum speed of 7000RPM.



Figure 14. Healthy 3D baseline signature between 600 and 7000RPM



Figure 15. Damaged 3D signature between 600 and 7000RPM

In this configuration the command module verifies for each step that the needed speed was reached before acquiring lsecond of vibration data. For these conditions, we may split the entire experimentation time into small segments where stationary conditions are verified. The segments intervals could be downsized depending on the acceleration capabilities of the motor. In other words, the more the acceleration is, the smaller the intervals are set.

While, semi-stationary conditions are verified for each segment, we computed for each interval, a simple power spectrum density algorithm; then we extracted for each rotation speed the location and the magnitude of the produced frequency peaks. The resulted data are plotted in figures 14 and 15. However, the 3D representations are quite difficult to analyze. To simplify and automatize the diagnosis, we extract statistically from the baseline (See Figure 14) a list of relevant frequency peaks. Then, we plot in 2D representation the magnitude of theses peaks versus the rotation speed.


Figure 16. Healthy baseline between 700 and 6200RPM



Figure 17. Abnormal signature between 700 and 6200RPM



Figure 18. Damaged signature between 700 and 6200RPM

The produced signatures could therefore be quickly studied using a pre-calculated abacus (See. Figure 16). Using this simple representation, the diagnosis is quite quick to perform. The thresholds are calculated statistically for a healthy behavior then compared to degraded signatures. In the example of figure 17, the frame of the phonic wheel has been burden with 25g. The signature stills basically the same, even if we notice a thin shift of spikes magnitudes at high rotation speed. In the example of figure 18, a faulty contact has been introduced onto the shaft of the phonic wheel. The signature response has been completely modified.

5. CONCLUSION

A scalable aerospace PHM technology based on embedded networked modules was proposed. The system was designed for in flight and on ground aircraft health management. Beside its capacity to spy most of avionics buses, the system is capable to monitor mechanical machineries in order to detect an abnormal event and predict an eventual failure. In this paper the proposed system was successfully tested on a representative mechanical rotating machine.

In addition, we presented a method for analysis and diagnosis vibro-acousitic data acquired using piezoelectric sensor. The method was successfully demonstrated for stationary data and pseudo-transient variations. Using a 2D representation of RPM-spectrogram, we managed to diagnosis abnormal behavior onto a phonic wheel. Actually, the developed algorithms were specially studied to be suitable for an embedded integration.

NOMENCLATURE

- CCDF Cohen's Class Distribution Function
- CI Condition Indicator
- CPU Core Processing Unit
- *DFT* Discrete Fourier Transform
- JTFA Joined Time Frequency Analysis
- *FFT* Fast Fourier Transform
- *FIFO* First In First Out
- FIR Finite Impulse Response
- FPGA Field-Programmable Gate Array
- PZT Lead Zirconate Titanate
- *PSD* Power Spectral Density
- *RPM* Rotation per Minutes
- STFT Short Time Fourier Transform
- WT Wavelet Transform

REFERENCES

- Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent fault diagnosis and prognosis* for engineering system. Hoboken, NJ: John Wiley & Sons, Inc
- Bechhoefer, E., He, D., and Dempsey P., (2011). Gear Health Threshold Setting Based On a Probability of False Alarm. Annual Conference of the Prognostics and Health Management

- Dempsey, P., Lewicki. D, Le. D,. (2007). Investigation of Current Methods to Identify Helicopter Gear Health. *NASA archive*
- Lewicki, D., Dempsey, P., Heath, G., and Shanthakumaran P. (2010), Gear Fault Detection Effectiveness as Applied to Tooth Surface Pitting Fatigue Damage, *Gear Technology*, November/December 2010.
- Escriba, C., Fourniols, J., Lastapis, M., Boizard, J., Auriol, G., Andrieu, S., (2012) New real-time structural health monitoring microsystem for aircraft propeller blades, *Aerospace and Electronic Systems Magazine, IEEE*, Vol.27, Issue: 2, 10.1109/MAES.2012.6163611
- Boukabache, H., Escriba, C., Zedek, S., Fourniols, (2013) J.
 Wavlet Decomposition based Diagnostic for Structural Health Monitoring on Metallic Aircrafts: Case of Crack Triangulation and Corrosion Detection, *International Journal of Prognostics and Health Management*, ISSN 2153-2648, 2013 003
- Klein, R. (2013) A Method for Anomaly Detection for Nonstationary Vibration Signatures, *Annual Conference of the Prognostics and Health Management Society*, 2013
- Byington, C., Watson, J., Sheldon, J., Lee H., Mott G., (2011) Joint Time Frequency Vibration Diagnostics of Main and Engine Accessory Gearboxes, AIAC14 Fourteenth Australian International Aerospace Congress, 2011
- Heng, A., Zhang, S., Tan, A. C., & Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, 23(3), 724-739.
- Cohen L., (1966) Generalized Phase-Space Distribution Functions, *Journal of Mathematical Physics*, Volume 7, Issue 5, May 1966
- Lazorenko, O.V. (2006), Ultrawideband Signals and Choi-Williams Transform, *Ultrawideband and Ultrashort Impulse Signals, The Third International Conference*, Sept. 2006 P300 -302.
- Boashash B., Black P.,(1987) An Efficient Real-Time Implementation of the Wigner-Ville Distribution, *IEEE* transactions on acoustics, speech, and signal processing, Vol assp35, No11
- Rajagopalan, S., Habetler, T.G., et al (2006)., Non-Stationary Motor Fault Detection Using Recent Quadratic Time-Frequency Representations, *Industry Applications Conference*, 2006, 41st IAS Annual Meeting, Conference Record of the 2006 IEEE, Volume 5, Oct. 8-12, 2006 P:2333 - 2339.
- PIPAME report : Maintenance et réparation aéronautique, base de connaissances et évolution. Online
- Richter, B., Ridenour-Bender, M., Tsao, M., Aircraft Turbine Engine Reliability and Inspection Investigations, *Report No. DOR/FAA/CT-92/29*, October 1993.
- Qian, S.; Sapang, C.(1999) Joint Time Frequency Analysis, Signal Processing Magazine, IEEE, Volume 16, Issue 2

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Remaining Useful Life Estimation of Stochastically Deteriorating Feedback Control Systems with a Random Environment and Impact of Prognostic Result on the Maintenance Process

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ABSTRACT

The objective and originality of this work are twofold. On one hand, it considers the degradation modeling and Remaining Useful Life (RUL) estimation for the closed-loop dynamic systems, which have not been addressed extensively in the literature. On the other hand, the paper examines how the prognosis result impacts the maintenance process. Indeed, due to their natural ageing and/or non desired effects of the operating condition, actuators deal with the loss of effectiveness which is a source of performance degradation of closedloop system. In this paper, we consider a control system with classical Proportional-Integral-Derivative controller and stochastically deteriorating actuator. It is assumed that the actuators are subject to shocks that occur randomly in time. An integrated model is proposed which jointly describes the states of the controlled process and the actuators degradation. The RUL can be estimated by a probabilistic approach which consists of two steps. First, the system state regarding the available information is estimated online by Particle Filtering method. Then, the RUL of the system is estimated by Monte Carlo simulation. To illustrate the approach and highlight the impact of the prognosis result on the maintenance process, a well-known simulated tank level control system is used. The maintenance decision rule is based on the quantiles of RUL histogram. In order to evaluate the performance of the maintenance policy, a cost model is developed.

1. INTRODUCTION

Respecting the growing demand of safety, reliability and availability of industrial production process, research activity on maintenance modeling has intensively evolved during the last decades. In the context of Condition-Based Maintenance (CBM) system health monitoring information is used to determine its current status and based on this information one can perform maintenance actions to avoid failure (Dieulle, Bérenguer, Grall, & Roussignol, 2003; Van Noortwijk, 2009; Huynh, Barros, & Bérenguer, 2012). However, the CBM approach does not consider specific knowledge about future usage of the system which can be useful information to improve the decision marking (Khoury, Deloux, Grall, & Berenguer, 2013). In this way, a predictive maintenance which combines the prognosis and CBM maintenance seem to be an appropriate approach (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006; Do Van, Levrat, Voisin, Iung, et al., 2012).

Generally, prognosis is defined as the prediction of future characteristic of the system such the Remaining Useful Life (RUL) (Si, Wang, Hu, & Zhou, 2011; Sikorska, Hodkiewicz, & Ma, 2011). According to (Jardine, Lin, & Banjevic, 2006) the prognostic approaches can be classified into three main categories: statistical approaches, artificial intelligence approaches and model-based approaches. Many studies are devoted to the RUL estimation of systems, subsystems or components (see reviews by (Peng, Dong, & Zuo, 2010),(Si et al., 2011).

In spite of that, according to the best knowledge of the authors the degradation modeling and RUL estimation process for closed-loop dynamic system such as feedback control system has not been addressed extensively. Indeed, the degradation or wear of components can lead to the gradually decreasing of the control system performance during its operation. One objective of this paper is to propose a probabilistic approach to assess the RUL of feedback control system with stochastically deteriorating actuator within a random environment. The other objective of the paper is to examine the use and the impact of prognostic information on the predictive maintenance decision-making process. In order to deal with the complex interaction between the deterministic behavior of the feedback control system and the stochastic degradation process, a Piecewise Deterministic Markov Process is adopted to describe the whole deteriorating closed-loop system. In this

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framework, the distribution of the RUL of the system is computed by using a two-step stochastic model-based technique.

The remainder of this paper is organized as follows. Section 2 is devoted to the description of the system characteristics. Section 3 describes the approach for computing the Remaining Useful Lifetime which is relevant to system state estimation using the available condition monitoring information. To illustrate the methodology and also highlight the use of prognostic result in the maintenance process, a specific case study is introduced in Section 4. Some numerical results are also discussed here. Finally, conclusion drawn from this work and possible ways for further studies are given.

2. System modeling and assumptions

This section is devoted to describe the characteristics of a deteriorating feedback control system whose actuator stochastically degrades through time due to its natural degradation and the impact of the operating condition. The stochastic evolution of set-point which depends on the operating mode is also characterized. No additional sensor is devoted to the monitoring of the actuator degradation, the measurement of controlled output is then used to assess the RUL.

2.1. General structure of a deteriorating feedback control system

Consider a dynamical process which can be described in statespace representation as:

$$\begin{cases} \dot{x}(t) = \mathbf{f}(t, x(t), u(t)) \\ y(t) = \mathbf{h}(t, x(t), u(t)) + \epsilon(t) \end{cases}$$
(1)

where x(t) is the state vector of process, u(t) denotes control force acting on the process, y(t) is the measurement of output. Process dynamic function **f** and process output function **h** can be nonlinear. Here, it is assumed that measurement noises $(\epsilon_t)_{t \in \mathbb{R}_+}$ are independent random variables with a probability density g, not necessarily Gaussian, independent of the process state $(x_t)_{t \in \mathbb{R}_+}$.

The objective of a conventional feedback control system is to maintain the process output y(t) within a desired range defined by a set-point. Such objective can be achieved by the feedback structure with a classical Proportional-Integral-Derivative (PID) controllers which are widely used in industrial applications thanks to their simplicity and performance (Aström & Hägglund, 1995), see Figure 1 for a general scheme of a feedback control system.

The PID controller output $u^{c}(t)$ is given by:

$$u^{c}(t) = K_{P}\left[e(t) + \frac{1}{T_{I}}\int_{0}^{t}e(\tau)\mathrm{d}\tau + T_{D}\frac{\mathrm{d}e(t)}{\mathrm{d}t}\right]$$
(2)

where e(t) is the error signal defined as $e(t) = y^{ref}(t) - y(t)$

with $y^{\text{ref}}(t)$ the desired set-point (the reference output), K_P is the proportional gain, T_I is the integral time and T_D is the derivative time of the PID controller. The adjustment of these three parameters for an optimal system response is extensively studied in control system design (Aström & Hägglund, 1995).



Figure 1. General block diagram of a feedback control system with notations

The output of actuator which is the real control variable acting on the process is defined as a function g depending on the required value $u^{c}(t)$ of the controller and on the actual capacity of actuator C(t). g is a decreasing function w.r.t. C(t):

$$u(t) = \mathbf{g}(u^c(t), C(t)) \tag{3}$$

At the initial stage of working, the actuators operate perfectly, i.e. $C(t) = c_0$ where c_0 is the initial nominal capacity of actuator. In reality, the natural ageing or wear of the parts of the actuator and/or the non desired effects of the operating condition are unavoidable, lead to the decreasing of the actuator's effectiveness C(t) in time and subsequently reduces the control system performance.

2.2. Set-point evolution and operating modes

The evolution of set-point (the mission profile) presents the environmental conditions the system evolves in. According to the demand e.g. of the production process, the desired set-point may change. The random evolution of the set-point is described by a time-homogeneous Markov chain with a finite state space $r_{set} = \{r_1, r_2, \ldots, r_m\}$ describing e.g. the *m* production phases. Moreover, depending on a operating mode, the transition rate of set-point may be different.

Let $Y^{\text{ref}}(t)$ be the set-point at time t. The evolution of the stochastic process $\{Y_t^{\text{ref}}, t \geq 0\}$ in the operating mode k is expressed by the transition probability matrix P^k with the (i, j)th element equal to:

$$p_{ij}^k(t) = \mathbb{P}(Y_{s+t}^{\text{ref}} = r_j \mid Y_s^{\text{ref}} = r_i)$$
(4)

Figure 2 exemplifies the evolution of a set-point which takes value in 2-states space and corresponds to 2 operating modes denoted OM1 and OM2. One can find that the change of set-point occurs more frequently in the operating mode OM2 which is more stressful.



Figure 2. An example of set-point evolution within two operating mode

In practical situation, the set-point and the operating mode is well known at each time and its evolution is easy to identify. In this work, only one set of PID controller parameters is chosen for all known value of set-point r_{set} .

2.3. Actuator degradation behavior

It is assumed that an actuator is subject to shocks that occur randomly through time. Each shock impacts a random quantity of damage to the actuator. Hence, the capacity of the actuator by time t before its failure can be expressed as:

$$C(t) = c_0 - \mathcal{D}(t) \tag{5}$$

where c_0 is the initial capacity of the actuator, $\mathcal{D}(t)$ describes the accumulated deterioration of the actuator at time t (in *capacity* unit)

On the one hand, the actuator is less efficient through time because of its natural degradation. On the other hand, the evolution of set-point also impacts the degradation process of actuator. For example, in a centrifugal pump, an increased demand of pump flow will cause bearing friction and impeller wear to increase at a faster rate.

Natural degradation Due to the natural ageing or wear of the mechanical and/or electrical parts, the actuator capacity decreases through time. At each time ξ_i^{nd} that a shock occurs according to a Poisson process with intensity λ^{nd} , the actuator capacity C(t) decreases a quantity W_i^{nd} which follows a uniform distribution on $[0; \Delta^{nd}]$.

Impact of operating condition As describe in 2.2 the operating conditions which represents the environmental conditions the system evolves in. Their impact on the degradation of the actuator is modeled through another shock process. The shock instant ξ_i^{om} follows a Poisson process with intensity λ^{om} which takes a value corresponding to the actual operating condition OMi. At each time ξ_i^{om} the capacity of the actuator C(t) decreases of a quantity W_i^{om} which follows a uniform distribution on $[0; \Delta^{om}]$. The more frequently the set-point changes in a operating mode OMi, the more frequent

quently damage shock occurs. This is represented by a big value of λ^{om_i} .

Under this modeling assumption, the degradation impacts the actuator only at discrete times. In case where the actuator has a monotone gradual degradation behavior, other processes should be considered e.g. the homogeneous Gamma process (Van Noortwijk, 2009).

2.4. Piecewise Markov Deterministic Markov Processes

In order to take into account the complex interaction between the stochastic degradation process of actuator and the deterministic behavior of control system, this paper considers the point of view of Piecewise Markov Deterministic Markov Processes (PDMP) which has been first introduced by (Davis, 1993). PDMPs were used to model fatigue growth in (Chiquet, Limnios, & Eid, 2009) and corrosion in (Brandejsky, De Saporta, Dufour, & Elegbede, 2011).

The whole behavior of deteriorating closed-loop system at time t can be resumed by a random variable as:

$$Z_t = \begin{pmatrix} x_t \\ C_t \\ \lambda_t^{om} \\ t \end{pmatrix}$$
(6)

with x_t is the physical state variable of controlled process, C_t is the actual capacity variable related to the actuator degradation, λ_t^{om} is a covariate representing the current operating mode of the system and t is the time. The time t is included for the process to be homogeneous in time especially because of the time-varying set-point.

Between two successive shocks reducing the actuator capacity as described by the actuator degradation model, the response of closed-loop system is described by differential equations which combine the process dynamic characteristic and PID controller behavior. Interest readers can refer to (Cocozza-Thivent, 2011; Lorton, Fouladirad, & Grall, 2013) for the detailed definition of a PDMP.

2.5. Condition monitoring model

In this work, no additional sensor is devoted to the monitoring of the actuator degradation. The controlled system output is considered as the only available healthy information. As known that a significant part of the dynamic behavior of the system is shown in the transient period which occurs immediately after a change of set-point, only observations of system output which characterizes the dynamics of deteriorating controlled system is taken in this period (see (Nguyen, Dieulle, & Grall, 2013) for more details of condition monitoring model).

Let introduce the time of prediction $T_{prog} > 0$ which is the time at which the system health can be estimated given all the collected knowledge and a residual lifetime can be de-

rived. If n is the total number of observations until T_{prog} , the observation dates and corresponding system output will be respectively denoted $0 < T_1 < \ldots < T_n \leq T_{prog}$ and Y_1, Y_2, \ldots, Y_n where the observation Y_i is defined from Eq. (1) as:

$$Y_i = \mathbf{h}(T_i, x(T_i), u(T_i)) + \epsilon(T_i)$$
(7)

3. RUL ASSESSMENT METHODOLOGY

The Remaining Useful Life at time $t RUL_t$ is defined as the remaining time (from t) before the system can no longer fulfill its requirement anymore:

$$RUL_t = \inf(s \ge t, Z_s \in \mathcal{F}) - t \tag{8}$$

where \mathcal{F} is the failure zone which refers to the set of undesired system states. In the context of the feedback control system, the actual capacity of the actuator has to be greater than a minimal capacity level which relates to the objectives of control system design.

The system state process $(Z_t)_{t\geq 0}$ is a Piecewise Deterministic Markov Process and as shown in (Lorton et al., 2013) the distribution of the RUL of the system conditionally to online available information up to time T_{prog} can be computed by a two-step approach as:

$$\mathbb{P}(RUL_{T_{prog}} > s | Y_1 = y_1, \dots, Y_n = y_n)$$

$$= \int R_z(s) \mu_{y_1, \dots, y_n}(dz)$$
(9)

where:

 μ_{y1,...,yn}(dz) is the probability law of the system state at time T_{prog} regarding the available observations y₁,..., y_n:

$$\mu_{y_1,\dots,y_n} = \mathcal{L}(Z_{T_{prog}} | Y_1 = y_1,\dots,Y_n = y_n) \quad (10)$$

• $R_z(s)$ is the reliability of the system at time s knowing that the initial state value is z:

$$R_z(s) = \mathbb{P}(Z_u \notin \mathcal{F} \quad \forall u \le s | Z_0 = z)$$
(11)

The detail of the approach will be given in the next paragraphs. On one hand, it require the estimation of probability law $\mu_{y_1,...,y_n}(dz)$. On the other hand, it involves the estimation of the conditional reliability knowing $Z_{T_{prod}}$.

3.1. Step 1: Particle Filtering State Estimation

The main task is to estimate the conditional density, $p(z_{T_k}|y_{1:k})$ which represents the probability law of the state at time T_k given the measured value $y_{1:k} = y_1, \ldots, y_k$ of the observation process $Y_{1:k} = \{Y_i, i = 1, \ldots, k\}$ for any $k \leq n$. Let Z_{T_0} be the initial state of the system.

Particle filtering is used here to allow for numerical computation of the filtering density $p(z_{T_k}|y_{1:k})$. The key idea is to approximate the targeted filtering density by a cloud of N_s i.i.d. random samples (particles) $\{z_{T_k}^{(i)}, i = 1, \ldots, N_s\}$ with associated weights $\{w_{T_k}^{(i)}, i = 1, \ldots, N_s\}$, which satisfy $\sum_i w_{T_k}^{(i)} = 1$, so that the target distribution at time T_k can be approximated by

$$p(z_{T_k}|y_{1:k}) \approx \hat{p}(z_{T_k}|y_{1:k}) = \sum_{i=1}^{N_s} w_{T_k}^{(i)} \delta_{z_{T_k}^{(i)}} (\mathrm{d}z_{T_k}) \quad (12)$$

where $\delta_{z_T^{(i)}}(dz_{T_k})$ is the Dirac delta mass located in $z_{T_k}^{(i)}$.

The used particle filter is similar to the Generic Particle Filter in (Arulampalam, Maskell, & Gordon, 2002) with deterministic re-sampling method because it seems to be a computationally cheaper algorithm (Kitagawa, 1996). Indeed, resampling is used to avoid the problem of degeneracy of the algorithm that is, avoiding the situation that all but one of the importance weights are close to zero (Doucet & Johansen, 2009). The algorithm uses the prior distribution $p(z_{T_k}|z_{T_{k-1}}^{(i)})$ based on the simulation of the actuator degradation process and the deterministic behavior of the controlled process which is derived from Eq. (1) to Eq. (5) using a discretized scheme of Eq. (1) and Eq. (2).

Therefore, the real-time state estimation procedure, given the sequence of measurement $y_{1:k}$ can be resumed by the algorithm in Algorithm 1.

3.2. Step 2: RUL estimation

The second step of the presented methodology for the RUL computation requires the estimation of the system reliability starting from the prognostic instant T_{prog} and knowing the approximated pdf of the system state at T_{prog} as given by Eq. (12). Actually, the reliability is computed with the classical Monte Carlo method. The histogram of the RUL is obtained straightforwardly. The mean value or quantiles of the RUL can also be derived. The procedure is illustrated by Algorithm 2.

4. RUL PROGNOSIS AND ITS IMPACT ON MAINTENANCE PROCESS: A CASE STUDY

In the previous section, a methodology to compute the conditional pdf of the RUL of a dynamic system was described. Here, it is illustrated on a well-known feedback control system: a double-tank level control system. A predictive maintenance decision rule which uses the RUL information is also presented which will be compared with an age remplacement strategy.

4.1. Description of the case study

Consider a double-tank level system with cross-sectional area of the first tank S_1 and the second one S_2 . Water or other Algorithm 1 Generic particle filter for system state estimation.

Initialization: $\forall i = 1, \ldots, N_s$.

Draw particle $z_{T_0}^{(i)}$ according to the initial condition of system

Assign corresponding weight $w_{T_0}^{(i)} = \frac{1}{N_0}$

At step k (corresponding to time
$$T_k$$
): Given $\left\{z_{T_{k-1}}^{(i)}, w_{T_{k-1}}^{(i)}\right\}_{i=1}^{N_s}$, do

(a) Importance sampling

Based on the system description (presented in Sections 2), draw particles $\tilde{z}_{T_k}^{(i)} \sim p(z_{T_k} | z_{T_{k-1}}^{(i)})$

(b) Weight update

Based on the likelihoods of the observations y_k collected (Eq. (7)), assign weights $w_{T_k}^{(i)} = w_{T_{k-1}}^{(i)} p(y_k | \tilde{z}_{T_k}^{(i)})$ (c) Weight normalisation

$$w_{T_k}^{(i)} = \frac{w_{T_k}^{(i)}}{\sum_{i=1}^{N_s} w_{T_k}^{(i)}}$$

(d) Re-sampling decision

If $\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_s} (w_{T_k}^{(i)})^2} < N_{thresh}$ then perform deterministic re-sampling: $\left\{ \tilde{z}_{T_k}^{(i)}, w_{T_k}^{(i)} \right\}_{i=1}^{N_s} \Rightarrow \left\{ z_{T_k}^{(i)}, \frac{1}{N_s} \right\}_{i=1}^{N_s}$

(e) Distribution

$$p(z_{T_k}|y_{1:k}) \approx \sum_{i=1}^{N_s} w_{T_k}^{(i)} \delta_{z_{T_k}^{(i)}}(\mathrm{d} z_{T_k})$$

Repeat till the prognostic instant T_{prog} is reached

Algorithm 2 RUL estimation.

 $\overline{\text{Given } \left\{z_{T_n}^{(i)}, w_{T_n}^{(i)}\right\}_{i=1}^{N_s}}, N_{depart} \text{ number of departure points,} \\ N_{traj} \text{ number of simulation trajectories for each point} \\ \mathbf{For } j = 1, \dots, N_{depart} \mathbf{do}$

• Generate uniform sample: $u_i \sim U(0, 1)$

• Select departure point:

 $\begin{aligned} z_{j}^{\text{selected}} &= z_{T_{n}}^{(k)} \text{ with } \sum_{l=1}^{k-1} w_{T_{n}}^{(l)} \leq u_{j} < \sum_{l=1}^{k} w_{T_{n}}^{(l)} \\ \bullet \text{ For } k = 1, \dots, N_{traj} \text{ do} \end{aligned}$

Simulate the trajectories according to the system description (presented in Sections 2) **End**

End

Obtain the empirical distribution of RUL

incompressible fluid (i.e. the mass density of fluid ρ is constant) is pumped into the first tank at the top by a pump motor drives. Then, the out flow from the first tank feeds the second tank.

The relation between the inlet flow rate and the pump motor control input u is represented as a first order system (Chen & Chen, 2008):

$$\frac{\mathrm{d}q_{in}}{\mathrm{d}t} = -\frac{1}{\tau_a}q_{in} + \frac{K_a}{\tau_a}u\tag{13}$$

where τ_a is the time constant of pump motor, K_a is the servo amplify gain (with the initial gain $K_{a_{init}}$). The pump saturates at a maximum input u_{max} and it cannot draw water from the tank, so $u \in [0, u_{max}]$.

The fluid leaves out at the bottom of each tank through valves with the flow rates according to the Torricelli rule:

$$q_{j,out} = K_{v_j} \sqrt{2gh_j}, \quad j = 1, 2$$
 (14)

where h_j is level of tank j, g is the acceleration of gravity and K_{v_j} is the specified parameter of the value j.

Using the mass balance equation, the process can be described

by following equations:

$$\begin{cases} \frac{\mathrm{d}h_1(t)}{\mathrm{d}t} = \frac{1}{S_1}q_{in} - \frac{K_{v1}}{S_1}\sqrt{2gh_1(t)}\\ \frac{\mathrm{d}h_2(t)}{\mathrm{d}t} = \frac{K_{v1}}{S_1}\sqrt{2gh_1(t)} - \frac{K_{v2}}{S_2}\sqrt{2gh_2(t)} \end{cases}$$
(15)

The water level of tank 2 is measured by a level measurement sensor and controlled by adjusting the pump motor control input which is calculated by a PID controller. The overall tank level control system is shown in Figure 3.



Figure 3. A double-tank level control system

Degradation process Due to degradation of the pump, its capacity $C(t) = K_a(t) = K_{a_{init}} - \mathcal{D}(t)$ stochastically decreases according to the presented model in Section 2.3. To have simple and comprehensible case study, we suppose that the set-point admits only two values r_1 and r_2 with $r_1 < r_2$.

It is assumed that the system evolves in a two-states operating mode: the normal mode (OM1) and the stressful mode (OM2). At each T_{change} time duration the operating mode can change. The evolution of operating mode is described by a Markov chain as represented as Figure 4 where set-point changes more frequently in OM2.



Figure 4. Operating mode Markov chain

The sojourn times in the different values of system set-point are characterized by a continuous-time Markov chain whose the transition rate matrix corresponding to the operating mode OMi is:

$$P_i = \begin{pmatrix} -\alpha_i & \alpha_i \\ \alpha_i & -\alpha_i \end{pmatrix}$$
(16)

where the parameters α_i describe transition rates of set-point of the operation mode OMi. Set-point changes more frequently in mode OM2 so $\alpha_2 > \alpha_1$. **Failure zone of the system** According to Eq. (13) and Eq. (15), the steady states are obtained at instant t_{ss} if

$$u(t_{ss}) = \frac{S_1}{S_2} \frac{K_{v_2}}{K_a(t_{ss})} \sqrt{2gh_2(t_{ss})}$$
(17)

Since $u(t_{ss}) \leq u_{max}$ then

$$K_a(t_{ss}) \ge \frac{S_1}{S_2} \frac{K_{v_2}}{u_{max}} \sqrt{2gh_2(t_{ss})}$$

that means the actual capacity of the actuator must be greater than a minimal capacity defined in the control system design phase. In this case of study, this accepted value is defined as:

$$K_{a_{\min}} = \frac{S_1}{S_2} \frac{K_{v_2}}{u_{max}} \sqrt{2g \max_i r_i} = \frac{S_1}{S_2} \frac{K_{v_2}}{u_{max}} \sqrt{2gr_2} \quad (18)$$

Thus, the RUL of the system is the remaining time before the process Z enters in the failure zone which is defined as:

$$K_a(t) \le K_{a_{\min}} \tag{19}$$

Under all these considerations, the behavior of water tank level control system can be summed up using the process $Z = (Z_t)_{t \in \mathbb{R}_+}$, where Z_t is given by:

$$Z_t = (K_a(t), h_1(t), h_2(t), \lambda^{om}(t), t)$$
(20)

The current state of the system at time t is then a five-component vector Z_t , which includes the current capacity of the pump, the water levels of two tanks, the current operating mode and the current time t.

4.2. Numerical illustrations

Numerical values for double-tank level control system are summed up in Table 1.

Figure 5 represents one trajectory of the process Z until the failure of system. The evolution of set-point with successive change of set-point values is illustrated in Figure 5(a). The water level of tank 1 and tank 2 $h_1(t)$ and $h_2(t)$ are reflected in Figure 5(b) and Figure 5(c). Figure 5(d) shows real (unobservable) value of actuator capacity $K_a(t)$.

As depicted in Figure 5, the actuator fails completely (i.e. $K_a = 0$) at 22129.4 time units, but the failure of system here is 15102.6 time units. One can find that after the system failure instant the water level of tank 2 (the controlled variable) cannot track the evolution of desired set-point.

The only available health information of the system is the noisy observations of the water level of the tank 2 which are recorded during the transient periods whenever the setpoint changes. For instance, let consider the prognostic time $T_{prog} = 8875.2$ time units i.e. at 64th change instant of the



Figure 5. A trajectory of the water tank level control system until failure of actuator: (a) Set-point, (b) Water level of tank 1, (c) Water level of tank 2 and (d) Actuator capacity

Table 1. Double-tank model

Physical parameters						
$S_1 = 25$	$K_{v_1} = 8$	$\tau_a = 1$				
$S_2 = 20$	$K_{v_2} = 6$	g = 9.82				
$u_{max} = 100$	$\sigma = 0.05$					
PID controller parameters						
$K_P = 12.9896$	$T_I = 99.8432$	$T_D = 2.3727$				
In	itial condition: t =	: 0				
$h_1(0) = 0$	$h_2(0) = 0$	$K_{a_{init}} = 5.0$				
Natural degradation						
$\lambda^{nd} = 10^{-3}$	$\Delta^{nd} = 0.5$					
Operating mode evolution						
$Pr_{11} = 0.75$	$Pr_{12} = 0.25$	$T_{change} = 250$				
$Pr_{21} = 0.75$	$Pr_{22} = 0.25$					
Varying set-point						
$\alpha_1 = 0.006$	$r_1 = 25$	$\lambda_1^{om} = 5.10^{-4}$				
$\alpha_2 = 0.01$	$r_2 = 40$	$\lambda_2^{om} = 10^{-3}$				
$\Delta^{om} = 0.3$						

set-point, this health information is shown in Figure 6.



Figure 6. Noisy observations of water level of tank 2

The first step of the method is to compute the conditional state of the system knowing the noisy measurement of h_2 until the prognostic time T_{prog} . Approximations of the pdfs are represented in Figure 7(a) for the water level of tank 1, Figure 7(b) for the water level of tank 2 and Figure 7(c) for the actuator capacity with $N_s = 500$ particles.

The last step of the method is to compute the distribution of the RUL of the system starting at T_{prog} knowing the approximated pdf of the system state at T_{prog} . The RUL distribution has been obtained by Monte Carlo simulation with 2500 trajectories describing the system evolution from its state at the prognostic time until its failure. The resulting RUL is depicted in Figure 8.



Figure 7. Conditional distribution of the system state at time $T_{prog} = 15046.8$ time units given the noisy measurements of h_2 for $N_s = 500$ particles



Figure 8. Remaining Useful Lifetime of the water tank level control system at time $T_{prog} = 8875.2$ time units

4.3. Maintenance strategies

To show how the prognosis information can be incorporated in maintenance decision-making, this section will compare a predictive maintenance which uses the on-line available information and an age based remplacement strategy. A cost model which is the long-run expected maintenance cost rate including the unavailability cost is developed in order to evaluated the performance of these maintenance strategies.

Predictive maintenance In this paragraph, a predictive maintenance policy is considered. Under this maintenance strategy, the system is replaced upon failure (corrective replacement action) or at a specified maintenance date which is calculated using the RUL information (preventive maintenance action). Both maintenance actions put the system back in asgood-as-new state, the interventions take negligible times and their costs are fixed. It is assumed that the replacement actions can only be performed at the opportunities (the instants of possible changes of operating mode, i.e. each time duration T_{change}). Therefore, there are a system inactivity after the stoppage of the system and an additional cost is incurred by the time d_i from the stoppage until the next replacement at a cost rate C_d which may correspond to production loss per unit of time.

The preventive maintenance date is updated through the working time of the system. Indeed, at each change of the setpoint, the associated RULs and the next maintenance time can be re-computed using the previously described methodology with the new arrival condition information. At each prognostic time T_{prog} the maintenance date which is the RUL of the system with a given failure probability η can be written using Eq. (9) as:

$$RUL(T_{prog}, \eta) = \sup\{\nu : \mathbb{P}(RUL_{T_{prog}} < \nu |$$

$$Y_1 = y_1, \dots, Y_n = y_n) \le \eta\} (21)$$

where η is a decision parameter to be optimized. For a tradeoff between the result accuracy and time computation, 500 particles and 2500 trajectories for RUL computation are chosen.

To assess the performance of the maintenance policy, a widely used criterion which is the expected maintenance cost per unit over an infinite time span is considered

$$C_{Pred}^{\infty}(\eta) = \lim_{t \to \infty} \frac{C_{Pred}(t,\eta)}{t}$$
(22)

where $C_{Pred}(t, \eta)$ is the cumulative maintenance cost at time t can be described as:

$$C_{Pred}(t,\eta) = \sum_{i=1}^{N_p(t)} C_p + \sum_{j=1}^{N_c(t)} C_c + C_d d(t)$$
(23)

where $N_p(t)$, $N_c(t)$ are respectively the number of preventive maintenance and of corrective replacement in [0, t]; d(t) is the total inactivity time of the system in [0, t].

This cost criterion is then evaluated by stochastic Monte Carlo simulation. The optimal value of decision parameters η is obtained by miminizing the expected cost rate, i.e.,

$$C_{Pred}^{\infty}(\eta^*) = \min_{\eta} \{ C_{Pred}^{\infty}(\eta), 0 < \eta < 1 \}$$
 (24)

Table 2. Maintenance costs

$$\begin{array}{c|cc} C_c & C_p & C_d \\ \hline 200 & 150 & 5 \end{array}$$

With the maintenance costs summarized in Table 2, the optimal values of $\eta = 0.45$ with the cost rate $C_{Pred}^{\infty}(\eta^*) = 0.08989$ (see Figure 9).



Figure 9. Long run expected maintenance cost per unit of time

Age-based remplacement strategy Like previously described predictive maintenance strategy, the maintenance actions are also executed only at the opportunities. The different point is that the system is preventively replaced at a specified date which does not change through the working time of the system. This specified date t_{Prev} is the parameter to be optimized.

Figure 10 illustrates the evolution of the system degradation behavior and the maintenance policy.



Figure 10. Illustration of considered systematic maintenance

The cumulative maintenance cost at time t in this strategy is:

$$C_{Prev}(t, t_{Prev}) = \sum_{i=1}^{N_p(t)} C_p + \sum_{j=1}^{N_c(t)} C_c + C_d d(t) \quad (25)$$

where $N_p(t)$, $N_c(t)$ are respectively the number of preventive maintenance and of corrective replacement in [0, t]; d(t) is the total inactivity time of the system in [0, t].

The long run expected maintenance cost per unit of time is:

$$C_{Prev}^{\infty}(t_{Prev}) = \lim_{t \to \infty} \frac{C_{Prev}(t, t_{Prev})}{t}$$
(26)

This cost criterion is then evaluated by stochastic Monte Carlo simulation. The optimal value of preventive replacement age t_{Prev}^* is obtained by minimizing the expected cost rate, i.e.,

$$C_{Prev}^{\infty}(t_{Prev}^{*}) = \min_{t_{Prev}} \{ C_{Prev}^{\infty}(t_{Prev}), t_{Prev} > 0 \}$$
(27)

As represented in Figure 11, the optimal values of $t^*_{Prev} = 4750$ with the cost rate $C^{\infty}_{Prev}(t^*_{Prev}) = 0.03722$.

On the considered case study, the opportunist age-based remplacement policy and the predictive one efficiencies are very close to each other. This shows the effect of maintenance opportunities in the structure of the decision rule. Indeed, as represented in Figure 11, the age-based strategy can easily take into account the effects of maintenance opportunities. The local optima on the expected cost rate are coincide with the opportunities dates which lead to the cancel the inactivity cost. On the other hand, the predictive maintenance does



Figure 11. Evolution of long run expected maintenance cost per unit of time

not take directly into account the existence of maintenance opportunities and the decision rule is not well suited. As the cost of inactivity per unit of time is very high compared to the unit replacement cost the predictive maintenance cost is slightly higher tant the age-based one.

5. CONCLUSION

The present paper proposes a modeling framework using PDMP that shows the ability to combine the deterministic behavior of a feedback control system with the stochastic degradation process for the actuator. On the one hand, the actuator is less efficient through time because of natural degradation process. On the other hand, the set-point level impacts also the degradation process of actuator. Particle filtering technique is used to estimate on-line the state of considered system regarding only the noisy observations of closed system output. By using a methodology based on the assumption of Markov property, the Remaining Useful Lifetime can be deduced with Monte Carlo simulation. A simulated double-tank level control system was used as a case study to illustrate the efficiency of the proposed approach and the use of the prognostic information in order to optimize the decision-making process. A predictive maintenance whose the decision rules use the RUL estimation is compared with an age-based remplacement strategy. The long run expected maintenance cost per time unit is then used to assess the performance of two strategies. The results show the useful of RUL information on maintenance decision-marking process. However, the impact of maintenance opportunities should be taken into account in the structure of predictive decision rule.

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REFERENCES

- Arulampalam, M. S., Maskell, S., & Gordon, N. (2002). A tutorial on particle filters for online nonlinear/nongaussian bayesian tracking. *IEEE Transactions on signal processing*, 50, 174-188.
- Aström, K. J., & Hägglund, T. (1995). *Pid controllers: theory, design and tuning* (2nd ed.). Research Triangle Park.
- Brandejsky, A., De Saporta, B., Dufour, F., & Elegbede, C. (2011). Numerical method for the distribution of a service time. In *Proceedings of the Conference ESREL* 2011.
- Chen, H.-M., & Chen, Z.-Y. (2008). Implement of a cascade integral sliding mode controller for a water tank level control system. In *Innovative computing information* and control, 2008. icicic'08. 3rd international conference on (p. 162-162).
- Chiquet, J., Limnios, N., & Eid, M. (2009). Piecewise deterministic markov processes applied to fatigue crack growth modelling. *Journal of Statistical Planning and Inference*, 139(5), 1657 - 1667.
- Cocozza-Thivent, C. (2011). Processus de renouvellement markovien, processus de markov déterministes par morceaux. Online book available on the webpage: http://perso-math.univmlv.fr/users/cocozza. christiane/recherchepageperso/PresentationRMetPDMP.html.
- Davis, M. H. (1993). *Markov models and optimization* (Vol. 49). Chapman and Hall.
- Dieulle, L., Bérenguer, C., Grall, A., & Roussignol, M. (2003). Sequential condition-based maintenance scheduling for a deteriorating system. *European Jour*nal of Operational Research, 150(2), 451 - 461.
- Doucet, A., & Johansen, A. M. (2009). A tutorial on particle filtering and smoothing: fifteen years later. *Handbook* of Nonlinear Filtering, 656-704.
- Do Van, P., Levrat, E., Voisin, A., Iung, B., et al. (2012). Remaining useful life (rul) based maintenance decision making for deteriorating systems. In 2nd ifac workshop on advanced maintenance engineering, service and technology (a-mest'12).
- Huynh, K. T., Barros, A., & Bérenguer, C. (2012). Adaptive condition-based maintenance decision framework for deteriorating systems operating under variable environment and uncertain condition monitoring. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 226(6), 602–623.
- Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483-1510.

- Khoury, E., Deloux, E., Grall, A., & Berenguer, C. (2013). On the use of time-limited information for maintenance decision support: A predictive approach under maintenance constraints. *Mathematical Problems in Engineering*, 2013.
- Kitagawa, G. (1996). Monte carlo filter and smoother for non-gaussian nonlinear state space models. *Journal of computational and graphical statistics*, 5(1), 1-25.
- Lorton, A., Fouladirad, M., & Grall, A. (2013). A methodology for probabilistic model-based prognosis. *European Journal of Operational Research*, 225(3), 443–454.
- Nguyen, D. N., Dieulle, L., & Grall, A. (2013). A deterioration model for feedback control systems with random environment. In *Proceedings of the Conference ESREL* 2013.
- Peng, Y., Dong, M., & Zuo, M. J. (2010). Current status of machine prognostics in condition-based maintenance:

a review. *The International Journal of Advanced Manufacturing Technology*, 50(1-4), 297-313.

- Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation: A review on the statistical data driven approaches. *European Journal of Operational Research*, 213(1), 1 - 14.
- Sikorska, J., Hodkiewicz, M., & Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, 25(5), 1803 - 1836.
- Vachtsevanos, G., Lewis, F., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent fault diagnosis and prognosis for engineering systems*. Wiley.
- Van Noortwijk, J. (2009). A survey of the application of gamma processes in maintenance. *Reliability Engineering & System Safety*, 94(1), 2-21.

Robust Passive Fault Tolerant Control Applied to Jet Engine Equipment

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ABSTRACT

In order to minimize the occurrence of unexpected costly flight failures modern aircraft engines industry focuses especially on increasing product's availability. In this work, we propose to monitor the health of a Variable Stator Vane (VSV), subsystem controlling the amount of airflow through the High Pressure Compressor (HPC), allowing optimum compressor performance. This control of airflow prevents the engine from stalling. The proposed methodology is based on an original approach for real time on-board Passive Fault Tolerant Control (PFTC). The objective of the proposed PFTC is to provide acceptable performance and preserve stability when faults occur. The method relies on the design of a specific Robust Virtual Sensor in a Linear Parameter Variable (LPV) polytopic framework. The robustness to model uncertainties is ensured by a Neural Extended Kalman Filter (NEKF) accommodating, in real time, the model prediction. In the proposed methodology, an off-line closed-loop identification scheme is first used to elaborate a multi local linear state space models, after that a multi-model observer based on Linear Matrix Inequalities (LMI) optimization is used to build the virtual sensor. The NEKF is added to circumvent online model accuracy The efficiency and limit of the approach are problems. shown and discussed through simulations on a complete numerical engine test bench.

1. INTRODUCTION

Over the past decades, dependability has gradually become one of the key challenges for the aeronautical industry. The concept of dependability was introduced in the mid-80s by Laprie. (1985). According to his concept, dependability encompasses two features: threats and means. In aeronautics, threats are events that can affect dependability, such as faults and failures. Means are ways to increase

dependability, namely removal, prevention, tolerance and forecasting.

During the last 30 years, System Health Monitoring (SHM) has emerged and has been extensively developed in order to improve the system dependability. SHM gives the system the capability to prevent, detect, diagnosis, respond to, and recover from conditions that may interfere with the nominal system operation. In this work, we are interested in developing SHM for a key subsystem of the aircraft engines, namely the Variable Stator Vane (VSV).

The purpose of the VSV system is to control the amount of airflow through the High Pressure Compressor to provide the optimum compressor performance. The control of airflow is aimed to prevent the engine from stalling. The actuators work in pairs as part of a closed-loop electrohydraulic system to constantly adjust the position of the first stages of the VSV. The off-line closed loop VSV actuation composed of a servovalve, a cylinder and a LVDT (Linear Variable Differential Transformer) sensor. The LVDT is connected to the controller through harnesses which are subject to vibrations. Consequently, this can engender sensor failures and jeopardize the availability of the VSV position, thereby threatening the stability and degrading the performance of the jet engine.

In the current economic context, a material redundancy is used to ensure the availability of measures. This solution no longer profitable, therefore, we would like to implement an original architecture control by replacing the material redundancy by an analytical one, but in our context this is not straight. For this, we propose a Fault Tolerant Control approach aiming to simplify the complexity of the control architecture by reducing the material redundancy while maintaining the reliability, dependability and performance of the nominal operation.

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2. PROBLEM STATEMENT

Fault Tolerant Control (FTC) attends to be an integral part of any SHM applications. FTC has the following characteristics: (i) the ability to accommodate automatically faults in components, actuators and sensors, (ii) the ability to keep the overall system stable and acceptable performance in the case of failure. An FTC system is a control system able to accommodate automatically for system failures. Hence the main task to be tackled in achieving fault-tolerance is the design of a controller with a suitable structure to maintain the overall system stability and acceptable performance. FTC may be called upon to improve the system reliability, maintainability and survivability. FTC systems have appeared since the early 1980s. Nowadays, FTC has gained in popularity among industrial and academic researchers. Several survey paper and books have appeared (Patton 1997), (Blanke, Staroswiecki et al. 2001), (Zhang et al 2008). Generally speaking, FTC systems can be classified in two types: passive (PFTCS) and active (AFTCS).

The *passive* methods, or *reliable control*, aim to achieve the insensitivity to some specific anticipated faults by making the system robust with respect to them. The controller is fixed and requires neither Fault Detection nor Diagnosis schemes (FDD) nor controller reconfiguration. In this approach, often fault-tolerance is achieved by considering faults as uncertainties that the controller can deal with. Hence, we assume that the faults occur in a predefined subset, and the controller should be designed to optimize the worst fault performed (Liao *et al.* 2002; Yang *et al.* 2010)).

In the aeronautical context, PFTC is increasingly introduced in control architectures *et al.* 2012; Richter *et al.* 2011) in order to optimize the Time Between Overhaul (TBO) and consequently, to reduce the Delays and Cancellations (D&C) which have a significant economic impact.

It is important to highlight that our PFTC approach is applied to control a closed-loop actuation Variable Stator Vane which returns a servo-actuator position. The physical non-linear equations describing the operation of the servoactuator VSV depend on non-measurable variables. Moreover, the complexity of these equations makes them non-embeddable for a real time computation of a VSV position.

In this paper, a real time on-board PFTC approach is proposed to control closed-loop actuation in spite of faulty sensor. The main purpose of the PFTC approach is to ensure availability of a feedback signal, while maintaining the performance of the nominal operation (De Oca *et al* 2010) without retuning on-line the parameters of the controller. The reconfiguration bloc contains a virtual sensor that estimates in real time the system's perturbations and compensates them.

In an industrial process, especially jet engine industry, the parameters of the controller are tuned off-line for the nominal operation. Changing them on-board with the occurrence of the fault is not allowed, this is why the PFTC approach is chosen in expense of the Active Fault Tolerant Control (AFTC) approach (Stubberud 2006), where the parameters of the controller are re-tuned in real time in order to adapt the controller.

Several approaches have been proposed to deal with PFTC in case of occurrence of partial sensor failure, which means that the sensor is available but provides a wrong feedback signal to the controller (De Oca 2010; De Oca *et al.* 2012; Richter *et al.* 2011). In this paper, we propose a new approach of PFTC for a total sensor failure, where total loss of feedback VSV position signal occurs, and this for a nonlinear system approximated by a multi-model system. In case of a total loss of the sensor, we ensure the availability of the feedback VSV position signal by a Multi-Input Multi-Output (MIMO) estimation of lost signal. At this stage, we consider the inaccuracy of the MIMO estimation as a sensor fault, which is compensated by the virtual sensor bloc reconfiguration.

The multi-model representation allows transforming nonlinear sub-systems in a set of linear sub-systems in which theories of linear systems are applicable, while guaranteeing the stability of the overall system during the transition from an operating point to another one.

In order to construct our multi-model, we propose an offline closed-loop identification that will be performed at several points of interest covering the entire operating domain. This is a specific method for system, such as a jet engine, that cannot be disconnected from the controller for economic and safety raisons. The purpose of this stage is to obtain a local linear state representation applicable for an operating point of the servo-actuator VSV.

In this paper, we propose two kinds of identifications. The first identification Single-Input Single-Output (SISO) aims to bring out the state space representation of VSV behavior.

The second one MIMO aims to get MIMO state space representation using a heterogeneous state vector, which is a concatenation of VSV position and other variable geometry's measures affecting the VSV position.

These two states space representations are used for the synthesis of a multi-model observer based on LMIs optimization. The observer built with the MIMO state space representation allows getting a MIMO VSV position estimation, which is used as an input signal for the virtual sensor. The second observer built with the SISO state space representation aims to estimate the sensor fault through the virtual sensor.

The LPV system receives a great interest in the nonlinear modelling literature (Bezzaoucha, *et al.* 2013, De Oca 2010, De Oca *et al.* 2012, Richter, et al. 2011, Bezzaoucha 2013). Indeed, the LPV framework can be seen as a "middle ground" between linear and non-linear dynamics. It concerns linear dynamical systems state-space representations of which depend on exogenous non-stationary parameters. LPV model consists of an indexed

collection of linear systems, in which the indexing parameter is *exogenous*, *i.e.* independent of the state.

On the other hand, the LPV framework allows us to extrapolate the identification from multitude local linear sub-systems, to the overall non-linear system. Thereby, from a mapping of the identified linear local sub-systems for several operation points we obtain one identified overall system describing the behavior of the servo-actuator for all operating phases.

Moreover, sub-systems identified from simulations on a complete numerical engine test bench are subject to uncertainties. This could degrades the accuracy of the estimator used in the virtual sensor, and consequently, can jeopardize the stability of the overall system VSV. To circumvent this problem, we propose a Neural Extended Kalman Filter, which compensates the lack of information given by the state-space representation resulting from the experimental identification. We find in the literature some works (Kramer *et al.* 2008, Owen *et al.* 2003, Stubberud (2006), Lobbia *et al.* 1995) dealing with the robust estimation using NEKF. Otherwise, NEKF is used to adapt in real-time the prediction model of the reference input signal.

This paper is structured as follows: First, we present VSV system and a closed-loop identification method of the VSV. After a synthesis of an observer for a LPV multi-model system is proposed. These results are used for the PFTC approach trough the virtual sensor, and finally, the robustness is addressed through the NEKF (Figure 1).



Figure 1: Architecture of a Robust PFTC applied to VSV actuation

3. DESCRIPTION OF THE SERVO-ACTUATOR

3.1. Physical description of the VSV

Before identifying the servo-actuator VSV, it is necessary to bring the physical equation describing the behaviour of the VSV, so that we could determine the order of the system.

The VSV system comprises a servovalve and a cylinder (Figure 2). A servovalve is a device aiming to transform the electric energy to hydraulic one. It is a control interface between the control and the cylinder that provide a suitable fuel flow to the cylinder.

The specifications of the closed-loop servo-actuator VSV impose to choose a three stages architecture, made of two stages servovalve called pilot stage, and a distribution slide. A command current drives the two stages servovalve, providing a fuel flow and a difference of pressure. These are used to actuate the slide distributor which the position is controlled through a spring by a feedback force.

A servovalve comprises a static part and a dynamic part. According to Tafraouti (2006), the dynamic part is represented by a second-order system. And the static part is non-linear function depending on non-measurable variables. The static part of the servovalve depends on its differential pressure, which is constant for a given operating point. Thus, we assume that non-linear equation describing the static part of the servovalve is a constant. Consequently, we model the behaviour of the servovalve in a given operating point by a second order system.

The servo-actuator comprises a servovalve and a cylinder which can be modelled according to (Tafraouti 2006) by a first order system. Thereby we model the servo-actuator VSV by a third order system.



Figure 2: Control architecture of the VSV system

3.2. Identification

In this section, the off-line MIMO and SISO identification are presented

In a jet engine, there are variables geometries, which may affect each other's. We would like to exploit the correlation between these variable geometries to build a multi-model observer. In this work, we bring out the coupling between a VSV position and another variable geometry.

After an influence study, we selected a VBV position (Variable Bleed Valve) (Figure 3) reflecting the opening of a valve to remove the excess of the air between the Low and High compressor, which can be the origin of stalling and thus a serious damage of the Low compressor blades.



Figure 3: VSV and VBV equipment

Consider the MIMO state space representation:

$$\begin{cases} \begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}_{k+1} = A_{MIMO} \begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}_{k} + B_{MIMO} \begin{pmatrix} U_{VSV} \\ U_{VBV} \end{pmatrix}_{k} \quad (1)$$
$$X_{VSV} = C_{MIMO} \begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}_{k} + D_{MIMO} \begin{pmatrix} U_{VSV} \\ U_{VBV} \end{pmatrix}_{k}$$

where:

 $\begin{pmatrix} X_{VSV} \\ X_{VBV} \end{pmatrix}$ is the MIMO state vector, X_{VSV} and X_{VBV} are

respectively the VSV and the VBV position

 $\begin{pmatrix} U_{VSV} \\ U_{VBV} \end{pmatrix}$ is the MIMO control current, U_{VSV} and U_{VBV} are

respectively the VSV and the VBV control current.

The off-line MIMO identification (1) allows to bring out the matrix A_{MIMO} , B_{MIMO} , C_{MIMO} , D_{MIMO} , using the Prediction error Method Algorithm.

On the other hand, we use the same method to identify the non-linear behavioral equations of the VSV and VBV by a third order system. This identification aims to obtain, for each operation point, a SISO state space representation, used is LPV Takagi-Sugeno framework.

4. ROBUST PASSIVE TOLERANT CONTROL

4.1. Multi-model observer

We brought out in the previous section the necessity to use LPV framework to identify the overall non-linear VSV system.

In this work, we introduce a Takagi-Sugeno formalism which is an interpolation of local linear subsystem using a convex transformation (Bezzaoucha *et al.* 2013, Bezzaoucha 2013). Several articles (Akhenak *et al.* 2007, Marx *et al.*

2013, Bezzaoucha 2013) deals with Takagi-Sugeno formalism and use it to: (i) model and design diagnostic strategy, (i) develop control's laws, (iii) study the stability of non-linear systems.

We brought out in the previous section local identified subsystems for each operating point. We use a Takagi-Sugeno formalism to write the overall non-system describing the behaviour of the VSV for a set of operating point.

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{n} \sigma_i(\xi(t)) (A_i x(t) + B_i u(t)) \\ y(t) &= \sum_{i=1}^{n} \sigma_i(\xi(t)) (C_i x(t) + D_i u(t)) \end{aligned}$$
(2)

where: $x(t) \in \mathbb{R}^{n_x}$ is the overall system state vector, $y(t) \in \mathbb{R}^{n_y}$ is the overall system output and $u(t) \in \mathbb{R}^{n_u}$ in the control input, with *n* number of subsystems

The overall non-linear system is an aggregation of the local linear subsystems by a weighting sum. Thereby, the linearity is transferred from the subsystems to the weighting functions. $\sigma_i(\xi(t))$ $i = 1 \dots n$, satisfying the convex sum property.

The purpose of the Takagi-Sugeno formalism is to use the linear framework for the synthesis of the observer and study the stability and extrapolate to the overall non-linear system using the convex sum. The weighting functions $\sigma_i(\xi(t))$ depend on a decision variable $\xi(t)$. In our application, $\xi(t)$ is measurable and allows us to determine the operating point In this paper, we propose to use the LPV framework to bring out the transition between the sub-systems.

The parameters of the matrix (A_i, B_i, C_i, D_i) of sub-systems vary according to a function $\theta(t)$ dependent on time.

Thus, we obtain Takagi-Sugeno formalism with time varying parameters, which guarantee a smooth transfer from a subsystem to another. This representation has not only the advantage to be mathematically equivalent to the overall non-linear system, but also to be easier to handle.

$$\begin{cases} \dot{x}(t) = \sum_{\theta(t)} \sigma_{\theta(t)} \left(\xi_{\theta(t)}(t) \right) \left(A \left(\theta(t) \right) x(t) + B \left(\theta(t) \right) u(t) \right) \\ y(t) = \sum_{\theta(t)} \sigma_{\theta(t)} \left(\xi_{\theta(t)}(t) \right) \left(C \left(\theta(t) \right) x(t) + D \left(\theta(t) \right) u(t) \right) \end{cases}$$
(3)

Instead of having an observer and a controller for each subsystem, the LPV Takagi-Sugeno representation defined in Eq. (3) allows to build a common strategy of observation valid for the overall nonlinear system.

The stability analysis and the observer synthesis are based on Lyapunov theory by minimising L_2 -gain under LMI constraint

$$\begin{cases} \hat{x}(t) = \sum_{i=1}^{n} \sigma_i(\xi(t)) \left(A_i x(t) + B_i u(t) + L(y(t) - \hat{y}(t)) \right) \\ \hat{y}(t) = \sum_{i=1}^{n} \sigma_i(\xi(t)) \left(C_i x(t) + D_i u(t) \right) \end{cases}$$
(4)

Let us find *L* a common observer gain for all subsystems such as $\hat{x}(t) \rightarrow x(t)$

Let define the error estimation $e(t) = \hat{x}(t) - x(t)$ written in the Takagi-Sugeno formalism:

$$\dot{e}(t) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_i \left(\xi(t)\right) \sigma_j \left(\xi_j(t)\right) \left(A_i - LC_j\right) e(t)$$
(5)

The gain of the multi-model observer L is found such as $\dot{e}(t)$ is stabilized

Let define a Lyapunov function:

<u>Theorem</u>: A system is stable, if there is a positive Lyapunov function such as $\dot{V}(t) < 0$. $V(t) = e^{T}(t)Pe(t)$ (6)

with
$$P \in \mathbb{R}^{n_x x n_x}$$
 a positive symmetric matrix.
 $\dot{V}(t)$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_i(\xi(t)) \sigma_j(\xi(t)) e^T(t) (P(A_i - LC_j) + (A_i - LC_j)P^T) e(t)$$

$$+ (A_i - LC_j) P^T) e(t)$$
with:
(7)

$$\begin{cases} \sum_{i=1}^{n} \sigma_i(\xi(t)) = 1\\ 0 \le \sigma_i(\xi(t)) \le 1 \quad i = 1 \dots n \end{cases}$$
(8)

Knowing that $\sigma_i(\xi(t)) \ge 0$.

introduced above.

$$\dot{V}(t) < 0 \Rightarrow PA_i - PLC_j + A_i^T P - C_j^T L^T P < 0$$

$$i, j = 1..n$$
(9)

In order to linearize Eq.(9), we define $\overline{L} = PL$. Thereby, we obtain *n* LMIs

$$\begin{cases} PA_i - \overline{L}C_j + A_i^T P - C_j^T \overline{L}^T < 0 & i, j = 1 \dots n \\ P > 0 \end{cases}$$
(10)

Finally, we obtain the multi-model $L = P^{-1}L^T$ We use this method to synthetize the two observers

4.2. Virtual sensor

In this subsection, we propose a PFTC strategy based on virtual sensor (Figure 4). This contains a multi-model LPV observer based on LMIs constrains, aiming to estimate in real time, faults of a VSV estimation based on MIMO identification.

Moreover, virtual sensor contains a bloc reconfiguration which is used to compensate the faults estimated the multimodel LPV observer. (De Oca 2010, De Oca *et al.* 2012, Nazari *et al.* 2013, Richter *et al.* 2011) propose a PFTC for LPV system.

In this paper, we propose an original method of reconfiguration without on-line re-tuning the parameters of the controller.

In general, PFTC approach supposes that the measure is available. Here in this work, we treat a case of a complete loss of the VSV sensor. Up to our knowledge (De Oca 2010, De Oca *et al.* 2012), the PFTC has not been used for thiscase. We ensure the availability of the input signal of the virtual sensor through MIMO VSV estimation.

This MIMO VSV estimation has the inconvenient to be inaccurate in the transient phases. This can have a negative effect for the stability of the overall VSV system. That is why we use a virtual sensor to estimate and compensate these inaccuracies that we consider as sensor fault.

We consider a following subsystem with a faulty sensor for a given operating point:

$$\begin{cases} \dot{x}(t) = A_i(\theta(t))x(t) + B_i(\theta(t))u(t) \\ y(t) = C_{f_i}(\theta(t))x(t) + D_i(\theta(t))u(t) \end{cases}$$
(11)

With C_{f_i} output subsystem matrix including the fault The virtual sensor applied to the polytopic LPV system can be written as following:

$$\begin{cases} \dot{x_{v}}(t) = \sum_{\theta(t)} \sigma_{\theta(t)} \left(\xi_{\theta(t)}(t) \right) \left(A(\theta(t)) x_{v}(t) + B(\theta(t)) u(t) + L_{v} \left(y_{v}(t) - y_{f}(t) \right) \right) \\ y_{v}(t) = \sum_{\theta(t)} \sigma_{\theta(t)} \left(\xi_{\theta(t)}(t) \right) \left(C_{f}(\theta(t)) x_{v}(t) \right) \end{cases}$$
(12)

with $x_v(t)$ the state vector of the virtual sensor state space and L_v the multi-model observer gain

de Oca and Puig (2010) brings out a reconfigurability condition:

$$Rank\left(C_{f}(\theta(t))\right) = Rank\begin{pmatrix}C_{f}(\theta(t))\\C(\theta(t))\end{pmatrix}$$
(13)

Consider the coefficient of reconfigurability P:

 $+D(\theta(t))u(t)$

$$P(\theta(t)) = C(\theta(t))C_f(\theta(t))^T (C_f(\theta(t))C_f(\theta(t))^T)^{-1}$$
(14)

Thereby, we obtain the output corrective matrix and output signal.

$$C_{\Delta}(\theta(t)) = C(\theta(t)) - P(\theta(t))C_{f}(\theta(t))$$
(15)

$$y_{\Delta}(\theta(t)) = C_{\Delta}(\theta(t)) x_{\nu}(\theta(t))$$
(16)

and thereby, we obtain the corrected output signal

$$y_{c}(t) = P\left(\theta(t)\right)y_{f}(t)y_{\Delta}(\theta(t))$$
(17)



Figure 4: PFTC diagram

4.3. Robustness-Neural Extended Kalman Filter

Kalman filter has received a great attention in aeronautical industry. In this paper, we propose a robust observer for inaccurate state space representation using a Neural Extended Kalman Filter.

Neural Extended Kalman Filter (Kramer *et al.* 2008, Stubberud 2006, Stubberud *et al.* 1995) is a robust and adaptive state estimator, with an approximate knowledge of the state space representation, or the physical equations describing the behaviour of the system.

This robust estimation method is often used for the complex system where a simplification is imposed as an embeddability constraint. This simplification may jeopardises the precision of the estimation and consequently affects all applications using the estimation ,like synthesis of observer for diagnostic or reconfiguration, control laws...etc.

In this paper, we propose to use an adaptive robust method, which consist of setting in real time, the parameter of the state-space representation in order to guarantee the robustness of estimation against the inaccuracy engendered by the identified model equations (Figure 5).

Consider a non-linear state space representation:

$$\begin{cases} x_{k+1} = f(x_k, u_k) + r_k \\ y_k = g(x_k, u_k) + q_k \end{cases}$$
(18)

where: f and g are nonlinear functions, r_k and q_k are respectively the noise process and the measure noise. Let remind the extended Kalman filter:

$$\begin{cases} K_{k} = P_{k|k-1} \frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}}^{T} \left(\frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}} P_{k|k-1} \frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}}^{T} + R_{k} \right)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{k} \left(y_{k} - g(\hat{x}_{k|k-1}) \right) \\ P_{k|k} = \left(I - K_{k} \frac{\partial g(\hat{x}_{k|k-1})}{\partial \hat{x}_{k|k-1}} \right) P_{k|k-1} \\ \hat{x}_{k+1|k} = f(\hat{x}_{k|k}, u_{k}) \\ y_{k} = g(\hat{x}_{k+1|k}) \\ P_{k+1|k} = \left(\frac{\partial f(\hat{x}_{k|k}u_{k})}{\partial \hat{x}_{k|k}} \right) P_{k|k} \left(\frac{\partial f(\hat{x}_{k|k}.u_{k})}{\partial \hat{x}_{k|k}} \right) + Q_{k} \end{cases}$$
(19)

We assume that the measure and process noises are Gaussian. where:

- $x \in \mathbb{R}^{n_x}$ state of the system
- $y \in \mathbb{R}^{n_y}$ output of the system
- *K* Kalman gain
- *Q* Covariance matrix of the measured noise
- *R* Covariance matrix of the process noise
- *P* Covariance matrix of state estimation error
- *f* Prediction function of the state
- *g* Output function

In our case, the function f is non-linear and embeddable. Thus, we approximate it by an off-line closed loop identification \overline{f} , which is added to an on board learned neural network (Kramer *et al.* 2008, Stubberud 2006, Lobbia *et al.* 1995)

$$f(x_k, u_k) = \overline{f}(x_k, u_k) + NN_f(x_k, \omega_k, u_k)$$
(20)

We assume that the function g is linear and we note: $h = \frac{\partial g}{\partial \hat{x}_{k|k-1}}$

$$\begin{cases} K_{k} = P_{k|k-1}h(\hat{x}_{k|k-1})^{T} \left(h(\hat{x}_{k|k-1})P_{k|k-1}h(\hat{x}_{k|k-1})^{T} + R_{k}\right)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{k} \left(y_{k} - g(\hat{x}_{k|k-1})\right) \\ P_{k|k} = \left(I - K_{k}h(\hat{x}_{k|k-1})\right)P_{k|k-1} \\ \hat{x}_{k+1|k} = \overline{f}(\hat{x}_{k|k}, u_{k}) + NN_{f}(\hat{x}_{k|k}, \omega_{k}, u_{k}) \\ y_{k} = g(\hat{x}_{k+1|k}) \\ P_{k+1|k} = \left(\frac{\partial f(\hat{x}_{k|k}, u_{k})}{\partial \hat{x}_{k|k}}\right)P_{k|k} \left(\frac{\partial f(\hat{x}_{k|k}, u_{k})}{\partial \hat{x}_{k|k}}\right) + Q_{k} \end{cases}$$

$$(21)$$

We define a new state vector, which a concatenation of state vector of the system and the adjustable parameters of the neural network and we note $A = \frac{\partial \overline{f}(x_{k|k})}{\partial x_{k|k}}$

$$\overline{X}_{k} = \begin{pmatrix} x_{k} \\ \omega_{k} \end{pmatrix}$$
(22)

$$\overline{X}_{k+1|k} = \begin{pmatrix} x_{k+1|k} \\ \omega_{k+1|k} \end{pmatrix} = \begin{pmatrix} \frac{\partial \overline{f}(x_{k|k})}{\partial x_{k|k}} + \frac{\partial NN_f}{\partial x_{k|k}} & \frac{\partial NN_f}{\partial \omega_k} \\ 0 & I_d \end{pmatrix} \begin{pmatrix} x_{k|k} \\ \omega_{k|k} \end{pmatrix}$$
(23)
$$\overline{X}_{k+1|k} = \begin{pmatrix} A + \frac{\partial NN_f}{\partial x_{k|k}} \end{pmatrix} = \begin{pmatrix} A - \frac{\partial NN_f}{\partial x_{k|k}} \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} A - \frac{\partial NN_f}{\partial x_{k|k}} \end{pmatrix}$$

$$\bar{x}_{k+1|k} = \underbrace{\left(A + \frac{\partial NN_f}{\partial x_{k|k}}\right)}_{\frac{\overline{A}}{\overline{A}}} x_{k|k} + \frac{\partial NN_f}{\partial \omega_k} \omega_{k|k}$$
(24)

According to the Eq. (22) the matrix \overline{A} is adjusted in real time by the partial differential of the neural network on the state vector.



Figure 5: Robust PFTC diagram

5. SIMULATION RESULTS

We use a jet engine simulator to simulate a flight scenario defined by a set of operation points. For this, we apply a flight maneuverer equivalent to what imposes the pilot through the control yoke during a flight. Indeed, each control yoke position determines target value of a fuel quantity which induces high pressure compressor's speed and thus low pressure compressor's speed and a certain configuration of variables geometries such as VSV position. Consider a flight maneuverer in which we include a VSV sensor failure.

In Figure 7, we simulate a maneuver with a faulty VSV sensor shown in Figure 6.



Figure 6 : Effect of the intermittent contacts on VSV sensor



Figure 7 : Control of the VSV position using a faulty sensor



Figure 8: Control of the VSV position in the nominal operation and with a PFTC

Figure 7, shows the effect of a periodic random switch in the electric input of the VSV sensor, which provide intermittent contact of the VSV sensor feedback signal. This kind of failure is the most probable to occur during a flight, and it may jeopardize the stability of the close-loop VSV actuation, and consequently engender irreversible damage in high pressure compressor.

In the Figure 8, we simulate the same maneuver, but we replace the faulty sensor by the model using a Robust Passive fault Tolerant Control approach.

We use a PFTC approach as soon as sensor failure is detected. Figure 8 shows the control of VSV actuation using an analytical VSV model as feedback signal, with a PFTC approach described below.

We notice in the Figure 8, oscillations. These are due to the inaccuracies of the analytical VSV model feedback signal. Indeed, the controller is tuned for the nominal operation, and it is not designed to reject model inaccuracies. Consequently, we tune controller off-line taking into account these model inaccuracies, not only in order to reject oscillations but also to reach performance requirements imposed in the specifications. Once tuned off-line, controller is unchanged on-line during the operation, respecting thereby the constraints which led us to choose the PFTC approach instead of the AFTC approach.



Figure 9: Control of the VSV position in the nominal operation and with a PFTC approach with new controller

Figure 9 shows the control of the VSV position using the PFTC with the new adjusted controller rejecting thereby the oscillations engendered by the analytical VSV model inaccuracies.

To test the robustness of the PFTC approach using the NEKF, we add uncertainties to the SISO identified state space matrix:

$$\begin{cases}
A_{real} = A_{identified} \pm \delta A \\
B_{real} = B_{identified} \pm \delta B \\
C_{real} = C_{identified} \pm \delta C
\end{cases} (25)$$

where, δB , δC are additive uncertainties modeled by Gaussian noise.

We replace the identified matrix in PFTC algorithm by the matrix defined in Eq.(25).



Figure 10: Control of the VSV with uncertain state space matrix-Robust PFTC

Figure 10 shows the rejection of state space matrix uncertainties using NEFK. Indeed, in spite of adding uncertainties to state space matrix, we obtain an analytical VSV model with an acceptable accuracy.

6. CONCLUSION

In this present paper, a Robust Passive Fault Tolerant Control approach was proposed in a LPV framework using LPV Takagi-Sugeno formalism. This approach is applied to jet engine equipment, a Variable Stator Vane actuation which is subject to sensor failure on-board. That may jeopardize the stability of the closed-loop actuation, affecting thereby the performance and the operability of the jet engine.

The work proposed in this paper, allows guaranteeing the availability of the feedback information to VSV position, with acceptable performance and operability of the jet engine, in spite of the inaccurate VSV model.

In a jet engine, there are several systems of closed-loop actuation with sensors subject to failure. We will propose in a future paper an extension of the work for the VBV

REFERENCES

- Akhenak, A., Chadli, M., Ragot, J. and Maquin, D., 2007. Design of sliding mode unknown input observer for uncertain Takagi-Sugeno model, *Control & Automation, 2007. MED'07. Mediterranean Conference* on 2007, IEEE, pp. 1-6.
- Bezzaoucha, S., Marx, B., Maquin, D. and Ragot, J., State and Parameter Estimation for Time-varying Systems: a Takagi-Sugeno Approach, .
- Bezzaoucha, S., Marx, B., Maquin, D. and Ragot, J., 2013. Nonlinear joint state and parameter estimation: Application to a wastewater treatment plant. *Control Engineering Practice*, **21**(10), pp. 1377-1385.
- Bezzaoucha, S., Marx, B., Maquin, D. and Ragot, J., 2013. Stabilization of nonlinear systems subject to actuator saturation, *Fuzzy Systems (FUZZ), 2013 IEEE International Conference on* 2013, pp. 1-6.
- Blanke, M., Staroswiecki, M. and Wu, N.E., 2001. Concepts and methods in fault-tolerant control, *American*
- Control Conference, 2001. Proceedings of the 2001 2001, IEEE, pp. 2606-2620.
- De oca, S.M. and Puig, V., 2010. Fault-tolerant control design using a virtual sensor for lpv systems, *Control and Fault-Tolerant Systems (SysTol), 2010 Conference on* 2010, IEEE, pp. 88-93.
- De oca, S., Puig, V, Witczak, M. and Dziekan, Ł, 2012. Fault-tolerant control strategy for actuator faults using LPV techniques: Application to a two degree of freedom helicopter. *International Journal of Applied*

Mathematics and Computer Science, **22**(1), pp. 161-171.

- Kramer, K.A. and Stubberud, S.C., 2008. Tracking of multiple target types with a single neural extended Kalman filter. *Intelligent Techniques and Tools for Novel System Architectures*. Springer, pp. 495-512.
- Laprie, J., 1985. Dependable computing and fault-tolerance. *Digest of Papers FTCS-15*, , pp. 2-11.
- Liao, F., Wang, J.L. and Yang, G., 2002. Reliable robust flight tracking control: an LMI approach. *Control Systems Technology, IEEE Transactions on*, **10**(1), pp. 76-89.
- Nazari, R., Seron, M.M. and De doná, J.A., 2013. Faulttolerant control of systems with convex polytopic linear parameter varying model uncertainty using virtualsensor-based controller reconfiguration. *Annual Reviews in Control*, **37**(1), pp. 146-153.
- Owen, M.W. and Stubberud, A.R., 2003. A neural extended Kalman filter multiple model tracker, *OCEANS 2003. Proceedings* 2003, IEEE, pp. 2111-2119.
- Patton, R.J., 1997. Fault-tolerant control systems: The 1997 situation, IFAC symposium on fault detection supervision and safety for technical processes 1997, pp. 1033-1054.
- Richter, J.H., Heemels, W., Van de wouw, N. and Lunze, J., 2011. Reconfigurable control of piecewise affine systems with actuator and sensor faults: stability and tracking. *Automatica*, **47**(4), pp. 678-691.
- Stubberud, S.C., 2006. System Identification using the Neural-Extended Kalman Filter for Control Modification, Neural Networks, 2006. IJCNN'06. International Joint Conference on 2006, IEEE, pp. 4449-4455.
- Stubberud, S.C., Lobbia, R.N. and Owen, M., 1995. An adaptive extended Kalman filter using artificial neural networks, *Decision and Control, 1995.*, *Proceedings of the 34th IEEE Conference on* 1995, pp. 1852-1856 vol.2.
- Tafraouti, M., 2006. Contribution à la modélisation et la commande des systèmes électrohydrauliques. Université Henri Poincaré-Nancy I.
- Yang, H., Jiang, B. and Cocquempot, V., 2010. Fault tolerant control design for hybrid systems, volume 397 de Lecture Notes in Control and Information Sciences.
- Zhang, Y. and Jiang, J., 2008. Bibliographical review on reconfigurable fault-tolerant control systems. *Annual reviews in control*, **32**(2), pp. 229-252.

Duplex ball bearing outer ring deformation- Simulation and experiments

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ABSTRACT

This paper presents a research of deformations influence on duplex ball bearings dynamic behavior. Despite the common use of duplex ball bearings, bearings subcomponents deformations are not thoroughly investigated. In order to investigate these effects, this study integrates the outcome of a 3D dynamic model, developed for assessment of the defect pattern and experimental results from a full scale CH-53 Swashplate test rig.

The ability to withstand high radial and bi-directional axial loads makes duplex bearings common in aircraft applications and specifically in helicopter rotors. The swashplate of the CH-53 is constructed of duplex angular contact ball bearings. Two spacers, internal between the static inner rings and external, between the rotating outer rings support the bearing rings. A structural defect is formed by a faulty external spacer, thus causing a lack of support to the top bearing and deformation of the outer rings.

Model results indicate that the lack of support has a defect pattern in both radial and axial directions. Test rig data acquired by accelerometers was analyzed by several diagnostic techniques including order tracking, envelope analysis and dephased algorithm in order to recognize the simulated pattern.

1. INTRODUCTION

Duplex (paired) bearings are used in a wide range of applications. The ability to withstand high radial and bidirectional axial loads makes duplex bearings common in aviation applications, specifically in helicopter rotors. The CH-53 swashplate is constructed of duplex angular contact ball bearings in a back-to-back arrangement (Figure 1). The bearings allow smooth relative motion between the static plate and a rotating plate while absorbing torques from the pitch control rods. The bearings are separated by two spacers, internal between the static inner rings and external between the rotating outer rings (Figure 2).



Figure 1. Cross section of a CH-53 Swashplate



Figure 2. Magnified section of the angular-contact ball bearings and the spacers separating the rings

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This study focuses on the recognition of deformation of the bearings outer rings caused by buckling of the external spacer. As shown in Figure 3, integration of dynamic model results and seeded test experiments serve as the methodology of the research. Time history data generated by the model was analyzed in order to define the fault expected pattern. Vibration signals generated by the experimental systems will be analyzed based on the model results in order to recognize the fault signature.

Development of diagnostic tools on a test stand is a complicated process due to environmental factors. These factors include structural dynamics, mounting, location, components history and reciprocal influence. This approach is designed to address the complexity of algorithms development based on test rig data. The integration of a physical model and hierarchical test systems is a method designed to assist in recognition of the fault pattern in the different experimental systems.



Figure 3. Research methodology- integration of model results and experiments at different scales

1.1. Research Background

A 3D dynamic model (Kogan et al., 2012) has been developed for assessment of the defect pattern and for comprehension of common effects such as radial load and misalignment. Time history data simulated by the model was analyzed in order to define the expected fault pattern.

Comparing the dynamic model results with vibration signals generated by different test systems is planned in phases. It is assumed that when advancing from one phase to another the measured data will simulate more realistically the signal and the environment of the helicopter rotor head. As a result, the difficulty to recognize the fault pattern is expected to increase from one phase to another, demanding more complex algorithms. Progress in phases is performed to guarantee the recognition of the defect signature among the variety of signals generated by the helicopter during a flight.

The experimental phases include a small scale specimen, full scale test rig and a CH-53 helicopter ground test. Further background of this work is presented in the paper (Battat at el., 2013) and includes description and results of the small scale specimen.

2. DYNAMIC MODEL

A 3D dynamic ball bearing model was developed by Kogan et al (2012) to study the effect of anomalies in bearing subcomponents on the bearing dynamic behavior. The nonlinear model was developed using Hertzian contact theory and has the ability to simulate effects of radial and axial loads, shaft unbalance, localized faults, and ring deformation. The algorithm was implemented numerically in MATLAB. Model validation by the small scale specimen was described in referenced work.

In order to simulate the bearings outer rings deformation, analytic approximation of the sagging was done. This approximation takes into account applied load, length of the defect, number of effected balls and structural parameters.

3. TEST RIG

In order to examine the effect of defects on the dynamic behavior of the CH-53 swashplate bearings, a specific test rig was constructed. The main purpose of the full scale test rig was to simulate the original work environment of the swashplate bearings without the environmental noise. The reduction of noise will help in recognition and isolation of the searched pattern.

The rig (Figure 4) is composed of an original CH-53 swashplate and provides a good simulation of the bearings support structure under laboratory conditions. The rotating plate is set in motion by a transmission of gears and a cog belt driven by an electric three phase motor. Controlled by a variable frequency drive, the motor is set to rotate the plate up to 189 RPM (3.15 Hz), the CH-53 main rotor speed. Table 1 lists the bearings parameters.

Pitch diameter	19.03 [in]	
Ball diameter	0.5 [<i>in</i>]	
Number of balls	92	
Outer race rotational speed	189 [<i>rpm</i>]	
Contact angle	30°	
Defect angular length	68°	

Table 1. Test rig bearings parameters



Figure 4. Full scale test rig and sensors locations

An aluminum external spacer separates the bearings outer rings. Unlike local defects, the buckling phenomenon is correlated with a relatively large length dimension. Hence, in order for the fault to be presented an arc length of nearly 70° was inserted to the external spacer. The defect is formed by milling both vertical ends of the spacer for a 300 mm arc (Figure 5). Milling the external spacer causes a lack of support to the bearings outer rings in the presence of axial load.

Simulation of the axial load on the swashplate is carried out using a hydraulic cylinder. By producing tension in the main shaft the piston loads the rotating plate, thus axially loading the bearing's outer rings. Figure 6 demonstrates the path of the load through the test rig.



Figure 5. Faulty external spacer separating the bearings outer rings. Lack of support is simulated by milling the spacer's vertical ends.



Figure 6. Load transformation over the test rig

The rotational speed of the plate is measured by a magnetic speed sensor. Vibration signals were collected by triaxial piezoelectric accelerometer positioned at several locations marked on Figure 4. The accelerometers are mounted with one of their axes parallel to the rigs axial axis (line of action). Data was collected in several rotational speeds and piston pressures in both healthy and faulty swashplates.

4. MODEL RESULTS

During a ball passage through the outer ring deflected zone, the load acting on the ball drops and the ball support of the outer ring is reduced. In order to compensate for the support reduction, the balls outside the deflected zone are overloaded. The interruption caused by interaction of a ball with the deflected zone causes a periodic impact. Cycle domain of the simulated results is presented in Figure 7. The axial direction coincides with the bearing axis, while Radial 1 and Radial 2 are directions of measurement located in the bearing plane. Model results simulate a sensor located at the center of the inner ring. Since the defect location varies with the shaft rotation shaft speed modulation is created in the radial directions.

Further analysis was performed using Power spectral density (PSD). The spectrum of the axial acceleration reveals peaks at harmonics of the Outer race Ball Pass Frequency (BPFO). BPFO harmonics are presented in Figure 8 as the repetitive high peaks. The spectrum of the radial acceleration reveals peaks at shaft speed sideband around the BPFO harmonics (Figure 9). In order to obtain a closer to reality simulation, a small value radial load was inserted. This modification is expressed by an additional sideband.



Figure 7. Simulated results: acceleration of the inner ring



Figure 8. Simulated results: Order of a faulty duplex bearing under combined load. Axial, radial 1 and radial 2 are in green, blue and purple respectively

Model simulations present the defect signature as BPFO harmonies with adjacent shaft speed sidebands. The BPFO is calculated for 44.95 [*order*] and is clearly visible as the main peak in the axial direction. Background sidelobes are significantly lower than the radial sidebands and therefore are not part of the pattern. Following harmonics present a similar image. Therefore this pattern was used for comparison to BPFO harmonics of the experimental results.



Figure 9. Simulated results: order of the BPFO first harmonic. Axial, radial 1 and radial 2 are in green, blue and purple respectively

5. EXPERIMENTAL RESULTS

Test rig results present a significantly more complex image. Vibration sensors are sensitive to data from a variety of elements in the system. In addition, effects of misalignment unbalance and transfer functions are present. Use of order tracking, envelope analysis and signal dephase are described in this section. These are applied in order to separate the fault pattern from the noisy environment.

Figure 10 presents the order representation (PSD of the resampled signal) of the measured signal of a piezoelectric tri-axial sensor mounted at location 1.



Figure 10. Measured data: Order representation of the triaxial data at location 1. Axial, radial 1 and radial 2 are in green, blue and purple respectively

Data was acquired at various locations (marked on Figure 4). The data was examined and location 1 was selected as the bearing was most noticeable in its signals. Through examining the analyzed data, it was found that the BPFO order is estimated at 44.98 and the inner race Ball Pass Frequency (BPFI) order is estimated at 47.03. The proximity of the bearings tones to a harmonic of the shaft speed causes a difficulty in recognition of the bearing tone and its sidebands in the vicinity of the first harmonic (see Figure 11). This illustrates the difficulties in recognizing the pattern in a realistic environment. A clear image of the defect pattern is obtained at the BPFO 7th harmonic and is presented in Figure 12. Unlike the model results, both the PBFO harmony and the shaft speed sidebands are presented in all measuring directions. The main reason for this is inherent in the behavior of the transfer function and related to the proximity of the sensor to the bearing.



Figure 11. Measured data: Order of the BPFO first harmonic. Axial, radial 1 and radial 2 are in green, blue and purple respectively



Figure 12. Measured data: Order of the BPFO 7th harmonic. Axial, radial 1 and radial 2 are in green, blue and purple respectively

5.1. Advanced analysis

An advanced analysis is used to identify the fault in noisy environment. The dephase algorithm (Klein et-al, 2012) attenuates peaks synchronous to the rotating speeds of shafts (gear mesh frequencies, shaft harmonics). By that, weak signals related to bearings that have been masked by other vibration sources might become visible. Figure 13 presents the dephased signal marked in green against the background of the order signal (in orange). The second BPFO harmonic was masked by the cog belt signal at order 90. Accordingly, BPFO sidebands are unrecognized without the dephased analysis. Figure 14 presents the dephased signal of the axial direction centered at the third BPFO harmonic.



Figure 13.Measured data: axial direction of the second BPFO harmonic. Order of the dephased signal (green) against the background of the order signal (orange).



Figure 14. Measured data: Order of the dephased axial direction, third BPFO harmonic

Envelope analysis is a known technique for identification of bearing faults. The envelope signal was calculated based on the dephased signal and is presented in Figure 15 and Figure 16. The order representation of the envelope shows a clear bearing pattern and good agreement with the model results.



Figure 15. Measured data: Order of the envelope axial direction, second BPFO harmonic



Figure 16. Measured data: Order of the envelope axial direction, third BPFO harmonic

6. CONCLUSION

This study focuses on the recognition of deformation faults in duplex ball bearings. Deformation of the bearing outer ring is a result of axial loading along with buckling of the external spacer. This study integrates the results of a 3D dynamic model, developed for assessment of the defect pattern, and results from experimental systems.

The dynamic model simulations present the defect signature as BPFO harmonics in the axial direction with adjacent shaft speed sidebands in the radial directions.

A small scale specimen was designed for preliminary results of the rings deformation. Experiments of the small scale specimen are presented in previous work (Battat at el., 2013) and are in good agreement with the model results. The full scale test rig was constructed to simulate more realistically the signals generated by the swashplate.

Experiments conducted on the test rig confirm the increase in noise sources and present the difficulty in recognizing the pattern in a realistic environment. The results present the defect pattern masked by noises, unbalance and effects of transfer function. Evident pattern can be observed in specific BPFO harmonics (e.g. the 7th harmonic) in which the presence of shaft harmonics is attenuated. Use of the dephased algorithm was required in order to recognize bearing tones and their sidebands around the BPFO first harmonics. A clear bearing pattern was observed by use of envelope analysis calculated based on the dephased signal.

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REFERENCES

- Battat, M., Kogan, G., Kushnirsky, A., Klein, R., & Bortman, J. (2013). Detection of CH-53 swashplate bearing deformation-from a 3D dynamic model to diagnostics. *Proceedings of PHM Conference*. October 7-14, New Orleans, LA
- Kogan, G., Bortman, J., Kushnirsky, A. & Klein, R. (2012). Ball bearing modeling for faults simulation. *The Ninth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies* (no. 1, pp. 1–8).
- Harris, T. A., & Kotzalas, M. N. (2007). *Essential Concepts* of *Bearing Technology* (Fifth Edit).USA: CRC Press.
- Taylor, I. J. & Kirkland, D. W. (2004). *The Bearing Analysis Handbook*, USA: VCI
- Bayoumi, A., Goodman, N., Shah, R., Roebuck, T., Jarvie,
 A. & Eisner, L. (2008). Conditioned-Based
 Maintenance at USC Part III: Aircraft Components
 Mapping and Testing for CBM. *The American Helicopter Society Specialists' Meeting on Condition Based Maintenance. Huntsville.*
- Klein, R., Rudyk, E., Masad, E. (2012) "Methods for diagnostics of bearings in non-stationary environment", *International Journal of Condition Monitoring*
- Blechertas, V., Bayoumi, A., Goodman, N., Shah, R. & Shin, Y. J., (2009). CBM Fundamental Research at the University of South Carolina: A Systematic Approach to U.S. Army Rotorcraft CBM and the Resulting Tangible Benefits. *The American Helicopter Society Technical Specialists' Meeting on Condition Based Maintenance. Huntsville.*
- Dempsey, P., Branning, J. & Arsenal, R. (2010). Comparison of Test Stand and Helicopter Oil Cooler Bearing Condition Indicators. *AHS 66th Annual Forum and Technology*.
- Budynas, R. & Nisbett, K. (2006). Shigley's Mechanical Engineering Design (*Mcgraw-Hill Series in Mechanical Engineering*). McGraw-Hill Science/Engineering/Math.

A Prognostic Framework For Electromagnetic Relay Contacts

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ABSTRACT

Electromagnetic relays provide a well proven solution to switching loads in a variety of applications. However, relays are known for their limited reliability due to mechanical wear of internal switching elements, essentially the life of the relay may be determined by the life of the contacts. Failure to trip, spurious tripping and contact welding, can in critical applications such as control systems in avionics and signaling for rail networks, cause significant costs due to downtime as well as safety implications. Prognostics provides a way to assess the remaining useful life of an electromagnetic relay based on its current state of health.

In this paper, the cause of failure and degradation for electromagnetic relays used in avionic power controllers are examined. A first principle model of an electromagnetic relay, including contact wear is proposed. The degradation observations and measurements form the basis for developing a model based remaining useful life prediction algorithm. Our overall aim is to derive a simple but accurate model of the relays contact degradation, and provide prediction of performance changes within the component.

1. INTRODUCTION

The electromagnetic relay has been around for a very long time, approximately 160 years and is essentially an electrically operated switch; the basic principle of most relays is to use an electromagnet to operate a mechanical switching mechanism. Relays are used for the control of circuits via a low power signal and offer a complete isolation between the control and the controlled circuit. Other advantages are their ability to deal with high surge currents and high voltage spikes, as well as having no leakage current. However, their main disadvantage is the life expectancy, which is low compared with their solid state counterpart.

Relays have many applications, amongst the first uses were in telephony and telephone exchanges as well as early computing. Modern uses are still many and varied, with applications such as amplifying a digital signal, switching large amounts of power with a small operating power; industrial control of machine tools, transfer machines, and other sequential control; detection and isolation of faults on transmission and distribution lines by opening and closing circuit breakers (protection relays); isolation of the control circuit from the controlled circuit and logic functions.

Amongst these applications are signaling in the rail network and the main emphasis of this work, the use of relays to control the power to a Full Authority Digital Engine Control (FADEC) on an aero engine. However, relays are known for limited reliability due to mechanical wear of internal switching elements, and **essentially the life of the relay, may be determined by the life of the contacts**. Failure to trip, spurious tripping and contact welding, can, in critical applications such as control systems for avionics and signaling in rail networks cause significant costs due to downtime as well as safety implications.

Prognostics provides a way to assess the remaining useful life (RUL) of an electromagnetic relay based on its current state of health and its anticipated future usage and operating conditions. In this paper, we examine the causes of contact wear on electromagnetic relays used in an avionic power controller. A first principle model of an electromagnetic relay contact wear is proposed. Our overall aim is to derive a simple but accurate model for electromagnetic relay contact degradation.

2. REVIEW OF ELECTRICAL CONTACTS AND FAILURE MODES

The reliability of electromagnetic relays has been the subject of research for many years; however over the last eight years, research has started to appear on the prediction of reliability within relays based on monitoring their dynamic parameters.

The traditional reliability assessment methods for electromagnetic relays are based on censored failure time data; this provides very little reliability information (Fang et al., 2006). In order to predict the life of the relay, a metric of degradation need to be defined, methods explored include dynamic contact resistance, pick-up time, over-travel time, the rebound duration, closing time, the fluctuation coefficient respectively as the predicted variables of the

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abrasion failure, bridging failure and the contamination failure (Qiong et al. & Xuerong et al., 2010).

The effects of the environment on the reliability prediction can be a major contributory factor, the failure process and failure mechanisms of electromagnetic relay may totally change along with the environment.

As well as the environment, influence factors such as material transfer to the contact gap, the combined influence of the arc energy and the contact surface morphology to the degradation rate of the contact gap, and use of fatigue cumulative damage theory has been explored to establish a failure physical degradation model of the electromagnetic relay contacts (Xuerong et al., 2012). Multiple degradation parameters may be required to give an accurate metric of the failure mechanism.

Due to the complexity of defining a model that can predict degradation throughout the electromagnetic relay, most methods of assessing reliability have been based around time series and regression techniques. (Qiong et al., 2010) showed by using time series analysis and by measuring characteristic parameters as predicted variables, the life of relay can be obtained. However, the conclusions showed the predicted accuracy is greatly influenced by the complex variations of characteristic parameters, and as a result it sometimes becomes too low to be accepted. Life prediction based on wavelet transform and ARMA (auto-regression moving average) time series was proposed to improve this (Yu, Q., 2009).

A linear regression analysis method has been used to establish the linear degradation model which regards the operation time as the independent variable and the predicted variables of the failure mechanisms as the dependent variable (Xuerong et al., 2012).

The work carried out by (Fang et al., 2012) proposes the analyses of the uncertainty of bounce time of contacts for the relay and its use in predicting operating reliability. It changes the contact bounce time into a symbolic series according to the threshold function. The analysis indicates that series entropy of bounce time for bad contacts descend as time goes on; the law can be used to predict the operating reliability.

The work above has been developed on ascertaining the reliability of relays via various methods, however, very little work has been carried out so far in producing a prognostic solution.

2.1. Failure and degradation modes in relays

The following table outlines the failure modes associated with general relays (Fujitsu Components Engineering Reference: Relays, 2009).

Table1.	Failure	modes	in	electromagneti	c relays	
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Parts	Stress	Failure	Failure Mode	
		Symptoms		
Contact	Voltage.	Transfer and	Poor release	
	Current.	wear of contact	Poor contact	
	Temp.	due to arc	Increased	
	Vibration.	discharge	contact	
	Humidity.	Weld and	resistance	
	Shock.	bridging of	Noise	
	Dust. Gas	contact	Change in	
		Sticking	operate/release	
		contact	time	
		Corrosion	Poor dielectric	
		(oxidation.	strength	
		sulfurization)	8	
		Foreign matter		
		(dust etc)		
		Deposits		
Winding	As above	Corrosion	Breakage of	
8		Foreign matter	coil	
		Voltage	Burning of coil	
		fluctuation	Poor working	
		Lead wire	release	
		vibration	operation	
			Change in	
			operate/release	
			time	
			Change in	
			operate/release	
			voltage	
			Malfunction	
Structural	As above	Fatigue and	Poor contact	
parts		creep of spring	Poor release	
1		Abnormal	Change in	
		wear	operate/release	
		Seizure	time	
		Foreign matter	Change in	
		(dust)	operate/release	
		Deposition of	voltage	
		worn contact	Insulation	
		materials	resistance	
		Corrosion		
Enclosure	As above.	Damage by	Damage	
	Chemicals	external force	(cracks etc.)	
		Chemical	, , ,	
		damage		

Pursuing manufacturer's data shows that general relays have a life electrical life expectancy of around 100,000 operations minimum with a resistive loading (this is greatly reduced with inductive loads) and a mechanical life expectancy in the order of one million and in some cases 10 and 100 million operations. The reason the electrical life is so low, compared with the mechanical life is because the contact life is application dependant. The electrical rating applies to contacts switching at their rated loads (Holm, 1967). If however, a set of contacts is used to switch a load less than the rated value, the contact life may be significantly higher. The rated electrical life also takes into account arc destruction of the contacts. Arc suppression may be used to lengthen the life of the contact.

As well as arcing, sparking may cause damage at voltages and currents less than those required for arc ignition. The spark is due to capacitive discharge, and compared to a arc is weak, and contributes less to the damage of the contact.

Contact life is deemed to have reached failure when the contacts stick or weld together, or if excessive material transfer has taken place to either one of both contacts and a good electrical contact make is no longer possible. These failure modes are due to successive switching operations and of material loss due to splattering.

The material transfer takes place as a result of joule heating. As the contact area separates, the area of the contacts diminishes. The load current is then force to flow through an ever more constricted area, and this causes a buildup of heat, which reaches such a point where the contact material is melted and then boils. With a dc load, this liquefied material tends to deposit on the cathode of the contact, simply due to the fact that it is cooler than the anode. Material transfer also occurs as a result of arcing, with the transfer being opposite to above and depositing the molten metal on the anode of the contact.

Material loss due to boiling and arcing is from splattering during contact bounce on the closure of the contacts. Although the amount of material loss is minuscule, over tens or hundreds of thousands of operations it becomes significant.

2.2. Contact bouncing

The making of the contacts is not usually finished at first touch, but as a consequence of bouncing (where the force of contacts impacting together causes them to bounce apart), the members make and break their contact several times before they reach a permanent state of contact. This can have implications due to the many disturbances bouncing brings. The exactitude of contact make is lost, and the material transfer by arcs and bridges is increased, since each bounce is the same as a new switch operation. A contact is particularly vulnerable to damage by re-bounce when the current begins with a high inrush as in the case of inductive loads, such loads may result in current in excess of eight times the normal operating current (McBride, 1991)

2.3. Arcing in a d.c. circuit and material transfer

An arc is produced from stored energy in a circuit due to the inductance L. If the current was to suddenly drop to zero in a circuit by the parting of the electrical contacts, then the stored energy in circuit inductance would result in large over voltages given by

$$V = -L\frac{dI}{dt} \tag{1}$$

In a d.c. circuit the duration of the arcing time is related to the magnitude of the arc voltage V_A compared with the circuit voltage V_C . When $V_A > V_C$ a finite time is required to dissipate the 0.5LI² energy stored in the circuit inductance. One of the most important consequences of arcing is the effect that the arc has on the erosion of the contact material. The contact erosion occurs because with stationary arcs both the cathode and the anode under the arc roots are heated to the boiling point of the contact material (Slade, 1999). The amount of erosion per contact operation depends upon may parameters as summarized by Slade (1999), e.g.,

- 1. the circuit current
- 2. the arcing time
- 3. the contact material
- 4. the contacts size and shape
- 5. the contacts opening velocity
- 6. the contact bounce on make
- 7. the open gap
- 8. arc motion on the contacts

Contact erosion is further complicated by mechanical stresses seen by the contact as a result of opening and closing. Slade (1999) defines that in principle the mass lost per operation of contact should be given by

mass loss = f(total power input into the contacts)

However, this simple equation presents complexities that prevent it ever being established. Firstly, how is mass loss defined? The total mass loss from a contact is a mixture of the following components:

> Metal vapor evaporated from the arc roots + Metal droplets ejected from the arc roots – Metal re-deposited back onto the contact faces – Metal deposited from the opposite contact.

As well as the mass loss, calculation of the total power input into the contacts can be difficult, in terms of measurement of arc voltage V_A and circuit current I_C .

Hence calculation of contact erosion is still a topic of research, there is a great deal of literature on contact erosion, but it tends to be application specific and subject to guidance when used for design.

Tables are available giving constant values for example see Holm (1967), for mean values of coefficients characterizing the arc material transfer on making or breaking contact during a long series of operations, ranging from 0.03 to 1.1. For the relay being used in this work, the contact material is a silver alloy consisting of Silver (Ag) and 40% Nickel (Ni). Hence from the table a material transfer rate $\gamma_p = 0.6$ and the loss due to evaporation from arcing is $\beta=0.8$.

To conclude, a degree of arcing can be useful to remove oxides and film that collect on the contacts of the relay, but excessive arcing causes reduced life and where arcing suppression is recommended by manufactures, it cannot be eliminated altogether and prediction of how long relay contacts will last.

3. DERIVATION OF DAMAGE AND PROGNOSTIC MODEL FOR ELECTRICAL SWITCHING CONTACTS

A framework for developing a electromagnetic relay contact prognosis takes the form of below.



Figure 1. Prognostic framework

3.1. Electrical contact resistance

Any solid surface studied through a microscope will show even the most seemingly smooth finish is in fact undulating. The micro-surface will be composed of peaks and valleys, whose height variations, shape and other geometric considerations vary considerably. When a contact is made between two metals, surface asperities of the contacting members will penetrate the natural oxide and other surface contaminant films, establishing localized metallic contacts and thus, conducting paths. As the force increases, the number and the area of these small metal to metal contact spots will increase as a result of the rupturing of the oxide film and extrusion of metal through the ruptures. These spots, termed a-spots, are small cold welds providing the only conducting paths for the transfer of electrical current. A direct consequence of this is a porous contact where infiltrating oxygen and other corrosive gases can enter to react with the exposed metal and reduce the metallic contact areas. This will eventually lead to disappearance of the electrical contact, although the mechanical contact between the oxidized surfaces may still be preserved (Slade, 1999).

Since electrical current passes only where the small contact spots (also known as *a*-spots) are electrically conducting (e.g., where electrically insulating films on the contact surfaces are displaced), electrical current is highly constricted as it passes across the interface, as illustrated in Figure. 2. Current constriction gives rise to a *contact resistance* very much like constriction of a water hose increases resistance to water flow. For a circular constriction of radius *a*, the constriction resistance R_C is given as

$$R_C = \frac{\rho}{2a} \tag{3}$$



Figure 2. Schematic diagram of contact *a*-spots and current flow in an electrical contact

The contact resistance R_C between two conductors of resistivity ρ_1 and ρ_2 , held together with a force F, is given as (Holm, 1967; Slade, 1999; Braunovic et al., 2006)

$$R_C = \frac{(\rho_1 + \rho_2)}{4} \sqrt{\frac{\pi H}{F}} \tag{4}$$

where H again, is the Vickers' micro-hardness of the softer of the two materials and F is the contact force.

Because the metals are not clean, the passage of electric current may be affected by thin oxide, sulphide, and other inorganic films usually present on metal surfaces. Consequently, the total contact resistance of a joint is a sum of the constriction resistance (R_s) and the resistance of the film (R_f)

$$R_{c} = R_{s} + R_{f} \tag{5}$$

$$R_{f} = \frac{\sigma}{\pi a^{2}} \tag{6}$$

where σ is the resistance per area of the film.

The contact resistance is the most important and universal characteristic of all electrical contacts and is always taken into account as an integral part of the overall circuit resistance of a device. Therefore, although it is significantly smaller as compared with the overall circuit resistance, the changes in the contact resistance can cause significant malfunctions of the device. This is because the contact resistance can vary significantly with the changes in the real contact area, contact pressure variations, resistive film non-uniformity, and other factors (Braunovic et al., 2006).

3.2. Effects due to switching

As we are only interested in the switching of direct currents, phenomenon related to this is considered here. In the case of d.c., the arc has no natural weak phase like a.c., where the arc passes through zero, therefore the switch has to extinguish the un-weakened arc at full current.

The function of the switch arc can be described as the generation of an emf V_a (the arc voltage) and a current I_a both of opposite direction to the emf E and current I of the system. If t_a is the life time of the arc, the available energy, W, of the system shall be consumed by the arc during this time with the consequence that, at t=t_a, the current through the switch is zero.

$$W = \int_0^{t_a} V_a I_a dt = \frac{1}{2} L I^2 + \int_0^{t_a} (EI - RI^2) dt$$
(7)

where $\frac{1}{2}LI^2$ is the inductive energy of the system, $\int_0^{t_a} V_a I_a dt$ is the energy that the system produces during t_a and $\int_0^{t_a} RI^2 dt$ is the energy consumed in the resistance, R, of the system as discussed in Holm (1967).

3.3. Modelling of contact degradation

In order to derive a model of the contact wear the heating due to arcing (Holm, 1967) from above is as $W = \int_0^{t_a} V_a I_a dt$

Differentiating this equation gives:

$$\frac{dW}{dt} = V_a I_a \tag{8}$$

This equation gives what is termed the Joule heating through the contact.

Further to this, the consideration of material loss and transportation need to be considered. The loss factor Υ depend upon the latent heat of evaporation and the factor β indicates how many bonds of a molecule are lost (Holm,

1967; Weißenfels & Wriggers, 2008). This factor depends on the choice of the materials and also on the temperature and can range from 0 to 1. Lower values have to be used, if each of the contact member possesses different materials. If the difference of the heat of evaporation between both materials is very high, the factor β decreases. If both members have the same material the value is around 0.2, and if the temperature is very high, at arcing for instance, the factor is close to one.

Equation 8 now becomes

$$\frac{dW}{dt} = \frac{\beta}{\gamma} VI$$

This is now the equation for the computation of wear, $D_{surface}$

$$\frac{dW}{dt} = \frac{\beta}{\gamma} D_{surface} \tag{9}$$

This wear is equivalent to the damage occurring due to the contact resistance changing through degradation. Introducing a new variable to represent the damage

$$\alpha^{contact} = V_{contact} \times I_{contact} \tag{10}$$

The resistance across the contact can be related to Ohms law, where $I_{contact} = \frac{V_{contact}}{R_{contact}}$, where $V_{contact}$ is the voltage measured across the contact and $I_{contact}$ is the current flowing through the contact.

Substituting for $R_{contact}$, $R_C = \frac{(\rho_1 + \rho_2)}{4} \sqrt{\frac{\pi H}{F}}$ an equation for the rate of damage due to Joule heating may be derived and can be determined by the relation.

$$\frac{d\alpha^{contact}}{dt} = \Delta V_{contact} I_{contact}$$
$$= (V_{contact} - V_{open}) \times \frac{V_{contact}}{\frac{(\rho_1 + \rho_2)}{4} \sqrt{\frac{\pi H}{F}}}$$
(11)

where V_0 is the voltage across the contact when it is open.

The above equation now gives the Joule heating equivalent to the voltage appearing across the contact given a derived theoretical contact resistance for the contact. This equation will form the basis for modeling of how the degradation will occur across the contact given a measurement of contact voltage, due to Joule heating. The degradation will increase in proportion to the voltage increasing across the contact.

A dynamic model may now be derived to enable a physical model of contact wear to be estimated.

$$\frac{dW}{dt} = \frac{\beta}{\gamma} D_{surfac}$$

can be re-written as a discrete equation by introducing the first order approximation for the change in wear the above equation may be written as

$$\frac{W_t - W_{t-1}}{\Delta t} = \frac{\beta}{\gamma} D_{surface}$$

which gives

$$W_t = W_{t-1} + \frac{\beta}{\gamma} D_{surface} \,\Delta t \tag{12}$$

similarly, the same procedure may be applied for the degradation equation.

$$\frac{d\alpha^{contact}}{dt} = (V_{contact} - V_{open}) \frac{V_{contact}}{(\rho_1 + \rho_2) \sqrt{\pi H}}$$
$$\frac{\alpha_t^{contact} - \alpha_{t-1}^{contact}}{\Delta t} = (V_{contact} - V_{open}) \frac{V_{contact}}{(\rho_1 + \rho_2) \sqrt{\pi H}}$$

which gives

$$\alpha_t^{contact} = \alpha_{t-1}^{contact} + \left(V_{contact} - V_{open}\right) \frac{V_{contact}}{\frac{(\rho_1 + \rho_2)}{4} \sqrt{\frac{\pi H}{F}}} \Delta t \quad (13)$$

following the framework in figure 1.,this now allows a statespace dynamic model to be formed, this is needed for the Kalman filtering (Grewal & Andrews, 2008). The general discrete state space model takes the form of below:

$$x_k = Ax_{k-1} + B_k u + v$$

$$y_k = C_k + D_k + w$$
(14)

where x is the state vector, y is the measurement vector, u is the input or 'control' vector, A is the "state (or system) matrix", B is the "input matrix", C is the "output matrix" and D is the "feed through (or feed forward) matrix", if the system does not incorporate feed thorough this is usually zero. Furthermore, v and w are normal random variables with zero mean and Q and R variance. Q is the model noise variance and is estimated from the model regression residuals and was used for the model noise in the Kalman filter implementation. The measurement noise R, is computed from experimental results.

3.4. Prognostic prediction process

j

The prediction process is concerned with how the estimate \hat{x}_k will vary when time changes from t_k to t_{k+1} is predicted.

$$\hat{x}_{k+1}^- = A\hat{x}_k$$
$$P_{k+1}^- = AP_k A^T + Q$$

where the first equation predicts the estimate and the second equation predicts the error covariance.

The equations of state are:

$$W_{t} = W_{t-1} + \frac{\beta}{\gamma} D^{contact} \Delta t$$

$$D_{surface} = \alpha_{t}^{contact}$$

$$\alpha_{t}^{contact} = \alpha_{t-1}^{contact} + \left(V_{contact} - V_{open}\right) \frac{V_{contact}}{\frac{(\rho_{1} + \rho_{2})}{4} \sqrt{\frac{\pi H}{F}}} \Delta t$$
(16)

The state model is given in matrix form as below:

$$\begin{bmatrix} W_t \\ \alpha_t^c \end{bmatrix} = \begin{bmatrix} 1 & \frac{\beta}{\gamma} \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} W_{t-1} \\ \alpha_{t-1}^c \end{bmatrix} + \begin{bmatrix} 0 \\ (V_c - V_o) V_c \Delta t \\ R_c \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} + \begin{bmatrix} v \\ w \end{bmatrix}$$
(17)

where R_c replaces $\frac{(\rho_1 + \rho_2)}{4} \sqrt{\frac{\pi H}{F}}$ and α^c is $\alpha^{contact}$. Inserting values for H, ρ , β , γ and using the maximum contact force allows a plot of the contact resistance and damage to be produced to verify the model



Figure 3. Output from model



Figure 4. Kalman Filter prediction of damage and contact resistance

(15)

In order to produce a forecast of the RUL, the Kalman filter forms a prediction of damage in terms of the future contact resistance from a present resistance measurement (figure 4). Manufactures literature gives the contact resistance when the contact operation is deemed unacceptable. The forecast of RUL, is the number of operations left to reach this point.

4. CONCLUSION

A great deal more work needs to be carried out to model failure modes in order to get a accurate prognostic model of relay contact failure. As well as this, other components in the relay need to be explored and their involvement in the process of the predicting the remaining useful life.

REFERENCES

- Feng, Y., Lul, J., Zheng, J., Huang, Z. (2006). Research on the Failure Diagnostics Parameters and the Reliability Prediction Model of the Electrical Contacts. Electrical contacts - 2006, proceedings of the fifty-second IEEE Holm Conference on Electrical Contacts, pages 69-72.
- Qiong, Y., Xuerong, Y., Guofu, Z. (2010). Reliability Assessment for Electromagnetic Relay Based on Time Parameters Degradation, 11th International Conference on Electronic Packaging Technology & High Density Packaging (ICEPT-HDP), pages 1269 - 1272
- Yu, Q., Qi M., Wang, S., Zhai, G. (2009). Research on Life Prediction Based on Wavelet, Transform and ARMA Model for Space Relay, 4th IEEE Conference on Industrial Electronics and Applications.
- Xuerong, Y., Yue, M., Hang, M., Guofu, Z. (2012). Degradation Failure Model of Electromagnetic Relay, 26th International Conference on Electrical Contacts, pages 116 – 123.
- Fang Y., Zhigang, L., Yachao, W., Cuiping, Y. (2012). Research on Uncertainty of Bounce Time for Electromagnetic Relay and Its Application in Operating Reliability Estimation, 26th International Conference on Electrical Contacts, pages 200-204
- Fujitsu Components Engineering Reference: Relays 2009 Fujitsu Components America
- McBride, J.W. (1991). An Experimental Investigation of Contact Bounce in Medium Duty Contacts, *IEEE Transactions on Components*, Hybrids and Manufacturing Technology, (Volume:14, Issue 2)
- Slade, Paul G. (1999). *Electrical Contacts: Principles and Applications*, CRC Press

- Holm, R. (1967). *Electrical Contacts*, NewYork, Springer-Verlag.
- Braunovic, M., Myshkin, N., & Konchits, V. (2006). Electrical Contacts: Fundamentals, Applications, CRC Press
- Weißenfels, C., & Wriggers, P. (2010). Numerical modeling of Electrical Contacts, *Computational Mechanics*, Volume 46, Issue 2, pp 301-31
- Grewal, M, & Andrews A. (2008). *Kalman Filtering: Theory and Practice Using MATLAB*, Wiley-Blackwell
Physics-Based Degradation Modelling for Filter Clogging

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ABSTRACT

Separation of solids from fluid is a vital process to achieve the desired level of purification in industry. Contaminant filtration is a common process in a variety of applications in industry. Clogging of filter phenomena is the primary failure mode leading to replacement or cleansing of filter. Reduced performance and efficiency or cascading failures are the unfortunate outcomes of a clogged filter. For instance, solid contaminants in fuel may lead to performance reduction in the engine and rapid wear in the fuel pump. This paper presents the development of an experimental rig to collect accelerated filter clogging data and a physics-based degradation model to represent the filter clogging. In the experimental rig, pressure drop across the filter, flow rate, and filter mesh images are acquired during the accelerated clogging experiments. The pressure drop across the filter due to deposition of suspended solids in the liquid is modelled and employed in the degradation modelling. Then, the physics based degradation model simulated using MatLab is compared with the real clogging data and the effectiveness of the degradation model is evaluated.

1. INTRODUCTION

Filtration is basically described as a unit operation that is separation of suspended particles from fluid utilizing a filtering medium where only the fluid can pass (Cheremisinoff, 1998). Driving force for filtration is the pressure gradient generated across the filter. Solid-liquid filtration processes can be classified into three categories. These are: 1. deep-bed filtration, 2. cross-flow filtration, and 3. cake filtration. Deep-bed filtration can be done using depth-filters. Depth filters retain the particulate through the porous packed bed. Sand filters are the common examples of depth filtration. In cross-flow filtration mechanism, slurry flows parallel to the filter medium where only clean liquid can pass to the other side leaving the particulate inside the filter. In cake filtration, the solid particles in suspension flowing through the filter media are retained building up an increasing thicker cake as shown in Figure 1. From now onward in this paper, we discuss in detail the cake filtration.



Figure 1. Schematic representation of cake build up on filter medium (Abboud and Corapcioglu, 1993)

Two types of cake filtration processes are common in the literature and industry. These are: 1. constant rate filtration, 2. constant pressure filtration. Figure 2 depicts the flow rate and pressure behaviors in each operating condition. Regime A represents constant rate filtration where fluid flow rate of the system remains constant. Pressure drop across the filter increases as the cake builds up. In most cases cake becomes compressed and more compact as the pressure increases, leading to higher cake resistance. Regime B represents constant pressure cake filtration where flow rate of the system declines as the cake builds up.

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Figure 2. Constant rate vs. constant pressure filtration

Filtration phenomenon is interest of several engineering processes including automotive, chemical, reactor, and process engineering applications. Besides, several industrial applications such as food, petroleum, pharmaceuticals, metal production, and minerals embrace filtration process (Sparks, 2011).

The goal of the filtration systems is to keep the rest of the system running smoothly. Filtration systems play a vital role in maintaining the process operating. Filtration and separation equipment plays a big portion in production of transport equipment manufacturing with 15.5 percentage. Modern commercial vehicles and automobiles have numerous types of filters including fuel, lubricant, and intake air (Sutherland, 2010).

Sharing an important role with pumps, fuel filters filtrate dirt, contaminants in the fuel system such as paint chips, dust, or rust particulate which have been released from a fuel tank due to moisture, or other numerous type of dirt, have been delivered via supply tanker (Wilfong et al., 2010). Consequences like engine and pump performance degradation due to increased abrasion and inefficient burning in the engine are the main motivators for fuel filtration. System flow rate and engine performance decreases once a fuel filter is clogged where it doesn't function well in its desired operation ranges. In today's conditions, fuel filters are replaced or cleansed on a regular basis. Monitoring and implementation of prognostics have the potential to avoid costs and increase safety.

The rest of the paper is organized as follows. Section two provides a brief literature review of physics-based degradation modeling studies done on cake filtration processes. Section three discusses in detail the filter clogging experimental scenario under accelerated aging conditions. The methodology of clogging modelling is given in section four. Comparison of the simulation results with experimental data is discussed in section 5. The paper concludes with discussion of the results and future work.

2. LITERATURE REVIEW

Researches have been attracted to model the pressure drop and cake formation in cake filtration processes since early 1930s. Darcy's Law has been used for calculating the permeability of a filter septum (Wakeman, 2007). Darcy described the volumetric flow rate (Q) of a system as a function of pressure drop (Δp), permeability (K), cross sectional area to flow (A), viscosity (μ) of the fluid, and the thickness (L) as shown in Eq. 1.

$$Q = \frac{KA}{\mu L} \Delta p \tag{1}$$

Kozeny-Carman (Carman, 1997) and Ergun (Ergun, 1952) equations are two commonly used formulations applied in the field of fluid dynamics to model the pressure drop of a fluid flowing through a porous medium. Detailed examination of the formulations is discussed in section four. (Tien and Ramarao, 2013) brought an issue that Kozeny-Carman equations are questionable when it comes to porosity calculation of compressible and randomly packed filter cakes in gas-solid separation processes. They claimed that Kozeny-Carman is appropriate when it's used only for pressure drop - flow rate correlations. (Tien and Bai, 2003) discussed a more accurate procedure of applying the conventional cake filtration theory. Conventional cake filtration theory has the capability of estimating the cake thickness, cake resistance, porosity, and pressure drop of the system.

Cake thickness and compressibility of the cake have the highest influence on pressure drop across the filter. Several methods have been implemented in order to measure the cake thickness depending on the filter geometry including ultrasonic, electrical conductivity techniques, nuclear magnetic resonance micro-imaging, optical observation, or cathetometer measuring (Hamachi and Mietton-Peuchot, 2001). (Ni et al., 2006) have modelled cake formation & pressure drop of a filtration mechanism in particle level (micro) where majority of the studies in literature are done in macro level. They simulated the cake filtration process using FORTRAN in both constant pressure and constant rate stages.

3. EXPERIMENTAL SETUP & DATA COLLECTION

This section discusses in detail the filter clogging experimental scenario & data collection for prognostic purposes under accelerated aging conditions.

3.1. Design & Installation

A peristaltic pump was installed in the system to maintain the flow of the prepared suspension as shown in Figure 3. The pump is a positive displacement pump providing constant flow rate where it takes the suspension with a desired flow rate and pumps it through the filter, letting the suspension pour into the reservoir. A stirrer was installed in the system to ensure that particles were fully mixed. This is necessary as the particles, even though they are meant to be naturally buoyant, sink after a while leaving the water clean. Upstream and downstream pressure transducers are installed in the system to measure the pressure drop across the filter; this is considered as the main indicator of clogging. A magnetic flow-meter is installed in the system in order to measure the flow rate of liquid.



Figure 3. Filter clogging rig system design

A high quality macro lens camera is installed in the system and macro pictures of the filter were taken every two seconds. The mesh inside the filter can clearly be captured and it can be utilized in image processing applications for clogging rate calculations which gives the ground truth information of clogging where other sensory information can be compared with the clogging rate obtained from the macro picture dataset. Polyether ether ketone (PEEK) particles have been selected to be used in accelerated aging experiments for clogging the filter. Distribution of the particles is shown in Figure 4.



Figure 4. PEEK particle size distribution

A box was designed to cover the filter area. The interior side of box was covered with a white colored material and a light source was directed inside the box to provide a constant uniform light so that the filter is isolated from varying environmental light. Components of the system were selected so that no other component will deteriorate other than the filter. Details of the system design and the data collected under different operation profiles can be found in (Eker et al., 2013).

3.2. Data Collection

This section provides the data collection details of accelerated clogging experiments.

Operation profiles were kept the same for the six run-tofailure accelerated aging experiments. 125 micron pore sized fuel filters have been utilized for clogging experiments in the lab environment. Suspension solid fraction rate was kept 0.14% for each experiment. Pressure and flow rate measurements have been collected. Each clogging experiment has been run and monitored until the filter has clogged where the pressure drop (e.g. Differential Pressure, $\Delta P = Upstream Pressure - Downstream Pressure$) value has reached its peak value and remains stable where flow rate value has reduced to half as shown in Figure 5.



Figure 5. Pressure drop and flow rate measurements

Fluctuations in pressure measurements are generated from the peristaltic pump reflecting the pump RPM shown in Figure 6. Final shape of the data is given by implementing low-pass filtering and sampling. One out of hundred data points has been selected in the sampling phase since data collection sampling rate defined was as 100Hz. Filtered and sampled version of all samples are shown in Figure 7 used in degradation modelling in section four. Each curve in the figure represents a run-to-failure experiment measurement.

A macro lens camera was set to take pictures once every two seconds during each clogging test. Filter mesh pictures will be employed in image processing phase and clogging rates will be calculated and correlated with pressure drop and flow rate measurements.



Figure 7. Filtered and sampled clogging indicators

4. METHODOLOGY

This section gives the governing formulations developed in pressure drop modelling of an accelerated clogging of filter.

In this study, the experimental rig is designed so that no other component is failed but the filter itself. Pressure drop across the filter, volumetric flow rate, cake thickness and porosity parameters are the main dynamic indicators showing the clogging level of a filter. These parameters need to be measured or derived from other parameters. In this study, correlations in between these parameters are modelled.

As mentioned in the introduction, Kozeny-Carman and Ergun equations are the most used models to calculate the pressure drop of a fluid through a packed bed of solids. Solid particles deposited on the filter mesh stands for the packed bed phenomena in cake filtration.

$$\Delta P = \frac{kV_{s}\mu}{\Phi_{s}^{2}D_{p}^{2}} \frac{(1-\epsilon)^{2}L}{\epsilon^{3}}$$
(2)

$$\Delta P = \frac{150V_{S}\mu(1-\epsilon)^{2}L}{D_{p}^{2}\epsilon^{3}} + \frac{1.75(1-\epsilon)\rho V_{S}^{2}L}{\epsilon^{3}D_{p}}$$
(3)

Where:

 $V_{\rm s}$

μ

 ϵ

 Φ_s

- Δp : Pressure drop
- *L* : *Total height of the bed*
 - : Superficial (empty-tower) velocity
 - : Viscosity of the fluid
 - : Porosity of the bed (or cake)
 - : Sphericity of the particles in the packed bed
- *D_p* : Diameter of the spherical particle

 ρ : Density of liquid

Eq. (2) represents the well-known Kozeny-Carman model whereas Eq. (3) stands for the Ergun equation. Viscosity & velocity of fluid, cake thickness, and porosity of cake are directly proportional to the pressure drop across the filter in contrast with particle diameter and sphericity. The Ergun equation is a detailed version of the Kozeny-Carman equation. The first term in the Ergun equation represents viscous effect whereas the second term associates with the inertial effect. Inertial effect is not considered in Kozeny-Carman model.

Cake thickness and porosity are the dynamic cake structure parameters required to be modelled separately. Cake structure is assumed uniform which means cake thickness is uniform along the cake. Cake thickness growth show similar profile with the pressure drop values across the filter as confirmed by several studies in the literature. Therefore we modelled the cake thickness growth as logarithmic as shown in Eq. (4). ' $\sum Qx$ ' term stands for cumulative particle volume retained in the filter chamber where 'Q' is flow rate, 'x' is solid fraction of the suspension. ' A_f ' stands for filtration area.

$$L = \frac{\ln(l_1 \frac{\Sigma Qx}{A_f})}{l_2} \tag{4}$$

Porosity ' ϵ ' defined as the void fraction of a filtration mechanism. We derived a porosity model of the filter as shown in Eq. (5). $\frac{\sum Qx}{V_f}$, term gives the solid fraction of the cake where ' V_f ' is the maximum filtration volume can be filled in the filter chamber.

$$\epsilon = 1 - \frac{e^{(p_1 \frac{\sum Qx}{V_f})}}{p_2} \tag{5}$$

 p_1' , p_2' , l_1' , and l_2' are the parameters to be optimized by fitting the model to the dataset. Pressure drop across the filter can be determined once the cake thickness and porosity values are calculated respectively. Comparison of the simulation results with the clogging data is given in the next section.

5. RESULTS

Simulation results of filter clogging employing Eqs. (2-5) in comparison with the collected data are discussed in this section. Tests have been conducted by setting the pump at 211 RPM to obtain 600 ml/min flow rate. Pump shows constant flow rate behavior until it reaches the critical clogging regime. The critical regime is reached in 500-600 seconds as shown in Figure 7. Then the pump reaches to the maximum pressure level it can provide where it remains constant at the top pressure level. Approximately 90% of the filter lifetime can be considered under constant rate filtration regime. Then the system passes to the constant pressure filtration regime for the rest of its life time. Operational profile, the parameters chosen for the simulation, and the optimized parameters are summarized in Table 1.

Table 1. Operation profile and fitted	parameters
Constant parameters	Value

Value
1290
998.23
0.14
5.8e-5
8.9e-4
0.001344
6.7e-06
Value
4e+4
899
1.2346
9.1464



Figure 8. Experimental data vs. simulation

Figure 8 plots show that the proposed simulation model of clogging fits to the data collected from the experimental test rig where the lines represents the simulation model and the circles are the pressure drop data points for each clogging experiment. Normalized root mean squared error (nRMSE) values are calculated for each simulation in order to evaluate the performance. The mean normalized RMSE value of six

experiments is 13.91%. Figure 9 depicts the porosity and cake thickness modelling plots for six samples. Porosity of the filtration starts with values close to 100% in the beginning of each experiment and decreases by time showing different degradation profile inversely proportional to the cake thickness simulation values. On the other hand, thickness of cake shows a logarithmic growth similar to the growth in pressure drop until the clogging regimes. Logarithmic growth in cake thickness during a cake filtration experiment is an expected type of degradation behavior which can be confirmed with the several studies conducted in the literature (Hamachi and Mietton-Peuchot, 2001; Ni et al., 2006).

Aim of the proposed methodology in this paper is to calculate the pressure drop across the filter given the varying flow rate. Flow rate of the filtration system varies during the experiments due to porosity change in the filter cake. Tracking and predictions of the future pressure drop levels can be achieved when the flow rate is constant since cake thickness and porosity is effected by the flow rate of the system.



Figure 9. Cake thickness and porosity simulation

6. CONCLUSION & FUTURE WORK

This paper presents a data collection and physics-based degradation modelling of an accelerated filter clogging experimental rig. Data acquisition, especially for the pressure drop across the filter and the flow rate of the pumping system, has been conducted. Degradation modelling of the pressure drop due to retaining particles on the filter mesh has been modelled and efficiency of simulation results has been evaluated by comparing with the actual dataset. Results show that the effectiveness of the proposed degradation model is satisfactory in terms of identifying the current pressure drop level in the system. Future studies will be based on physics-based prognostic modelling of the cake filtration mechanism. Cake thickness, porosity, and the pressure drop will be modelled dynamically and utilized in prognostic modelling.

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REFERENCES

- Abboud, N. M. and Corapcioglu, M. Y. (1993), "Modeling of Compressible Cake Filtration", *Journal of colloid and interface science*, vol. 160, no. 2, pp. 304-316.
- Carman, P. G. (1997), "Fluid flow through granular beds", *Chemical Engineering Research and Design*, vol. 75, no. 1 SUPPL., pp. S32-S46.
- Cheremisinoff, N. P. (1998), *Liquid Filtration*, Second Edition ed, Elsevier Inc.
- Eker, O. F., Camci, F. and Jennions, I. K. (2013), "Filter Clogging Data Collection for Prognostics", *Proceedings of the Annual Conference of the Prognostics and Health Management Society*, 14-17 Oct 2013, New Orleans LA, USA, pp. 624-632.
- Ergun, S. (1952), "Fluid Flow through Packed Columns", *Chemical Engineering and Processing*, vol. 48, pp. 89-94.
- Hamachi, M. and Mietton-Peuchot, M. (2001), "Cake thickness measurement with an optical laser sensor", *Chemical Engineering Research and Design*, vol. 79, no. 2, pp. 151-155.
- Ni, L. A., Yu, A. B., Lu, G. Q. and Howes, T. (2006), "Simulation of the cake formation and growth in cake filtration", *Minerals Engineering*, vol. 19, no. 10, pp. 1084-1097.
- Sparks, T. (2011), Solid-Liquid Filtration: A User's Guide to Minimizing Cost & Environmental Impact, Maximizing Quality & Productivity, First Edition ed, Elsevier Science & Technology Books.
- Sutherland, K. (2010), "Mechanical engineering: The role of filtration in the machinery manufacturing industry", *Filtration and Separation*, vol. 47, no. 3, pp. 24-27.
- Tien, C. and Ramarao, B. V. (2013), "Can filter cake porosity be estimated based on the Kozeny-Carman equation?", *Powder Technology*, vol. 237, pp. 233-240.
- Tien, C. and Bai, R. (2003), "An assessment of the conventional cake filtration theory", *Chemical Engineering Science*, vol. 58, no. 7, pp. 1323-1336.
- Wakeman, R. (2007), "Filter media: Testing for liquid filtration", *Filtration and Separation*, vol. 44, no. 3, pp. 32-34.

Wilfong, D., Dallas, A., Yang, C., Johnson, P., Viswanathan, K., Madsen, M., Tucker, B. and Hacker, J. (2010), "Emerging challenges of fuel filtration", *Filtration*, vol. 10, no. 2, pp. 107-117.

BIOGRAPHIES



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Prof. Ian Jennions Ian's career spans over 30 years, working mostly for a variety of gas turbine companies. He has a Mechanical Engineering degree and a PhD in CFD both from Imperial College, London. He has worked for Rolls-Royce (twice), General Electric and Alstom in a number of

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A generic ageing model for prognosis - Application to Permanent Magnet Synchronous Machines

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ABSTRACT

In the context of more electrical aircrafts, Permanent Magnet Synchronous Machines are used in a more and more aggressive environment. It becomes necessary to supervise their health state and to predict their future evolution and remaining useful life in order to anticipate any requested maintenance operation. Model-based prognosis is a solution to this issue. Any prognosis method must rely on knowledge about the system ageing. A review of existing ageing laws is presented. The generic ageing model proposed in (Vinson, Ribot, Prado, & Combacau, 2013) is extended in this paper. It allows representing the ageing of any equipment and the impact of this ageing on its environment. The model includes the possible retroaction of the system health state to itself through stress increase in case of damage. The proposed ageing model is then illustrated with Permanent Magnet Synchronous Machines (PMSM). Two critical faults are characterized and modeled : inter-turns short-circuits and rotor demagnetization. Stator and rotor ageing are well represented by the proposed ageing model. The prognosis method developed in (Vinson et al., 2013) is extended to consider this new generic ageing model. In order to test the prognosis algorithm, ageing data are needed Since no real measurements are available, a virtual prototype of PMSM is developed. It is a realistic model which allows running a fictive but realistic scenario of stator ageing. The scenario comprises apparition and progression of an inter-turns short-circuit and its impact on stator temperature, which value has an impact on the ageing speed. The prognosis method is applied successfully to the PMSM during this scenario and allows estimating the Remaining Useful Life (RUL) of the stator and the machine.

1. INTRODUCTION

In the context of the more electrical aircrafts, electrical motors such as permanent magnet synchronous machines are more and more used for critical functions in the actuators, such as landing gear extension/retraction, braking systems, or flight control. They are often used in very aggressive environments. The future transition from 270V to 540V of supply voltages, and the increase in switching frequencies, also applies a lot of additional stress on the motors. In this aggressive context, permanent magnet synchronous machines (PMSM) may have more and more degradation and faults. In order to ensure the operational availability of critical functions, one option is to implement a Health-Monitoring module. This Health-Monitoring module consists in a detection and diagnosis module, that allows assessing the current health state of equipments, and a prognosis module, that allows predicting the future health state of equipments, and their remaining useful life (RUL). With prognosis, the maintenance action can be anticipated in advance. The goal is to optimize maintenance planning and avoid any operational interruption or flight delays due to equipment faults.

Predicting the future health-state of equipments requires to know how they are ageing. This knowledge can take several forms, it can be based on experience, on degradation and ageing data obtained in service or in tests, or on ageing physical models. Knowledge on system ageing can always be put into the form of an ageing model, that can be more or less precise but can be represented in a generic way. A generic ageing model, partly published in (Vinson et al., 2013), allows representing the behavior and ageing of any kind of equipment, that may be heterogeneous and complex. This model has be to extended to consider the impact of the ageing on its environment. Then the model has to take into account the possible retroaction of the system health state to itself through stress increase in case of damage. The generic prognosis method

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proposed in (Vinson et al., 2013) has also to be extended to deal with new aspects in the ageing model. An illustration is proposed on PMSM, with the modeling of two critical progressive degradation: inter-turns short-circuits and rotor demagnetization. Ageing data are needed to test the prognostic algorithms on PMSM, but real data are not available. A complete PMSM virtual prototype is then developed to obtain these ageing data. This is a precise model that represents a lot of phenomena linked to the ageing of PMSM. The virtual prototype allows simulating a short-circuit virtual scenario, from the start of the degradation to the increasing speed of the short-circuit gravity and the associated loss of performance until the end of life of the stator.

This paper is organized as follows. A survey of ageing laws is presented in Section 2 that motivates the need of a generic representation. The generic ageing model is presented in Section 3 and is illustrated with two PMSM faults ageing models: inter-turns short-circuit and rotor demagnetization. The generic prognosis method based on the model is extended on Section 4. This section also presents the virtual protoype of the PMSM and the application of the diagnosis and prognosis algorithms on a virtual short-circuit scenario. Finally Section 5 proposes some conclusions and perspectives.

2. Ageing models for Prognosis

In order to predict the system RUL, prognosis requires knowledge about the system ageing that is contained in a model. This model describes the evolution of the system ageing state, it is a priori known and used on-line for predictions. In the literature, several prognosis methods already exist which rely on different models:

- experience-based prognosis,
- data-driven prognosis,
- and model-based prognosis.

The choice of one of these methods depends on the level of knowledge contained in ageing model and is mainly characterized by the availability of sensors that allow obtaining online data of the system state. Every approach has pros and cons, and it is often useful to combine them.

2.1. Experience-based prognosis

Experience-based approaches, like case-based reasoning or reliability analyses, are the only alternative when no sensors nor physical knowledge of the system ageing is available. This form of prognostic model is the simplest and only requires failure history to determine the probability of failure within a future time (Gebraeel, Elwany, & Pan, 2009). Reliability techniques are used to fit a statistical distribution to the failure data.

The Weibull law is often used due to its flexibility in reliability analyses for mechanical or electrical components. It can represent a time-dependent failure rate by describing the different phases of a component life with three parameters. (van Noortwijk & Klatter, 2002) models the cost of structure replacement with Weibull distributions by applying the maximum likelihood estimation method on life data obtained from broken structures. The main drawback of the Weibull law is the difficulty of estimating these three parameters. The exponential law is simpler as it depends on only one parameter, the failure rate, which is constant. It can represent a component ageing without wear, i.e. the abrupt failures. It is used a lot for life duration of electronic devices. For progressive failure, the Gamma law seems to be well suited. It can represent a failure rate increasing in time and is used to model progressive failures like crack evolution in (Lawless, 2004) or erosion in (van Noortwijk, Kallen, & Pandey, 2005). It is also possible to use several laws simultaneously like in (Huynh, Castro, Barros, & Berenguer, 2012) which combines a Gamma law with a Poisson process to model progressive degradation and abrupt failures.

Models used by experience-based approaches use available data without dedicated effort. This approach does not take into account the way the equipment is used, or its past. This might be useful for the manufacturer, but not for the user that is interested in one particular component.

2.2. Data-driven prognosis

Evolutionary and trend monitoring methods are used when on-line observed data are available. These prognostic method use on-line estimators or indicators to evaluate the system current degradation state relying on the on-line observations. To get the estimators, failure history is required (identification of fault patterns). Such estimators may be obtained by learning techniques (neural networks or Bayesian networks) or by identifying parameters of classical estimators like for Kalman filters (Hu, 2011).

Neural networks allow building a grey/black box ageing model to estimate and predict the current and future trend of the system degradation from specific indicators (Goh, Tjahjono, Baines, & Subramaniam, 2006). Neural networks are used in (Das, Hall, Herzog, Harrison, & Bodkin, 2011) to perform prognosis on systems of high-speed milling. (Adeline, Gouriveau, & Zerhouni, 2008) tests and compares different methods based on neural networks in terms of prediction precision, computation cost and requirements related to the implementation. Fuzzy neural networks combines neural networks and fuzzy logic to deal with ambiguous, inaccurate, noisy or incomplete data (El-Koujok, Gouriveau, & Zerhouni, 2010). Fuzzy systems use knowledge as expert rules. They are recommended in case where no qualitative information about the system degradation is available but only causal rules describe fault propagation within the system. They can be automatically adjusted and do not require physics-based knowl-

edge.

Ageing models can be represented by Bayesian networks that are acyclic graphs defined by a set of nodes and relations with conditional probabilities. Each node may represent a potential degradation mode of the system and transition probabilities from a current mode to possible future modes result from a learning phase. The RUL is then predicted from transition probabilities of the network. Theory of Bayesian networks is well explained in (Bouaziz, Zamai, & Duvivier, 2013) which shows its relevant application in the semi-conductor industry. (Weber, P.Munteanu, & Jouffe, 2004) uses dynamical Bayesian networks and Markov chains to model the ageing of a system composed of a pump and a valve. (Muller, Suhner, & Iung, 2008) combines Bayesian networks with an event-based approach to monitor degradation of an automatic mechanical system of lamination. A priori knowledge is based on experience and trend monitoring is performed on line thanks to data. Physics-based knowledge allows determining causal relations of component degradations.

(Greitzer & Pawlowski, 2002) proposes a parametric model of the vibration waveform for different faults (particularly for bearing faults) on a diesel motor to apply a trend monitoringbased prognosis approach. (Byington & Stoelting, 2004) performs diagnosis and prognosis on an EMA of a flight control system with a model whose parameters are estimated from on-line data. Diagnosis estimates the current health state of the system with classification tools. Prognosis computes the rate of change of state at current time and anticipates it in the future. In this study, prognosis is a simple temporal prediction of the indicator evolution that does not take into account the equipment environment. (Lacaille, Gouby, & Piol, 2013) studies the wear of turbojets and proposes a simple algorithm to build a degradation indicator from successive measurements of exhaust gas temperature after each flight according to the operating time.

Data-driven method transform a huge amount of noisy data into a few relevant data for prognosis. The main drawback is that the method efficiency highly depends on the quantity and quality of data. In aeronautics, equipment are generally very reliable, and preventive maintenance is realized before the failure occurrence, so there are very few degradation data. Tests can be done to obtain data, but they are costly, time consuming, and destructive.

2.3. Model-based prognosis

Model-based prognosis relies on a deep knowledge of the equipment ageing. The model provides more information by extrapolating on-line data by physics-based reasoning. The ageing model can be an analytical model, represented as a set of equations which involve physical quantities corresponding to environmental constraints (Onori, Rizzoni, & Cordoba-Arenas, 2012; Bregon, Daigle, & Roychoudhury, 2012), or a simulation model identified from tests results. In (Gucik-Derigny, Outbib, & Ouladsine, 2011), the ageing model is represented as a set of nonlinear differential equations with multiple time scales (short for the system behavior dynamic and large for its degradation). The fast dynamic state is estimated thanks to observers and the parameters of the ageing model (i.e. the slow dynamic) are determined. The illustrative example is an electromechanical oscillator. In (Khorasgani, Kulkarni, Biswas, Celaya, & Goebel, 2013), the ageing of electrolytic capacitors with temperature is represented by a complex nonlinear physics-based model. Particle filtering is then used to estimate the parameters of the degradation model.

Physics-based ageing models can be divided into three types depending on their output format. They can directly compute the RUL or progressive evolution of degradation by evaluating the damage or a failure rate to anticipate the future behavior of the equipment. (Venet, 2007) uses the Arrhenius law to model the impact of temperature on the lifetime of liquid electrolyte capacitors but it can also be applied for dielectric components, semiconductors or batteries. The inverse power law describes the impact of damaging factors on the component lifetime like voltage on electronic components for example. It can also be used for mechanical components subjected to fatigue. A specific case of the inverse power law is the Coffin Manson law that gives the number of cycles leading to the rupture when components are subjected to temperature variations. The generalized Eyring model allows taking into account any type of damaging factor (like temperature, voltage, humidity, etc.) in ageing of electronic components or mechanical components subjected to rupture. The Paris law is used in (Pommier, 2009-2010) to model the damage for a component by computing the crack propagation according to the number of cycles. The Miner's law models the accumulation of linear damages due to fatigue. It can be used for metals only until yield strength. The Wlher curve gives the number of cycle leading to damage thanks to a characteristic parameter like maximal constraint for example. The american military norm MIL-HDBK-217 gives the failure rates for some components such as transistors, resistors, etc. For example, the law Belvoir Research Development & Engineering evaluates the failure rate of a solder joint. The Cox model, based on a failure risk function, is mainly used in the medicine and maintenance fields to study the impact of different variables involved in the component degradation process.

A physics-based ageing model can also be determined from tests performed in controlled conditions in order to identify characteristic parameters of the system degradation. In this case, the damage evolution is assumed to be measured from tests. Moreover, simulation is interesting as no component destruction nor deterioration is needed to study the system degradation. The main difficulty consists in elaborating and validating the ageing simulation model, since equipment are complex and faults are multiple and difficult to be understood as a whole (Bansal, Evans, & Jones, 2005).

In some cases, it can be useful to combine different types of information in a common ageing model. For example, by combining failure history and physical laws, a statistical physics-based model can be obtained. In such a model, physical stress is represented through a parameter of the statistical law which is then adapted to the operational environment of the component. The difficulty is to assign a physics-based law to one or several parameters of the statistical law (Byington, Roemer, & Galie, 2002; Brissaud, Lanternier, Charpentier, & Lyonnet, 2007; Nima, Lin, Murthy, Prasad, & Yong, 2009; Gebraeel et al., 2009). (Ray, 1999) builds a stochastic model for the crack propagation in a metallic material from test data. The non-stationary probability density function depends on the instant of crack initiation and its actual size (in order to deduce the speed of the crack propagation).

(Hall & Strutt, 2003) proposes a statistical model of physics of failure that results from Monte-Carlo simulations performed with different parameters of the physics-based degradation model. These values are then represented with the Weibull distribution whose parameters are well chosen to fit data.

2.4. Synthesis

The choice of a prognostic method depends on available knowledge, the presence of sensors or physics-based models that allow monitoring and analyzing the real condition of the system. This ageing knowledge can be represented as an experience, a known qualitative or quantitative model or an estimated model obtained by learning and classification methods. The prognostic model may vary from a very poor model (that cannot handle on-line observations for example) to a very rich one (that can handle on-line observations and can extrapolate these observations in terms of physical reasons for the component to fail in the future). In an industrial context such as aeronautics, a lot of equipment is similar but no identical. So in this paper, the challenge consists in defining a generic ageing model, whatever the available knowledge about the system degradation, in order to apply a generic model-based prognosis method.

3. A GENERIC AGEING MODEL AND ITS APPLICATION TO PERMANENT MAGNET SYNCHRONOUS MACHINES

3.1. The generic ageing model

In (Vinson et al., 2013) a structural and functional model is presented. A system Σ is a set of *n* components C^i . Parameters *p* represent physical quantities in a component. There are three kinds of parameters. Input parameters *ip* values depend on the environment, private parameters *pp* belong to only one component, and output parameters *op* are a combination of input and private parameters through functional relationships ar. The values of parameters at time t are p(t). The rank r of a parameter p is the set of possible values, such as $\forall t$, $p(t) \in r(p)$. Components are connected through the structure st via their input and output parameters to form the system. Two parameters structurally connected are such as $ip^{i,j} = st(op^{k,l}) \Rightarrow \forall t$, $ip^{i,j}(t) = op^{k,l}(t)$. This structural and functional model is represented on the first layer of the modeling framework on Figure 1. The ageing model developed hereby enriches the functional model.

3.1.1. Damage and ageing laws

During operational life an equipment ages, it is damaged. Ageing is due to stresses, that can be thermal, electrical, mechanical or chemical. Stresses are modeled with damaging factors. The set of damaging factors of one component C^i is $\mathcal{D}^i = \{df_l^i\}$. The set of damaging factors of the system Σ is $\mathcal{D}^{\Sigma} = \bigcup_{i=1}^n \mathcal{D}^i$. The value of a damaging factor at time t is df(t). Ranks are defined for damaging factors, they are noted $r(df_i^i)$ and they are such as $\forall t, v(df_i^i, t) \in r(df_i^i)$.

The equipment ageing is characterized by its damage. Damage is irreversible. It is null at the beginning of the equipment life and increases with the ageing.

Since they do not vary for functional purposes and they are intrinsic to one component, we decide to use private parameters and their values to represent the system and component health state. A private parameter modification represents therefore a damage. The damage $e^{i,j}$ at time t is modeled as the distance between $pp^{i,j}(t)$ and the initial value $pp_0^{i,j}$:

$$e^{i,j}(t) = d(pp_0^{i,j}, v(pp^{i,j}, t))$$
(1)

with
$$pp_0^{i,j} = pp^{i,j}(t_0)$$
 and $e^{i,j}(t_0) = 0$.

There is one damage per private parameter, but every component may have several damages represented by different private parameters.

The damage depends on stresses. The ageing law ag allows the calculation of damage e as a function of the damaging factor values $df_1^i, ...df_n^i$:

$$\begin{cases} ag: \mathbb{C} \times T \longrightarrow \mathbb{C} \\ (df_1^i, ...df_n^i, t) \longmapsto e^{i,j}(t) = ag(df_1^i, ...df_n^i, t) \end{cases}$$
(2)

It is possible to define a global damaging factor as a combination of damaging factors, in order to have a unique parameter for the ageing law, and to include known ageing laws (described in Section 2) in this approach.

3.1.2. The retroaction law

The stress that undergoes an equipment depends on its environment and depends also on its own damage. Indeed a damaged component often has a more negative impact on its environment and on itself. For instance the wear of a component will increase the level of pollution in a mechanical system, and pollution is certainly a stress for the component and its environment.

This is modeled by the fact that damaging factors values depend on the system health state. The function f_{df} assesses a damaging factor rank. The rank may depend only on the system environment. Otherwise, if the rank of a damaging factor depends on the system health state, the function f_{df} is defined as follows:

$$\begin{cases} f_{df} : \mathcal{D}^{\Sigma} \times Supp(df_l^i) \longrightarrow I_{\mathbb{R}} \\ df_l^i \longmapsto r(df_l^i) = f_{df}(\{e^{x,y}(t)\}) \end{cases}$$
(3)

We highlight that the damage depends on damaging factors through ageing laws and that damaging factors depend on the damage through the retroaction laws. Figure 1 presents both the functional and structural model on the first layer and the ageing model on the second layer. The two models communicate through the private parameters, that is to say through the health state: the ageing model affects the functional model.



Figure 1. Modeling of a system Σ damage: ageing laws and retroaction laws.

All kind of knowledge can be represented with this generic modeling framework, as will be shown on our industrial application.

3.2. Application: the ageing model of PMSMs

3.2.1. The functional model of PMSMs

The functional and structural model of PMSMs is shown on Figure 2. The PMSM has two components, the stator and

the rotor that are combined to perform the PMSM function: to transform supply voltage U_{ab}, U_{bc}, U_{ca} into a given mechanical speed Ω , independently of the torque C applied by the environment on the shaft of the PMSM. The stator transforms the voltages into phase currents, I_a , I_b , I_c , independently of the induced voltages E_a , E_b , E_c produced by the rotor. The stator private parameters are the phase resistances R_a, R_b, R_c and inductances L_a, L_b, L_c . The rotor transforms the phase currents into a mechanical speed. Its private parameters are the magnets electromagnetic remanent field B, the rotor inertia J and the friction coefficient K_f . The relationships between parameters are explained in details in (Vinson, Combacau, & Prado, 2012).



Figure 2. Modeling of the PMSM.

Thanks to a Failure Modes Effects Analysis and Criticity two faults were selected as candidates for model-based prognosis, corresponding with the two components of the PMSM: interturns short circuits in the stator and demagnetization of a part of the rotor.

3.2.2. The stator ageing : inter-turns short-circuits progression

A common and critical degradation of PMSM are short - circuits, and especially inter-turns short-circuits, that come from the stator insulation ageing and degradation. A short-circuit model is proposed in (Vinson, Combacau, Prado, & Ribot, 2012). There is the creation of a short-circuit loop in one of the three phases, phase A for instance. Two fault parameters, R_f and S_a , represent the gravity of the short-circuit. R_f is the resistance of the insulation at the short-circuit point and progressively decreases until 0Ω in case of direct short-circuit. S_a is the percentage of short-circuited turns and varies between 0 and 100%.

The private parameter that represents the damage of the stator is chosen to be the short-circuited phase resistance, R_a , for the three following reasons. It varies with short-circuit, it depends on the two fault parameters, R_f and S_a , and unlike them it can actually be measured on a real PMSM. R_a , the equivalent resistance of phase A with the short-circuit loop of resistance R_f , is expressed as:

$$Ra(t) = Ra_0(1 - S_a(t)) + \frac{Ra_0 S_a(t) R_f(t)}{Ra_0 S_a(t) + R_f(t)}$$
(4)

The stator damage e^s is then:

$$e^{s}(t) = |Ra_{0} - Ra(t)|.$$
 (5)

During the stator ageing the damage e^s progressively increases. Two thresholds are defined to estimate the gravity of the shortcircuit: the degradation threshold e_d^s and the fault threshold e_p^s . According to the comparison between the damage value and these thresholds, the stator is considered nominal when $e^s(t) < e_d^s$, degraded when $e_d^s < e^s(t) < e_p^s$, or faulty when $e^s(t) > e_p^s$.

Ageing law The insulation degradation is due to thermal and electrical stresses. The damaging factors are the magnitude V and frequency f of the supply voltage, and the statoric temperature $T_S: D\mathcal{F}^s = \{V, f, T_s\}.$

Since no real ageing data are available to estimate the stator ageing law, a law obtained in (Lahoud, Faucher, Malec, & Maussion, 2011) is used for illustrative purpose. This law was obtained with tests on insulation boards. We consider that the shape of the law is correct for the stator, and the parameters K_1 , K_2 , K_3 and b values are adjusted to fit with realistic life duration known from experience. L is the stator life duration and depends on the stator temperature T_s :

$$L(t) = K_1 + K_2 \times exp(-b \times T_s(t)) \tag{6}$$

The proposed ageing law aq^s is then :

$$e^{s}(t) = ag^{s}(T_{s}, t) = \frac{K_{3}}{L(t)}$$
 (7)

For one particular PMSM V and f are constant so we consider that the ageing law only depends on T_s . There is a correlation between L and e^s that is known from experience.

Retroaction law Short-circuits increase the temperature T_s because of the high currents that circulate in the phases and in the short-circuit loop. The following retroaction law is proposed:

$$T_s(t) = f_{df}^s(e^s, t) = \begin{cases} 70^{\circ}C \ if \ e^s(t) < e^s_d \\ 80^{\circ}C \ if \ e^s_d < e^s(t) < e^s_p \\ 90^{\circ}C \ if \ e^s_p < e^s(t) \end{cases}$$
(8)

This is the only retroaction function of the stator ageing model since we consider that there is no influence of the short-circuit on f and V.

3.2.3. The rotor ageing : demagnetization progression

Another degradation that may occur on PMSMs is rotor demagnetization, which means that the remanent electromag-



Figure 3. The Wohler curve and the mechanical ageing of a rotor magnet.

netic field B of one or several magnets decreases. This can be due to two kinds of degradation. Cracks or breaks of the magnets induce air gaps, which consequence at the electromagnetic level is the diminution of B. High currents or high temperature variations can modify the physical composition of magnets which also leads to a diminution of their remanent electromagnetic field B.

An analytical demagnetization model is proposed in (Vinson, Combacau, Prado, & Ribot, 2012). The fault parameter is the percentage of demagnetization of one magnet, which is proportional to the loss of B of this magnet. The private parameter that represents the damage of the rotor is B. The rotor damage e^r is then :

$$e^{r}(t) = |B_0 - B(t)|$$
(9)

At every effort cycle the fatigue of the magnet is accumulated because it is sized to resist to the effort. There is a macroscopically elastic deformation. The maximal number of cycles that the magnet can bear being reached, it breaks up. From this state, every part of the magnet undertakes a similar ageing process than the first one until it breaks again.

During this evolution the brutal rupture of a magnet is expressed with the Wohler curve described on Figure 3. It represents the limit of endurance σ of a material as a function of a number of fatigue cycles. When the limit is reached the material breaks.

We assume that the more the magnet is broken the more it becomes fragile. Calling N_i the date of the i^{th} rupture, we suppose that $\forall i, N_i - N_{i-1} > N_{i+1} - N_i$, because the duration between two breaks is shorter and shorter.

If the number of cycles between breaks i and i + 1 is divided

by a factor k > 1 compared with the number of cycles between breaks i-1 and i, the number of breaks increases more and more rapidly. We define $T_x = \frac{Ni+1}{Ni}$ as the acceleration factor of the degradation. The number n of ruptures at time tis defined as:

$$n(t) = \frac{\log(T_x) - \log(T_x + t \times (1 - T_x))}{\log(T_x)}$$
(10)

Every break devides the remanent induction of a factor K > 1, due to the air gap. We obtain a law giving the remanent induction as a function of the number of use cycles. The proposed rotor ageing law ag^r , is then:

$$e^{r}(t) = ag^{r}(t) = B_0(1 - K^{n(t)})$$
(11)

In this ageing law, the only considered damaging factor is the time (i.e. the number of fatigue cycles). As a perspective, if sufficient data are available, it would be possible to add other damaging factors, such as short-circuit currents I_{cc} or stator temperature T_s , that may accelerate the rotor degradation.

4. The prognosis

4.1. The generic prognosis method

A Health-Monitoring module is proposed in (Vinson et al., 2013). It is based on the generic model of the system and comprises a fault detection and diagnosis module. The prognosis algorithm is developed in Figure 4 and Algorithm 1. Its input is the result of diagnosis Δ^{Σ} , which allows estimating all the parameter values, even if they are not observable, at current time t. The prognosis module predicts the future values of damaging factors thanks to retroaction laws (Equation 3). It then predicts the future values of private parameters thanks to ageing laws (Equation 7), and the input and ouput parameters values thanks to the knowledge of the future external solicitation of the system, and to the analytical laws between parameters. The future values of damages are estimated (Equation 1) and the time of degradation or fault can be predicted. The principle of the prognosis operation are presented on Figure 4.

The prognosis operation is similar to a diagnosis operation, but realized in the future. The main difference is that parameters values are predicted instead of being observed. The parameters or damaging factors are observable if their value at current time is known, for instance they are measured with sensors. The parameters or damaging factors are predictable if their future value can be estimated thanks to the ageing model or the functional model. The sets of predictable parameters and damaging factors are $\mathcal{P}_{pred} \subset \mathcal{P}$ and $\mathcal{DF}_{pred} \subset \mathcal{DF}$.

The prognosis is a sequence of diagnoses realized at future



Figure 4. The prognosis algorithm.

degradation time t_i , until the fault time t_f :

$$\Pi^{\Sigma}(t) = \{\Delta^{\Sigma}(t), \Delta^{\Sigma}(t_1), \dots, \Delta^{\Sigma}(t_f)\}$$
(12)

The prognosis algorithm uses the generic formalism developed in this paper, as shown in Algorithm 1. It is developed on Matlab and needs to be validated on degradation and fault data. Since no real data are available, a virtual prototype is built on Matlab Simulink.

4.2. Development of a virtual prototype

The virtual prototype is a very precise and complete functional and ageing model of the PMSMs. It is used only for simulation purposes in order to obtain a realistic set of data to validate the prognosis algorithm, built with a simple functional and ageing model of PMSMs. In the virtual prototype the equation of dissipation of thermal power allows predicting the stator temperature T_s . Phase resistances are computed thanks to an ageing law that depends on T_s , V and f, and thanks to the equation of copper resistivity that depends on T_s . This coupled phenomena are represented on Figure 5.



Figure 5. Virtual prototype: relationships between stator temperature and phase resistance

To model the virtual prototype we consider the following hypothesis:

Algorithme 1 Prognosis Input: $\Sigma, t, \Delta^{\Sigma}$ Output: $\Pi^{\Sigma}(t)$ Initialization: $k \leftarrow 1$ while $RUL \neq 0$ do $t \leftarrow t + \Delta t$ for all $pp^{i,k} \in \mathcal{PP}$ do $r(pp^{i,k}) = r_x^{\Sigma}(pp^{i,k}) \%$ values known from diagnosis end for for all $df_I^i \in \mathcal{DF}$ do $r(df_l^i) = f_{df}(\{r(pp^{i,k})\})$ end for for all $pp^{i,j} \in \mathcal{PP}^i_{pred}$ do $r(pp^{i,j}) = ag^{i,j}(\{df_l^i\})$ end for for all $ip^{i,j} = st(op^{k,l},t) \in \mathcal{IP}^i_{pred}$ do $ip^{i,j}(t) = op^{k,l}(t)$ end for for all $op^{i,j} \in \mathcal{OP}^i_{pred}$ do $op^{i,j}(t) = ar(\{p^{i,k}\})$ end for for all $pp^{i,j} \in \mathcal{PP}_{pred}$ do if $e^{i,j} \ge e_x^{i,j}$ then $t_k \leftarrow t$ go out of loop end if end for Diagnose the system at time t_k $\Pi^{\Sigma}(t) \leftarrow \Delta^{\Sigma}(t_k)$ $k \leftarrow k + 1$ end while Return $\{\Pi^{\Sigma}\}$

- the ambient temperature is constant (the ventilation is working well);
- the motor shell acts as a constant thermal resistance R_{th2} , and a uniform temperature ;
- the insulator acts as a constant thermal resistance R_{th1} ;
- the winding temperature is uniform ;
- only the steady state is considered since the transition state is short.

Although these hypothesis are restrictive, building a more representative model is one of this work perspectives.

Variation of the short-circuit resistance The ageing law allows deducing the short-circuit resistance value R_f . The health points PV are used to correlate the life duration L with R_f .

The initial number of health points PV_0 corresponds with the initial life duration value L_0 . Between t and t+dt the proportion of consumed health points is $PV(t)-PV(t+dt) = \frac{dt}{L(t)}$, so

$$PV(t) = \int_0^t \frac{1}{L(z)} dz \tag{13}$$

The integration of the ageing law can be done by approximation with a piecewise continuous function having the value $L(T(t_{k+1}))$ between times t_k and t_{k+1} :

$$\begin{cases} PV(0) = 0 \\ PV(t_{k+1}) = PV(t_k) + \frac{(t_{k+1} - t_k)}{L(T(t_{k+1}))} \end{cases}$$
(14)

To the best of our knowledge the law that gives the shortcircuit evolution as a function of health points does not exist. We choose an exponential shape because we assume that the degradation accelerates with time:

$$R_f(t) = R_{f0}(1 - exp(-k\frac{PV(t) - PV_0}{PV_0})).$$
 (15)

Variation of phases resistivity At temperature T the resistance R of a coil is $R(T) = (\rho(T) \times L)/s$, where l is the length of the cable and s is its section. T_0 is the nominal temperature, $R_0 = R(T_0)$. Besides the short-circuited phase resistance modification due to the short-circuit loop with resistance R_f , the three phase resistances R_a , R_b and R_c respect the following equation:

$$R(T) = R(T_0) + \frac{l}{s} \times (\rho(T) - \rho(T_0))$$
(16)

where the copper resistivity is $\rho(T) = 17.24 \times (1 + 4.2 \times 10^{-3} \times (T - 20)) \times 10^{-6}$.

Thermal power dissipation

$$T_s = (R_{th1} + R_{th2}) \times P_d + T_a$$
 (17)

The stator temperature is obtained from the dissipated stator thermal power P_d , that depends on phase resistance R_a , R_b and R_c , on the short-circuit intensity through S_a and R_f , and on phase and short-circuit currents. The equation can be found on (Vinson et al., 2013).

4.3. Application: Permanent Magnet Synchronous Machine prognosis

A short-circuit scenario is simulated on the virtual prototype. The resulting fault resistance and stator temperature can be seen on Figures 6 and 7. The short-circuit resistance decreases progressively with the short-circuit, until 0Ω when the short-circuit is direct. Meanwhile, the stator temperature progressively increases with the degradation.

During the degradation progression, phase currents are observed on the virtual prototype. This allows the diagnosis of the stator and the PMSM thanks to the diagnosis algorithm developed in (Vinson, Combacau, Prado, & Ribot, 2012) which



Figure 6. Evolution of the short-circuit resistance R_f during an inter-turns short-circuit.



Figure 7. Evolution of the stator temperature T_s during an inter-turns short-circuit.

uses a short-circuit indicator based on the phase currents. The damage e^s is estimated thanks to the diagnosis algorithm, as shown on the top left of Figure 8. The diagnosis module evaluates the health-state of the stator according to the damage value: it is first nominal, the degraded, and then faulty (top-right on Figure 8). The prognosis module is run every time when a threshold is passed by the stator damage. It can predict the future values of the stator temperature T_s thanks to the retroaction law described by 8 (bottom-left on Figure 8). It can then predict the life duration L of the stator thanks to the ageing law represented by Equation 7 (bottom-right on Figure 8. Two predictions are realized with two different values of the parameter b (Equation 7), in order to represent uncertainties on the ageing law. The real life duration can be compared with the two predicted life duration.

5. CONCLUSION

In this paper a study about related work on existing ageing models and prognosis methods was first proposed. It motivated the idea of designing a generic ageing modeling framework in order to represent every kind of known ageing law, whatever the nature of available knowledge. The proposed generic modeling framework contains all information to perform diagnosis and prognosis. Besides a diagnosis algorithm presented in details in a previous paper (Vinson et al., 2013), a prognosis algorithm based on this generic ageing model is extended. It uses predictable parameters and damaging factors to estimate the future degradation and faults occurrences.



Figure 8. Results obtained by the diagnosis and prognosis algorithms on a short-circuit scenario.

An illustration is shown on Permanent Magnet Synchronous Machines, which ageing is successfully modeled by the proposed model. A virtual prototype is designed in order to obtain ageing data, and is run with a realistic short-circuit scenario. The end of life of the stator and the machine is predicted by the prognosis algorithm.

The developed modeling framework and prognosis algorithm are intended to be applied to other critical equipment in aeronautics, such as hydraulic pumps or electromechanical actuators. The efficiency of the method should be stated thanks to real case studies. In order to adjust the proposed ageing model with ageing and retroaction laws, it seems essential to perform some degradation tests. The generic ageing model we proposed is a common representation of ageing of any equipment type. But the level of knowledge contained in the model is directly characterized by the availability of sensors, experience or physics-based models and may vary from one component to another. The higher the level of knowledge about ageing is, the more accurate the prognosis results. It becomes interesting to define and implement performance metrics for prognosis based on the level of knowledge contained in out generic aging model in order to compare the results obtained for the components and qualify the prognosis result at the system level.

REFERENCES

- Adeline, R., Gouriveau, R., & Zerhouni, N. (2008). Pronostic de défaillances: Maitrise de l'erreur de prédiction. In *7ème Conference Internationale de Mobilisation et* Simulation, (MOSIM'08).
- Bansal, D., Evans, D.-J., & Jones, B. (2005). Application of a real-time predictive maintenance system to a production machine system. *International Journal of Machine Tools and Manufacture*, 45(10), 1210-1221.
- Bouaziz, M.-F., Zamai, E., & Duvivier, F. (2013). Towards bayesian network methodology for predicting the equipment health factor of complex semiconduc-

tor systems. International Journal of Production Research, 51(15).

- Bregon, A., Daigle, M., & Roychoudhury, I. (2012). An integrated framework for model-based distributed diagnosis and prognosis. In *Annual Conference of the Prognostics and Health Management Society (PHM'12)*.
- Brissaud, F., Lanternier, B., Charpentier, D., & Lyonnet, P. (2007). Modélisation des taux de défaillance en mécanique, combinaison d'une loi de weibull et d'un modèle de cox pour la modélisation des taux de défaillance en fonction du temps et des facteurs d'influence. In *3ème congrès Performances et Nouvelles Technologies en Maintenance (PENTOM'07.*
- Byington, C. S., Roemer, M. J., & Galie, T. (2002). Prognostic enhancements to diagnostic systems for improved condition-based maintenance. *IEEE Aerospace Conference Proceedings*, 6, 2815-2824.
- Byington, C. S., & Stoelting, P. (2004). A model-based approach to prognostics and health management for flight control actuators. In *IEEE Aerospace Conference*.
- Das, S., Hall, R., Herzog, S., Harrison, G., & Bodkin, M. (2011). Essential steps in prognostic health management. In *IEEE Conference on Prognostics and Health Management (PHM'11)* (p. 1-9).
- El-Koujok, M., Gouriveau, R., & Zerhouni, N. (2010). A neuro-fuzzy self built system for prognostics: a way to ensure good prediction accuracy by balancing complexity and generalization. In *International Conference on Prognostics and Health Management (PHM'10)*.
- Gebraeel, N., Elwany, A., & Pan, J. (2009). Residual life predictions in the basence of prior degradation knowledge. *IEEE Transactions on Reliability*, 58, 106-117.
- Goh, K., Tjahjono, B., Baines, T., & Subramaniam, S. (2006). Ra review of research in manufacturing prognostics. In *IEEE International Conference on Industrial Informatics* (p. 412-422).
- Greitzer, F. L., & Pawlowski, R. A. (2002). Embedded prognostics health monitoring. In *International instrumentation symposium on embedded health monitoring workshop.*
- Gucik-Derigny, D., Outbib, R., & Ouladsine, M. (2011). Observer design applied to prognosis of system. In *International Conference on Prognostics and Health Management (PHM'11)*.
- Hall, P., & Strutt, J. (2003). Probabilistic physics-of-failure models for component reliabilities using monte carlo simulation and weibull analysis: a parametric study. *Reliability Engineering and System Safety*, 30, 233-242.
- Hu, C. (2011). Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. In *IEEE International Conference on Prognostics and Health Management (PHM'11)*.
- Huynh, K., Castro, I., Barros, A., & Berenguer, C. (2012). On

the construction of mean residual life for maintenance decision-making. In 8th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS'12).

- Khorasgani, H., Kulkarni, C., Biswas, G., Celaya, J. R., & Goebel, K. (2013). Degredation modeling and remaining useful life prediction of electrolytic capacitors under thermal overstress condition using particle filters. In Annual Conference of the Prognostics and Health Management Society (PHM'13). New Orelans, USA.
- Lacaille, J., Gouby, A., & Piol, O. (2013). Wear prognostic on turbofan engines. In Annual Conference of the Prognostics and Health Management Society (PHM'13). New Orleans, USA.
- Lahoud, N., Faucher, J., Malec, D., & Maussion, P. (2011). Electrical ageing modeling of the insulation of low voltage rotating machines fed by inverters with the design of experiments (doe) method. In *IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives (SDEMPED).*
- Lawless. (2004). Covariates and random effects in a gamma process model with application to degradation and failure. *Lifetime Data Analysis*, *10*, 213-227.
- Muller, A., Suhner, M.-C., & Iung, B. (2008). Formalisation of a new prognosis model for supporting proactive maintenance implementation on industrial system. *Reliability Engineering and System Safety*, 93, 234-253.
- Nima, G., Lin, M., Murthy, M., Prasad, Y., & Yong, S. (2009). A review on degradation models in reliability analysis. In Proceedings of the 4th world Congress on Engineering Asset Management.
- Onori, S., Rizzoni, G., & Cordoba-Arenas, A. (2012). A prognostic methodology for interconnected systems: preliminary results. In 8th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS'12).
- Pommier, S. (2009-2010). *Mecanique des materiaux*. ENS Cachan.
- Ray, A. (1999, Jan). Stochastic modeling of fatigue crack damage for risk analysis and remaining life prediction. *Journal of Dynamic Systems, Measurement, and Control (ASME)*, 121(3).
- van Noortwijk, J., Kallen, M., & Pandey, M. (2005). Gamma processes for time-dependant reliability of structures. In *European Safety and Reliability Conference (ES-REL'05)*.
- van Noortwijk, J., & Klatter, H. (2002). The use of lifetime distributions in bridge replacement modelling. In *Irst International Conference on Bridge Maintenance, Safety and Management (IABMAS).*
- Venet, P. (2007). Hdr: Amelioration de la srete de fonctionnement des dispositifs de stockage d'energie. Unpublished doctoral dissertation, Universite Claude Bernard - Lyon 1.

- Vinson, G., Combacau, M., & Prado, T. (2012). Permanent magnet synchronous machines faults detection and identification. In 8th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS'12).
- Vinson, G., Combacau, M., Prado, T., & Ribot, P. (2012). Synchronous machine faults detection and diagnosis for electromechanical actuators in aeronautics. In 38th Annual Conference of IEEE Industrial Electronics (IECON'12).
- Vinson, G., Ribot, P., Prado, T., & Combacau, M. (2013).

A generic diagnosis and prognosis framework: application to permanent magnets synchronous machines. In *IEEE Prognostics and System Health Management Conference (PHM'13).*

Weber, P., P.Munteanu, & Jouffe, L. (2004). Dynamic bayesian networks modelling the dependability of systems with degradations and exogenous constraints. In 11th IFAC Symposium on Information Control Problems in Manufacturing (INCOM'04).

A Model-Based Prognostics Framework to Predict Fatigue Damage Evolution and Reliability in Composites

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ABSTRACT

In this work, a model-based prognostics methodology is proposed to predict the remaining useful life (RUL) of composite materials under fatigue loads. To this end, degradation phenomena such as stiffness reduction and increase in matrix micro-cracks density are predicted by connecting microscale and macro-scale damage models in a Bayesian filtering framework. The proposed Bayesian filtering framework also allows incorporating various uncertainties in the prediction that are generally associated with material defects, sensing and monitoring noise, modeling errors, etc., to name a few. This, however, results in a explosion of search space due to high dimensionality, and hence a high computational complexity not conducive for real-time monitoring and prediction. To reduce the dimensionality of the problem without significantly compromising on prediction performance (precision and accuracy), a model tuning is first carried out by means of a Global Sensitivity Analysis. This allows identifying and subsequently down selecting the parameters for online adaptation that affect prediction performance the most. Resulting RUL estimates are then used to compute a timevariant reliability index for composite materials under fatigue stress. The approach is demonstrated on data collected from run-to-failure tension-tension fatigue experiments measuring the evolution of fatigue damage in CRFP cross-ply laminates. Micro-cracks are considered as the primary internal damage mode that are estimated from measurements obtained by active interrogation using PZT sensors. Results are presented and discussed for the prediction of growth in micro-cracks density and loss of stiffness for a given panel along with the reliability index calculation for the damaged component.

1. INTRODUCTION

Composites are high-performance materials used extensively in the construction of engineering structures, with a wide range of applications such as aeronautical, marine and mechanical structures. Most of these applications involve components subject to cyclic loads, which make them susceptible to fatigue degradation. This degradation leads to a progressive decrease of the performance reliability of the material, and ultimately, to the catastrophic failure of the structure. The prediction forward in time of such fatigue degradation and the reliability of the composite structure is of a paramount importance for safety and cost reasons, however it is still a partially understood problem.

In contrast to metals, fatigue damage in composites is governed by complex multi-scale processes driven by internal fracture mechanisms that ultimately lead to the alteration of the macro-scale mechanical properties (Reifsnider & Talug, 1980; Jamison, Schulte, Reifsnider, & Stinchcomb, 1984). The inherent complexity of this process implies uncertainty, that comes not only from the variability of loading conditions and material heterogeneity, but also from the incomplete knowledge of the underlying damage process. This uncertainty can increase dramatically when dealing with fullscale structures in real environments. Nevertheless, real time measurements of the structural performance are now available through state-of-art Structural Health Monitoring (SHM) techniques, and a large variety and amount of response data can be readily acquired, processed and further analyzed to assess various health-related properties of structures. Thus a SHM-based prognostic approach is best suited to deal with this uncertainty, and furthermore to accurately predict the service life and the time-varying reliability of the composite structure.

In the last few years, the topic of fatigue damage prognostics

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is slowly gaining interest. There is an increasing number of articles dealing with probability-based approaches for fatigue damage prognostics (Myötyri, Pulkkinen, & Simola, 2006; Cadini, Zio, & Avram, 2009; Guan, Jha, & Liu, 2011; Zio & Di Maio, 2012; An, Choi, & Kim, 2013; Gobbato, Kosmatka, & Conte, 2014), most of them in the context of metals. However the number of contributions for composites materials is still very limited (J. Chiachío, Chiachío, Saxena, Rus, & Goebel, 2013), precisely where the benefits of the probabilistic SHM-based prognostic approach can be fully exploited to deal with the variability and complexity of the fatigue damage accumulation process.

Damage prognostics is concerned with determining the health state of system components and predicting their RUL based on predefined thresholds, given an evolutionary damage model. As with diagnostics, prognostics methods are typically categorized as either model-based or data-driven, depending on whether the damage model is based on physical first principles, or, alternatively uses damage data to capture trends of degradation. Model-based approaches provide RUL estimates that are more accurate than data-driven approaches, when suitable models are available (M. Daigle & Goebel, 2010). Specifically, model-based approaches have the ability to adapt to different systems (specimen, materials, conditions, etc.) without much training, and furthermore, they can incorporate monitoring data in a SHM context.

This paper integrates a model-based damage prognostics problem with reliability theory in application to fatigue in composite materials, which distinguishes from the recent paper presented by the authors at PHM2013 (2013 Annual Conference of the Prognostics and Management Society) (J. Chiachío et al., 2013). In that article, a model-based prognostics framework was proposed to sequentially estimate the health state as well as the parameters of the underlying damage model, based on available SHM data. From this estimation, the RUL of the estructure was computed. A Sequential Importance Resampling algorithm (Arumlampalam, Maskell, Gordon, & Clapp, 2002) was used for the joint state-parameter sequential estimation, and an artificial dynamics approach (Liu & West, 2001; M. J. Daigle & Goebel, 2013) was adopted to improve the predictability of the algorithm.

The new contributions of this research work with respect to (J. Chiachío et al., 2013) are (i) the consideration of two different-scale damage signatures to represent the health state of the system: matrix-cracks density and longitudinal stiffness reduction, and (ii) the prediction of the time-varying reliability of the structure, as a unified health indicator of the system.

As a case study, SHM data from a tension-tension fatigue experiment in a cross-ply CFRP laminate is used. Damage data used in this example are taken from the Composite dataset, NASA Ames Prognostics Data Repository (Saxena, Goebel, Larrosa, & Chang, 2008), corresponding to laminate L1S19. More details about these tests are reported in (Saxena et al., 2011). Results shows the suitability and accuracy of the proposed approach.

The rest of the paper is organized as follows. Section 2 discusses the theory behind fatigue damage in composites and presents the proposed methodology for fatigue damage modeling. The sequential state estimation problem by means of particle filters is presented in Section 3. Section 4 formally defines the prognostics problem and describes the methodology to compute the time-varying reliability. Section 5 presents the demonstration of the approach on real data of fatigue considering a cross-ply CFRP laminate. Finally, some concluding remarks are presented in Section 6.

2. FATIGUE DAMAGE MODELING

The progression of fatigue damage in composites involves a progressive or sudden change of the macro-scale mechanical properties, such as stiffness or strength, as a consequence of different fracture modes that evolve at the micro-scale along the lifespan of the structure (Jamison et al., 1984). In this work the longitudinal stiffness loss is chosen as the macroscale damage variable, given that, in contrast to the strength, it can be measured through non-destructive methods during operation. This is of key importance for the filtering-based prognostics approach proposed. At the micro-scale level, matrix micro-cracking (J. A. Nairn, 2000) is selected as the dominant fracture mode for the early stage of damage accumulation. Matrix cracks usually initiate from internal defects in 90° plies during first loading cycles, and grow rapidly along fibers direction spanning the entire width of the specimen (J. A. Nairn, 2000). Continued loading leads to formation of new cracks between the already formed cracks thereby progressively increasing the matrix-crack density of the ply until saturation. This saturated state, usually termed as characteristic damage state (CDS) (Reifsnider & Talug, 1980), is long recognized as a precursor of more severe fracture modes in adjacent plies, such as delamination and fiber breakage (Lee, Allen, & Harris, 1989; Beaumont, Dimant, & Shercliff, 2006), which may subsequently lead to the catastrophic failure of the laminate. In addition, matrix micro-cracking may itself constitute failure of the design when micro-crack induced degradation in properties exceeds the predefined threshold.

To accurately represent the relation between the internal damage and its manifestation through macro-scale properties, several families of *damage mechanics* models have been proposed in the literature (Talreja & Singh, 2012). These models, that are based on first principles of admissible ply stress fields in presence of damage, can be roughly classified into 1) computational methods, 2) semi-analytical methods and 3) analytical methods. Among them, computational and semianalytical methods have been shown to be promising, however they are computationally prohibitive in a filtering based prognostics approach, where a large number of model evaluations is required. Therefore, we focus here on the set of analytical models, that depending on the level of assumptions, they can be classified into *shear-lag* models (Garrett & Bailey, 1977; Highsmith & Reifsnider, 1982), *variational* models (Hashin, 1985), and *crack opening displacement* based models (Gudmundson & Weilin, 1993; Lundmark & Varna, 2005).

Shear-lag models use one-dimensional approximations of the equilibrium stress field after cracking to derive expressions for stiffness properties of the cracked laminate. Their main assumption is basically that, in the position of matrix cracks, axial load is transferred to uncracked plies by the axial shear stresses at the interfaces. These models have received the most attention in the literature and, as a consequence, a vast number of modifications and extensions can be found. However, as stated by Talreja and Singh (Talreja & Singh, 2012), all the one-dimensional shear-lag models are virtually identical, except for the choice of the shear-lag parameter, as explained later in this section. Variational models are based on a twodimensional approximation of the equilibrium stress field, that in contrast to shear-lag analysis, is obtained from the Principle of Minimum Complementary Energy (Reddy, 2002; Dym & Shames, 2013). Finally, COD-based models use a 3-D homogenization procedure derived from the study of the average crack-face opening displacement of a single matrix crack as a function of the applied load, that can be calculated either analytically (Gudmundson & Weilin, 1993) or numerically (Varna, Akshantala, & Talreja, 1999; Joffe, Krasnikovs, & Varna, 2001; Lundmark & Varna, 2005). The reader is referred to the recent work of Talreja and Singh (Talreja & Singh, 2012) for a detailed overview of these models.

Variational and COD models are expected to better capture the various complex damage mechanisms, since they involve a more complex damage mechanics analysis, but it might be at expense of more information extracted from the data (J. Chiachío et al., 2014). Then, if such models are utilized for future prediction, as arises in prognostics, the results are expected to significantly depend on the details of the available data. In contrast, the most simple shear-lag model provide reasonable accuracy results while it extracts less information from data. To this end, it is expected to be less sensitive to the noise on data. It is an example of the principle of Ockham's razor in the context of fatigue of materials, that has been shown to hold true for composites materials by a recent study (J. Chiachío et al., 2014).

2.1. Stiffness reduction model

Following the unifying formulation of (Joffe & Varna, 1999), the effective longitudinal Young's modulus E_x^* can be calculated in $\left[\phi_{\frac{n_{\phi}}{2}}/90_{n_{90}}/\phi_{\frac{n_{\phi}}{2}}\right]$ laminates (where $\phi \in [-90^{\circ}, 90^{\circ}]$) as a function of the crack-spacing in 90° layers for both, shear-lag and variational models, as follows:

$$E_x^* = \frac{E_{x,0}}{1 + a\frac{1}{2\bar{l}}R(\bar{l})}$$
(1)

In the last equation, $E_{x,0}$ is the longitudinal Young's modulus of the undamaged laminate, $\overline{l} = \frac{l}{t_{90}}$ is the half crack-spacing normalized with the 90° sub-laminate thickness, $R(\overline{l})$ is the average stress perturbation function, and a is a function of ply and laminate properties, defined as follows:

$$a = \frac{E_2 t_{90}}{E_1 t_{\phi}} \left(1 - \nu_{xy}^{(\phi)} \frac{\frac{\nu_{xy}^{(\phi)} t_{90}}{E_y^{(\phi)}} + \frac{\nu_{12} t_{\phi}}{E_2}}{\frac{t_{90}}{E_y^{(\phi)}} + \frac{t_{\phi}}{E_1}} \right) \frac{1 - \nu_{12} \nu_{xy}^{(\phi)}}{1 - \nu_{12}^2 \frac{E_2}{E_1}} \quad (2)$$

In the last equation, the superscript (ϕ) denotes: "property referred to the $\left[\phi_{\frac{n_{\phi}}{2}}\right]$ -sublaminates". The reader is referred to the Nomenclature section for a description of the ply and laminate properties used in the calculations.

It should be noted that the matrix-cracks density is usually termed as $\rho = \frac{1}{2l}$, so that the normalized half crack-spacing \bar{l} can be expressed as a function of ρ as $\bar{l} = \frac{1}{2\rho t_{90}}$. For shear-lag models, the function $R(\bar{l})$ takes the next expression (Joffe & Varna, 1999):

$$R(\bar{l}) = \frac{2}{\xi} \tanh(\xi \bar{l}) \tag{3}$$

where ξ is the aforementioned shear-lag parameter. Depending on the choice of ξ , different shear-lag models, that have been proposed in the literature, can be obtained. See (Talreja & Singh, 2012) for further discussion about shear-lag analysis. In this paper, the "classical" shear-lag model (Garrett & Bailey, 1977; Manders, Chou, Jones, & Rock, 1983) is adopted. For this model, ξ takes the following expression:

$$\xi = \sqrt{G_{23} \left(\frac{1}{E_2} + \frac{t_{90}}{t_{\phi} E_x^{(\phi)}} \right)}$$
(4)

2.2. Damage propagation model

Having identified the model to express the relationship between the effective Young's modulus and micro-cracks density, the next step is to address the time evolution of the microcracks density. To this end, the previously explained shear-lag model is used to obtain the energy released per unit crack area due to the formation of a new crack between two existing cracks, denoted here as G. This energy, known as energy release rate (ERR), can be calculated as (J. A. Nairn, 1989):

$$G = \frac{\sigma_x^2 h}{2\rho t_{90}} \left(\underbrace{\frac{1}{\underbrace{E_x^*(2\rho)}}_{\text{Eq. 1}} - \underbrace{\frac{1}{\underbrace{E_x^*(\rho)}}_{\text{Eq. 1}}}_{\text{Eq. 1}} \right)$$
(5)

where σ_x is the applied axial tension, and h and t_{90} are the laminate and 90° sublaminate half-thickness, respectively. The energy released calculated by Eq. (5) is further introduced into the modified Paris' law (J. Nairn & Hu, 1992) to obtain the evolution of matrix-cracks density as a function of fatigue cycle n, as shown below:

$$\frac{d\rho}{dn} = A(\Delta G)^{\alpha} \tag{6}$$

where A and α are fitting parameters, and ΔG is the increment in ERR for a specific stress amplitude, i.e., $\Delta G = G(\sigma_{x,max}) - G(\sigma_{x,min})$. Due to the complexity of the expression for ΔG , which involves the underlying micro-damage mechanics model for the computation of $E_x^*(\rho)$, a closed-form solution for Eq. (6) is hard to obtain. To overcome this drawback, the resulting differential equation can be solved by approximating the derivative using "unit-time" finite differences, considering that damage evolves cycle-to-cycle as:

$$\rho_n = \rho_{n-1} + A \left(\Delta G(\rho_{n-1}) \right)^{\alpha} \tag{7}$$

To summarize, a shear-lag damage-mechanics model is selected to compute $E_x^*(\rho)$, i.e. the relationship between the effective longitudinal Young's modulus (macro-scale) and the matrix-cracks density (micro-scale). The evolution of matrixcracks density is modeled using the modified Paris' law in Eq. (7), that incorporates the damage mechanics model to evaluate the increment in ERR.

3. FILTERING-BASED STATE-PARAMETER ESTIMATION

3.1. Stochastic embedding

For the purpose of filtering and prognostics, a probabilitybased description of the deterministic models described in Section 2 is needed. To this end, let consider a generic model defined by a deterministic relationship $\mathbf{g} = \mathbf{g}(\mathbf{u}, \boldsymbol{\theta}) : \mathbb{R}^{N_i} \times \mathbb{R}^{N_d} \to \mathbb{R}^{N_o}$, between the model input $\mathbf{u} \in \mathbb{R}^{N_i}$ and the model output $\mathbf{g} \in \mathbb{R}^{N_o}$, given a set of N_p model parameters $\boldsymbol{\theta} \in \boldsymbol{\Theta} \subset \mathbb{R}^{N_p}$. This damage model can be "embedded" stochastically (Beck, 2010) by adding a model-error term \mathbf{v} that represents the difference between the actual system response \mathbf{x} and the model output \mathbf{g} , as follows:

$$\mathbf{x} = \mathbf{g}(\mathbf{u}, \boldsymbol{\theta}) + \mathbf{v} \tag{8}$$

The probability model chosen for the error term v in Eq. (8) determines the probability model for the system output x. For example, if v is assumed to be a zero-mean Gaussian distribution, then the system output x will be also distributed as a

Gaussian, as shown below:

$$\mathbf{v} = \mathbf{x} - \mathbf{g}(\mathbf{u}, \boldsymbol{\theta}) \sim \mathcal{N}(0, \Sigma) \implies \mathbf{x} \sim \mathcal{N}(\mathbf{g}(\mathbf{u}, \boldsymbol{\theta}), \Sigma)$$

where $\Sigma \in \mathbb{R}^{N_o \times N_o}$ is the covariance matrix. Thus, a stochastic damage model can be defined as a function of model parameters $\boldsymbol{\theta} \in \boldsymbol{\Theta}$, as ¹

$$p(\mathbf{x}|\mathbf{u},\boldsymbol{\theta}) = \left((2\pi)^{N_o} |\Sigma| \right)^{-\frac{1}{2}} \exp\left(-\frac{1}{2} \left(\mathbf{x} - \tilde{\mathbf{x}} \right)^T \Sigma^{-1} \left(\mathbf{x} - \tilde{\mathbf{x}} \right) \right)$$
(9)

where $\tilde{\mathbf{x}} = \mathbf{g}(\mathbf{u}, \boldsymbol{\theta})$. As discussed in Section 2, the progression of damage is studied at every cycle *n* by focusing on two of its manifestations: the matrix-cracks density, ρ_n , and the normalized effective stiffness, defined as $D_n = \frac{E_x^*}{E_{x,0}}$. Then, according to Eq. (8), the actual damage response can be represented by:

$$\rho_n = \underbrace{g_1(\rho_{n-1}; \mathbf{u}, \boldsymbol{\theta})}_{\text{Eq. 7}} + v_1 \tag{10a}$$

$$D_n = \underbrace{g_2(\rho_n; \mathbf{u}, \boldsymbol{\theta})}_{\text{Eq. 1}} + v_2 \tag{10b}$$

where subscripts 1 and 2 denote the corresponding damage subsystems: matrix-crack density and relative stiffness reduction, respectively.

From Eqs. (10a) and (10b), the three main elements defining the stochastic damage model in Eq. (9) are identified: (1) the actual system output $\mathbf{x}_n = [\rho_n, D_n]$, (2) the damage model $\mathbf{g} = [g_1, g_2]$, and (3) the corresponding model error vector $\mathbf{v} = [v_1, v_2]$. A key concept here is the consideration of model errors v_1 and v_2 as stochastically independent, even though the models corresponding to the damage subsystems, g_1 and g_2 , are mathematically related, as shown in Section 2. This means that the covariance operator Σ is a diagonal matrix, and therefore, the stochastic damage model of the overall system can be readily expressed as a product of univariate Gaussians, as:

$$p(\mathbf{x}_n | \mathbf{u}, \boldsymbol{\theta}) = p(\rho_n | \rho_{n-1}; \mathbf{u}, \boldsymbol{\theta}) p(D_n | \rho_n; \mathbf{u}, \boldsymbol{\theta})$$
(11)

where

$$p(\rho_n|\rho_{n-1};\mathbf{u},\boldsymbol{\theta}) = \mathcal{N}\big(g_1(\rho_{n-1};\mathbf{u},\boldsymbol{\theta}),\sigma_{v_1}^2\big)$$
(12a)

$$p(D_n|\rho_n; \mathbf{u}, \boldsymbol{\theta}) = \mathcal{N}(g_2(\rho_n; \mathbf{u}, \boldsymbol{\theta}), \sigma_{v_2}^2)$$
(12b)

The parameters σ_{v_1} and σ_{v_2} in Eq. 12a and 12b are the standard deviation of the error terms v_1 and v_2 , respectively. Observe that the stochastic damage model provided in Eq. (11) implicitly encloses a stochastic *state transition equation*, so that Eq. (8) can also be expressed as:

$$\mathbf{x}_n = \mathbf{g}(\mathbf{x}_{n-1}; \mathbf{u}_n, \boldsymbol{\theta}_n) + \mathbf{v}_n \tag{13}$$

 $^{{}^{1}}p(\cdot)$ is used here to express a probability density function, whereas $P(\cdot)$ is used to denote probability

where a new variable $\mathbf{z}_n = {\mathbf{x}_n, \boldsymbol{\theta}_n} \in \mathcal{Z} \subset \mathbb{R}^{N_o \times N_p}$ can be suited defined as the system (health) state at time or fatigue cycle *n*. As explained before, Eq. (13) can be expressed probabilistically as:

$$p(\mathbf{x}_{n}|\mathbf{x}_{n-1}\mathbf{u}_{n},\boldsymbol{\theta}_{n}) = \mathcal{N}(\mathbf{g}(\mathbf{x}_{n-1};\mathbf{u}_{n},\boldsymbol{\theta}_{n}), \Sigma_{\mathbf{v}_{n}})$$
$$= \mathcal{N}(g_{1},\sigma_{v_{1_{n}}}^{2})\mathcal{N}(g_{2},\sigma_{v_{2_{n}}}^{2})$$
(14)

3.2. Filtering equations

Let suppose that the actual system response \mathbf{x}_n can be measured during operation and that, at a certain fatigue cycle n, the measured system response can be expressed as a function of \mathbf{x}_n as:

$$\mathbf{y}_n = \mathbf{x}_n + \mathbf{w}_n \tag{15}$$

where $\mathbf{y}_n = \left[\hat{\rho}_n, \hat{D}_n\right]$ is a vector of measurements for matrixcracks density and normalized effective stiffness, respectively, and \mathbf{w}_n is a measurement error that can be defined as zero mean Gaussian process, i.e., $\mathbf{w}_n \sim \mathcal{N}(0, \Sigma_{\mathbf{w}_n})$. Then, the *measurement equation* defined in Eq. (15) can be expressed in probabilistic terms as:

$$p(\mathbf{y}_n | \mathbf{x}_n) = \mathcal{N}(\mathbf{y}_n; \mathbf{x}_n, \Sigma_{\mathbf{w}_n})$$
(16)

Note that, since the measurements of each subsystem (microcracks and stiffness loss) are considered to be stochastically independent, the covariance matrix will be a diagonal matrix, and the measurement equation defined in Eq. (15) can be readily expressed as:

$$p(\mathbf{y}_n|\mathbf{x}_n) = p(\hat{\rho}_n|\rho_n)p(\hat{D}_n|D_n) \tag{17}$$

$$= \mathcal{N}(\hat{\rho}_n; \rho_n, \sigma_{w_{1_n}}) \mathcal{N}(\hat{D}_n; D_n, \sigma_{w_{2_n}})$$
(18)

Then, the focus of the filtering problem is on sequentially updating the probability density function (PDF) of the system state given a set of system measurements up to time n, $\mathbf{y}_{1:n}$, i.e., $p(\mathbf{x}_n, \boldsymbol{\theta}_n | \mathbf{y}_{1:n}) = p(\mathbf{z}_n | \mathbf{y}_{1:n})$, using the previously defined state transition equation and measurement equation. A *particle filter* (Arumlampalam et al., 2002) is used to approximate the joint state-parameter distribution by a set of discrete weighted *particles*, $\{\mathbf{z}_n^i, \omega_n^i\}_{i=1}^N$, as

$$p(\mathbf{z}_n | \mathbf{y}_{1:n}) \approx \sum_{\substack{i=1\\N}}^N \omega_n^i \delta(\mathbf{z}_n - \mathbf{z}_n^i)$$
(19a)

$$=\sum_{i=1}^{N}\omega_{n}^{i}\delta(\mathbf{x}_{n}-\mathbf{x}_{n}^{i})\delta(\boldsymbol{\theta}_{n}-\boldsymbol{\theta}_{n}^{i}) \qquad (19b)$$

where $\mathbf{y}_{1:n} = {\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n}$ denotes the sequence of measurements, N denotes the number of particles, \mathbf{z}_n^i denotes the estate estimate for particle i, and ω_n^i the "weight" of particle i. Particle filters are best suited to sequential estate estimation in nonlinear systems with possibly non-Gaussian noise, where optimal solutions are unavailable or intractable, as in

our problem. We employ the sampling importance resampling (SIR) particle filter, and implement the resampling step using systematic resampling (Arumlampalam et al., 2002). In our problem, the system state is defined as $\mathbf{z}_n = \{\rho_n, D_n, \theta_n\}$ and the measurements $\mathbf{y}_{1:n}$ are compounded by simultaneous measurements of both, micro-cracks density and normalized effective stiffness $\mathbf{y}_{1:n} = \{\hat{\boldsymbol{\rho}}_{1:n}, \hat{\boldsymbol{D}}_{1:n}\}$. Thus, Eq. (19) can be rewritten as:

$$p(\rho_n, D_n, \boldsymbol{\theta}_n | \mathbf{y}_{1:n}) \approx \sum_{i=1}^N \omega_n^i \delta(\rho_n - \rho_n^i) \delta(D_n - D_n^i) \delta(\boldsymbol{\theta}_n - \boldsymbol{\theta}_n^i)$$
(20)

As observed in Eq. (20), model parameters augment the state vector, then the particle filter is being used to perform joint state-parameter estimation. Here the parameters θ_n evolve by some unknown random process that is independent of the state \mathbf{x}_n , so that the particles with parameter values closest to the true ones should be assigned higher weights, thus allowing the particle filter to converge to the true values. In this context, standard Sequential Monte Carlo (SMC) methods (Doucet, De Freitas, & Gordon, 2001) fail and it is necessary to rely on more sophisticated algorithms. Although this problem is still open in the specific literature (Liu & West, 2001; Storvik, 2002; Kantas, Doucet, Singh, & Maciejowski, 2009), here we choose the "artificial dynamics" approach (Liu & West, 2001) due to its pragmatism and simplicity, by which model parameters performs a random walk by introducing a small (and decreasing with n) artificial white noise term, as $\boldsymbol{\theta}_n = \boldsymbol{\theta}_{n-1} + \boldsymbol{\xi}_n$. Thus,

$$p(\boldsymbol{\theta}_n | \boldsymbol{\theta}_{n-1}) = \mathcal{N}(\boldsymbol{\theta}_{n-1}, \sigma_{\boldsymbol{\xi} n})$$
(21)

To sequentially reduce the standard deviation of this artificial error sequence, $\sigma_{\xi n}$, there are many alternative methods in the literature (Kantas et al., 2009). In this paper, the recent method proposed by (M. Daigle & Goebel, 2010; M. J. Daigle & Goebel, 2013) is chosen by its simplicity and efficiency.

A pseudocode for a single step of the SIR filter proposed for estimating Eq. (20) is provided in Algorithm 1.

Note that the proposed sequential state-parameter estimation approach for damage prognostics in composites involves a filtering problem defined over a multi-dimensional parameter space $\Theta \subset \mathbb{R}^{N_p}$. It is clear that the higher N_p is, the higher the complexity and computational cost of the filtering and prognostics algorithms. To this end, GSA (Saltelli, Ratto, Tarantola, & Campolongo, 2006) is used to simplify the model parameterization by identifying the subset of most sensitive model parameters θ among the set of mechanical and fitting parameters defining the damage models.

Through this study, the ply properties $\{E_1, E_2, t\}$ together with the Paris' law fitting parameter $\{\alpha\}$ emerged as the key parameters in terms of model output uncertainty. Then the set

Algorithm 1 Particle Filter

1: At n = 02: Generate $\{(\rho_0^i, D_0^i, \boldsymbol{\theta}_0^i)\}_{i=1}^N$, sampling from prior PDFs $\pi_{\theta}(\cdot), \pi_{\rho}(\cdot)$ and $\pi_{D}(\cdot)$, respectively. 3: Assign the initial weights: $\{\omega_0^i = 1/N\}_{i=1}^N$ 4: At $n \ge 1$ for $i=1 \rightarrow N$ do 5: Sample from Eq. (21): $\boldsymbol{\theta}_n^i \sim p(\cdot | \boldsymbol{\theta}_{n-1}^i)$ 6: Sample from Eq. (12a): $\rho_n^i \sim p(.|\rho_{n-1}^i, \boldsymbol{\theta}_n^i)$ 7: Sample from Eq. (12b): $D_n^i \sim p(\cdot | \rho_n^i, \boldsymbol{\theta}_n^i)$ 8: Update weights: $\omega_n^i \propto p(\hat{D}_n | D_n^i) p(\hat{\rho}_n | \rho_n^i) \omega_{n-1}^i$ 9: 10: end for 11: for $i = 1 \rightarrow N$ do Normalize $\omega_n^i \leftarrow \omega_n^i / \sum_{i=1}^N$ 12: 13: end for $\{(\rho_n^i, D_n^i, \boldsymbol{\theta}_n^i)\}_{i=1}^N \leftarrow \text{Resample} \{(\rho_n^i, D_n^i, \boldsymbol{\theta}_n^i), \omega_n^i\}_{i=1}^N$ 14:

of updatable parameters was defined by adding the standard deviation of the model error and measurement error to the last choice, i.e., $\boldsymbol{\theta} = \{\alpha, E_1, E_2, t, \sigma_v, \sigma_w\}$. The rest mechanical and geometrical parameters act as static non-updatable input parameters.

4. DAMAGE AND RELIABILITY PROGNOSTICS

4.1. Damage prognostics

As previously explained in Section 3.1, $\mathbf{z}_n \in \mathcal{Z} \subset \mathbb{R}^{N_o \times N_p}$ represents the actual health state of the structure, which may enclose different degradation modes (e.g., micro-cracks, stiffness loss, delaminations, etc). We define the *useful domain* as the non empty subset $\mathcal{U} \subset \mathcal{Z}$ of "authorized" damage states of our system. The complementary subset $\overline{\mathcal{U}} = \mathcal{Z} \setminus \mathcal{U}$ represents degradation states that do not fulfill the design requirements, even though the system could still work.

For predicting the RUL of a composite laminate, we are interested in predicting the time when the damage grows beyond the useful domain, using the most current knowledge of the system state estimated by means of the particle filter (Eq. 20). The time or fatigue cycle at which it occurs is known as the expected end of life (EOL).

To compute EOL as a probability, each particle (damage state) is propagated forward in time using the stochastic damage model as state transition equation, until the boundary of the useful domain is reached. To this end, a *threshold function* $T_{\mathcal{U}}(\mathbf{z}_n)$ can be defined such that it that maps a given point in the joint state-parameter space to the Boolean domain $\{0, 1\}$ (M. Daigle & Goebel, 2011), as follows:

$$T_{\mathcal{U}}(\mathbf{z}_n) = \begin{cases} 0 & \text{if } \mathbf{z}_n \in \mathcal{U} \\ 1 & \text{if } \mathbf{z}_n \in \bar{\mathcal{U}} \end{cases}$$
(22)

Thus, the EOL of a given particle *i* at cycle *n* can be defined as the time $n' \ge n$ such that $T_{\mathcal{U}}(\mathbf{z}_{n'}) = 1$ by first time. Mathematically:

$$EOL_n^i = \inf\{n' \in \mathbb{N} : n' \ge n \land T_{\mathcal{U}}(\mathbf{z}_{n'}^i) = 1\}$$
(23)

Using the updated weights at the starting time n, a probabilistic estimation of the EOL can be obtained as:

$$p(EOL_n | \mathbf{y}_{1:n}) \approx \sum_{i=1}^N \omega_n^i \delta(EOL_n - EOL_n^i)$$
(24)

where ω_n^i is the weight of the *i*th particle at time or cycle n. Once EOL_n is estimated, the remaining useful life can be readily obtained as $RUL_n = EOL_n - n$. Thus,

$$p(RUL_n|\mathbf{y}_{1:n}) \approx \sum_{i=1}^N \omega_n^i \delta(RUL_n - RUL_n^i)$$
(25)

An algorithmic description of the proposed prognostic procedure is provided as Algorithm 2. Note that the prediction requires hypothesizing future inputs of the system \mathbf{u}_n (recall Eq. (14)). For simplicity but no loss of generality, we assume in this work that no variation of inputs parameters are expected on future states.

Algorithm 2 RUL prediction		
1:	Requires: $\{(\rho_n^i, D_n^i, \boldsymbol{\theta}_n^i), \omega_n^i\}_{i=1}^N$	
2:	Output: $\{EOL_n^i, \omega_n^i\}_{i=1}^N$	
3:	for $i = 1 \rightarrow N$ do	
4:	Calculate: $T_{\mathcal{U}}\left(\rho_{n}^{i}, D_{n}^{i}, \boldsymbol{\theta}_{n}^{i}\right)$	
5:	while $T_{\mathcal{U}} = 0$ do	
6:	Sample from Eq. (21): $\boldsymbol{\theta}_{n+1}^i \sim p(\cdot \boldsymbol{\theta}_n^i)$	
7:	Sample from Eq. (12a): $ ho_{n+1}^i \sim p(. ho_n^i, oldsymbol{ heta}_{n+1}^i)$	
8:	Sample from Eq. (12b): $D_{n+1}^i \sim p(\cdot \rho_{n+1}^i, \theta_{n+1}^i)$	
9:	$\left(ho_n^i, D_n^i, oldsymbol{ heta}_n^i ight) \leftarrow \left(ho_{n+1}^i, D_{n+1}^i, oldsymbol{ heta}_{n+1}^i ight)$	
10:	$n \leftarrow n+1$	
11:	end while	
12:	$EOL_n^i \leftarrow n$	
13:	$RUL_n^i = EOL_n^i - n$	
14:	end for	

4.2. Time varying reliability estimation

In addition to know the remaining useful life of the structure, it is also of much interest to estimate and predict the probability of the system to fulfill the design requirements, using the most up-to-date information of the system at cycle n, $y_{1:n}$. In mathematical terms, the performance reliability of the system at cycle n can be defined as (M. Chiachío, Chiachío, & Rus, 2012):

$$R_{n|n}(\mathbf{z}_n) = P(\mathbf{z}_n \in \mathcal{U}|\mathbf{y}_{1:n}) = \int_{\mathcal{U}} p(\mathbf{z}_n|\mathbf{y}_{1:n}) d\mathbf{z}_n \quad (26)$$

where $p(\mathbf{z}_n | \mathbf{y}_{1:n})$ is the updated PDF of the system health state at time *n*. Given that the event $\{\mathbf{z}_n \in \mathcal{U}\}$ is the comple-

mentary of $\{\mathbf{z}_n \in \overline{\mathcal{U}}\}\)$, then $P(\mathbf{z}_n \in \mathcal{U}|\mathbf{y}_{1:n}) = 1 - P(\mathbf{z}_n \in \overline{\mathcal{U}}|\mathbf{y}_{1:n})\)$; thus the reliability can be rewriten as:

$$R_{n|n}(\mathbf{z}_n) = 1 - \int_{\mathcal{Z}} T_{\mathcal{U}}(\mathbf{z}_n) p(\mathbf{z}_n | \mathbf{y}_{1:n}) d\mathbf{z}_n \qquad (27)$$

where $T_{\mathcal{U}}$ is the threshold function previously defined in Eq. (22). Using the particle filter approximation of $p(\mathbf{z}_n | \mathbf{y}_{1:n})$ defined in Eq. (19), the last multidimensional integral can be estimated as follows:

$$R_{n|n}(\mathbf{z}_n) \approx 1 - \int_{\mathcal{Z}} T(\mathbf{z}_n) \sum_{i=1}^N \omega_n^i \delta(\mathbf{z}_n - \mathbf{z}_n^i) d\mathbf{z}_n \quad (28a)$$
$$= 1 - \sum_{i=1}^N \omega_n^i T_{\mathcal{U}}(\mathbf{z}_n^i) \qquad (28b)$$

For a forward time reliability prediction at general cycle $n + \ell$, where $\ell \in \mathbb{N} > 1$, a probability-based estimation of the damage state at cycle $n + \ell$ is needed, i.e., $p(\mathbf{z}_{n+\ell}|\mathbf{y}_{1:n})$. It can be accomplished by Total Probability Theorem using the updated state of the system at cycle n, as (Doucet et al., 2001)

$$p(\mathbf{z}_{n+\ell}|\mathbf{y}_{1:n}) = \int_{\mathcal{Z}} \left[\prod_{t=n+1}^{n+\ell} p(\mathbf{z}_t|\mathbf{z}_{t-1}) \right] p(\mathbf{z}_n|\mathbf{y}_{1:n}) d\mathbf{z}_{n:n+\ell-1}$$
(29)

Note that last equation can be sampled by drawing one conditional sample trajectory $\mathbf{z}_{n+1:n+\ell}^j = {\mathbf{z}_{n+1}^j, \mathbf{z}_{n+2}^j, \dots, \mathbf{z}_{n+\ell}^j}$ from the state transition equation, by means of conditional sampling (Doucet et al., 2001). Thus, an estimate of the ℓ step predictive ahead PDF can be expressed as

$$p(\mathbf{z}_{n+\ell}|\mathbf{y}_{1:n}) \approx \sum_{j=1}^{N} \omega_n^j \delta(\mathbf{z}_{n+\ell} - \mathbf{z}_{n+\ell}^j)$$
(30)

where ω_n^j is the weigh of particles updated at time *n*. Finally, the reliability at cycle $n + \ell$ using the updated information at cycle *n* can be obtained as:

$$R_n(\mathbf{z}_{n+\ell}) = 1 - \int_{\mathcal{Z}} T(\mathbf{z}_{n+\ell}) p(\mathbf{z}_{n+\ell} | \mathbf{y}_{1:n}) d\mathbf{z}_{n+\ell} \quad (31a)$$

$$\approx 1 - \sum_{j=1}^{N} \omega_{n+\ell|n}^{j} T(\mathbf{z}_{n+\ell}^{j})$$
(31b)

5. CASE STUDY

The proposed framework is exemplified using SHM data obtained from a set of carefully designed run-to-failure fatigue experiments in cross-ply graphite-epoxy laminates. Both stiffness data and NDE measurements of internal damage, such as micro-crack density and delamination area, were periodically measured during the fatigue test (Saxena et al., 2011). Torayca T700G unidirectional carbon prepreg material was used for 15.24 $cm \times 25.4 cm$ coupons with dogbone geometry and $[0_2/90_4]_s$ stacking sequence, whose mechanical properties are listed in Table 1. A notch (5.1 $mm \times 19.3 mm$) was created in these coupons to induce damage modes others than matrix-cracks, such as delamination, thereby introducing additional sources of uncertainty and then demonstrating the proposed framework under more realistic conditions.

Fatigue tests were conducted under load-controlled tensiontension cyclic loading, with a maximum applied load of 31.13 KN, a frequency f = 5 Hz, and a stress ratio R = 0.14 (relation between the minimum and maximum stress for each cycle). Monitoring data were collected from a network of 12 piezoelectric (PZT) sensors using Lamb wave signals and three triaxial strain-gages. Additionally, periodic X-rays were taken to visualize and characterize subsurface damage features, in particular, the micro-cracks density. This information was then used to develop a mapping between PZT raw signals and micro-cracks density, as reported in Larrosa and Chang (Larrosa & Chang, 2012). More details about these tests are reported in the Composite dataset, NASA Ames Prognostics Data Repository (Saxena et al., 2008). Damage data used in this example correspond to laminate L1S19 in (Saxena et al., 2008).

Results for sequential state estimation for both micro-cracks density and stiffness loss are presented in Figures 1a and 1b, respectively. Every time new data arrive, the damage variables (ρ_n, D_n) together with model parameters θ_n are updated using a SIR algorithm with N=500 particles. This information is further used to propagate the models into the future to compute the RUL, calculated as: $RUL_n = EOL_n - n$, using the methodology described in Section 4.1. For this example, the useful domain is defined as $\mathcal{U} = \{(\rho, D) \in [0, 0.42] \times [1, 0.88]\} \subset \mathbb{R}^2$. The predictions of RUL are plotted against time in Figure 1c.

Observe that the RUL prediction is appreciably inaccurate within the first stage of the fatigue process. This stage corresponds to the interval of cycles required for data to train model parameters. From this period, the prediction precision clearly improves with time. We use the two shaded cones of accuracy at 10% and 20% of true RUL, denoted as RUL* to help evaluating the prediction accuracy and precision. Notice also in Figure 1a that accuracy seems to depart from true RUL at the final stage, which indicates that the model and its variance structure do not fully capture the damage dynamics towards the end. Such behavior have been previously reported in (Saxena, Celaya, Saha, Saha, & Goebel, 2010) and may be related with the asymptotic behavior of the micro-crack evolution, which requires more efficient algorithms for prognostics in such cases.

To show the time-varying reliability prediction of the material, a multi-step forward prediction of the health state is computed every time new SHM data arrive, using the methodology described in Section 4.2. Figure 2 shows several examples of time-varying reliability predictions at different cycles. Observe in figure 2a that the prediction gradually improves as more SHM data are available. Note also that the prediction of the cycle for which reliability vanishes is consistent with the RUL estimation.

6. CONCLUSIONS

A SHM-based prognostics framework to predict the remaining useful life and reliability of composites under fatigue conditions is proposed. We consider physics-based models for damage evolution due to the benefits for estimating the RUL and reliability. Two damage variables, micro-cracks density and stiffness loss, are simultaneously considered to represent the health state of the laminate. The validity of this framework is demonstrated on SHM data collected from a tensiontension fatigue experiment using CFRP cross-ply laminate. Reliability emerges as a suitable unified system-health indicator for prognostics, as it encapsulates information of the system health state while it allows predicting the RUL of the system. More research effort is need to achieve more efficient prognostic algorithms to improve the accuracy at the final stage of the process, where damage typically reaches an asymptotic behavior, and to incorporate other damage features like delamination in the proposed model-based framework.

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NOMENCLATURE

h	Laminate half-thickness
$E_x^{(\phi)}$	Longitudinal Young's modulus
$E_y^{(\phi)}$	Transverse Young's modulus
$\nu_{xy}^{(\phi)}$	In-plane Poisson ratio
t_{90}	$[90_{n_{90}}]$ -sublaminate half-thickness
t_{ϕ}	$\left[\phi_{\frac{n_{\phi}}{2}}\right]$ -sublaminate thickness
t	Ply ^{thickness}
E_1	Longitudinal Young's modulus
E_2	Transverse Young's modulus
ν_{12}	In-plane Poisson ratio
\sim	

 G_{23} Out-of-plane shear modulus

REFERENCES

- An, D., Choi, J.-H., & Kim, N. H. (2013). Prognostics 101: A tutorial for particle filter-based prognostics algorithm using matlab. *Reliability Engineering & System Safety*, 115, 161–169.
- Arumlampalam, M., Maskell, S., Gordon, N., & Clapp, T. (2002). A tutorial on particle filters for on-line nonlinear/non-Gaussian Bayesian tracking. *IEE Transactions on Signal Processing*, 50(2), 174–188.
- Beaumont, P., Dimant, R., & Shercliff, H. (2006). Failure processes in composite materials: getting physical. *Journal of Materials Science*, *41*(20), 6526–6546.
- Beck, J. L. (2010). Bayesian system identification based on probability logic. *Structural Control and Health Monitoring*, 17, 825–847.
- Cadini, F., Zio, E., & Avram, D. (2009). Monte Carlo-based filtering for fatigue crack growth estimation. *Probabilistic Engineering Mechanics*, 24, 367–373.
- Chiachío, J., Chiachío, M., Saxena, A., Rus, G., & Goebel, K. (2013). An energy-based prognostics framework to predict fatigue damage evolution in composites. In *Proceedings of the conference* (Vol. 1, pp. 45–49).
- Chiachío, J., Chiachío, M., Saxena, A., Sankararaman, S., Rus, G., & Goebel, K. (2014). Bayesian model class selection and parameter estimation for fatigue damage progression in composites. *Submitted to International Journal of Fatigue*.
- Chiachío, M., Chiachío, J., & Rus, G. (2012). Reliability in composites - A selective review and survey of current development. *Composites Part B*, 43(3), 902–913.
- Daigle, M., & Goebel, K. (2010). A model-based prognostics approach applied to pneumatic valves. *International Journal of the PHM Society*, 2(8), 16.
- Daigle, M., & Goebel, K. (2011). Multiple damage progression paths in model-based prognostics. In *Aerospace conference*, 2011 IEEE (pp. 1–10).
- Daigle, M. J., & Goebel, K. (2013). Model-based prognostics with concurrent damage progression processes. Systems, Man, and Cybernetics: Systems, IEEE Transactions on, 43(3), 535-546.
- Doucet, A., De Freitas, N., & Gordon, N. (2001). Sequential monte carlo methods in practice. Springer Verlag.
- Dym, C., & Shames, I. H. (2013). Solid mechanics: A variational approach, augmented edition. Springer.
- Garrett, K., & Bailey, J. (1977). Multiple transverse fracture in 90° cross-ply laminates of a glass fibre-reinforced polyester. *Journal of Materials Science*, *12*(1), 157– 168.
- Gobbato, M., Kosmatka, J. B., & Conte, J. P. (2014). A recursive bayesian approach for fatigue damage prognosis: an experimental validation at the reliability component level. *Mechanical Systems and Signal Processing*, 45, 448–467.

- Guan, X., Jha, R., & Liu, Y. (2011). Model selection, updating, and averaging for probabilistic fatigue damage prognosis. *Structural Safety*, *33*(3), 242–249.
- Gudmundson, P., & Weilin, Z. (1993). An analytic model for thermoelastic properties of composite laminates containing transverse matrix cracks. *International Journal* of Solids and Structures, 30(23), 3211–3231.
- Hashin, Z. (1985). Analysis of cracked laminates: a variational approach. *Mechanics of Materials*, 4(2), 121– 136.
- Highsmith, A., & Reifsnider, K. (1982). Stiffness-reduction mechanisms in composite laminates. *Damage in composite materials, ASTM STP*, 775, 103–117.
- Jamison, R., Schulte, K., Reifsnider, K., & Stinchcomb, W. (1984). Characterization and analysis of damage mechanisms in tension-tension fatigue of graphite/epoxy laminates. *Effects of defects in composite materials, ASTM STP*, 836, 21–55.
- Joffe, R., Krasnikovs, A., & Varna, J. (2001). Cod-based simulation of transverse cracking and stiffness reduction in $[S/90_n]_s$ laminates. *Composites Science and Technology*, 61(5), 637-656.
- Joffe, R., & Varna, J. (1999). Analytical modeling of stiffness reduction in symmetric and balanced laminates due to cracks in 90 layers. *Composites Science and Technology*, 59(11), 1641–1652.
- Kantas, N., Doucet, A., Singh, S. S., & Maciejowski, J. M. (2009). An overview of sequential monte carlo methods for parameter estimation in general statespace models. In *15th* IFAC Symposium on System Identification (Vol. 15).
- Larrosa, C., & Chang, F. (2012). Real time in-situ damage classification, quantification and diagnosis for composite structures. In *Proceedings of the 19th International Congress on Sound and Vibration* (Vol. 15).
- Lee, J., Allen, D., & Harris, C. (1989). Internal state variable approach for predicting stiffness reductions in fibrous laminated composites with matrix cracks. *Journal of Composite Materials*, 23(12), 1273–1291.
- Liu, J., & West, M. (2001). Combined parameter and state estimation in simulation-based filtering. In A. Doucet, N. Freitas, & N. Gordon (Eds.), *Sequential monte carlo methods in practice* (p. 197-223). Springer New York. doi: 10.1007/978-1-4757-3437-9₁0
- Lundmark, P., & Varna, J. (2005). Constitutive relationships for laminates with ply cracks in in-plane loading. *International Journal of Damage Mechanics*, *14*(3), 235– 259.
- Manders, P. W., Chou, T.-W., Jones, F. R., & Rock, J. W. (1983). Statistical analysis of multiple fracture in 0/90/0 glass fibre/epoxy resin laminates. *Journal of Materials Science*, 18(10), 2876–2889.
- Myötyri, E., Pulkkinen, U., & Simola, K. (2006). Application of stochastic filtering for lifetime prediction. *Reliability*

Engineering & System Safety, 91(2), 200–208.

- Nairn, J., & Hu, S. (1992). The initiation and growth of delaminations induced by matrix microcracks in laminated composites. *International Journal of Fracture*, 57(1), 1–24.
- Nairn, J. A. (1989). The strain energy release rate of composite microcracking: a variational approach. *Journal of Composite Materials*, 23(11), 1106–1129.
- Nairn, J. A. (2000).

In R. Talreja & M. J.A.E. (Eds.), *Polymer matrix composites* (pp. 403–432). Amsterdam: Elsevier Science.

- Reddy, J. (2002). *Energy principles and variational methods in applied mechanics*. Wiley.
- Reifsnider, K., & Talug, A. (1980). Analysis of fatigue damage in composite laminates. *International Journal of Fatigue*, 2(1), 3–11.
- Saltelli, A., Ratto, M., Tarantola, S., & Campolongo, F. (2006). Sensitivity analysis practices: Strategies for model-based inference. *Reliability Engineering & System Safety*, 91(10), 1109–1125.
- Saxena, A., Celaya, J., Saha, B., Saha, B., & Goebel, K. (2010). Metrics for offline evaluation of prognostic performance. *International Journal of the PHM Society*, 1(1), 20.
- A., Saxena, Goebel, K., Larrosa, C., & Chang, F. (2008).CFRP Composites dataset. (NASA Ames Prognostics Data Reposi-[http://ti.arc.nasa.gov/project/prognostic-datatory, repository], NASA Ames, Moffett Field, CA)
- Saxena, A., Goebel, K., Larrosa, C., Janapati, V., Roy, S., & Chang, F. (2011). Accelerated aging experiments for prognostics of damage growth in composites materials. In *The 8th International Workshop on Structural Health Monitoring*, F.-K. Chang, editor. (Vol. 15).
- Storvik, G. (2002). Particle filters for state-space models with the presence of unknown static parameters. *Signal Processing, IEEE Transactions on*, 50(2), 281–289.
- Talreja, R., & Singh, C. V. (2012). Damage and failure of composite materials. Cambridge University Press.
- Varna, J., Akshantala, N. V., & Talreja, R. (1999). Crack opening displacement and the associated response of laminates with varying constraints. *International Journal of Damage Mechanics*, 8(2), 174–193.
- Zio, E., & Di Maio, F. (2012). Fatigue crack growth estimation by relevance vector machine. *Expert Systems with Applications*, 39(12), 10681–10692.

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Table 1. Ply properties used in the calculations.

Figure 1. Results for sequential estate estimation for (a) micro-crack density, (b) normalized longitudinal Young's modulus and (c) remaining useful life. At each cycle n, the filtered estimation is calculated using the data available up to that cycle.



Figure 2. Time-varying reliability prediction at different cycles along the process. At each cycle n, the estimation is calculated using the data available up to that cycle.

On-board SHM System Architecture and Operational Concept for Small Commuter Aircraft

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ABSTRACT

Significant R&D progress has been done in the area of SHM technologies in recent years. However real SHM application on aircraft board is still challenging and puts specific requirements on the SHM system design and operation. These challenges include assurance of reliable and provable damage detection capabilities, taking over decision-making responsibilities instead of a human inspector and other challenges related to on-board installation and operation during the flight. Further, minimal weight and dimension, and system reliability and durability should be considered. Due to these challenging requirements the SHM has not been widely implemented in aerospace industry yet.

The paper deals with system architecture and operational concept of SHM system for L-410 NG commuter aircraft. The SHM system is based on excitation, sensing and analysis of ultrasonic guided waves using PZT actuators / sensors. The SHM system is designed for monitoring of PSEs of metallic airframe that are hard to access or completely inaccessible for common inspection methods used in the aircraft maintenance. The design puts emphasis on integration of the SHM system within aircraft avionic system in order to achieve highly automated data acquisition and data transfer process to make the health data available for on-ground analysis. Finally, scenario of the SHM system operation in accordance to the L-410 NG maintenance plan is proposed in the paper. The scenario assumes replacement of common inspections that are done within regular maintenance checks by the automated inspections using SHM system. Challenges of the proposed scenario from the point of view of the aircraft certification and operation are discussed as well.

1. INTRODUCTION

Effort to utilize all aircraft parts and components efficiently

leads to transition to on Condition Based Maintenance (CBM) philosophy with taking into account real operating conditions and load. In the area of aircraft structure, the CBM approach to aircraft maintenance is enabled by implementation of "Structure Health Monitoring" (SHM) system, which monitors actual state of aircraft structure parts. Maximum efficiency of SHM system application can be achieved if it is taken into consideration during aircraft design and development phase. This allows SHM system integration into avionics information systems, which is in compliance with current trends in the development of new aircraft and higher-order innovation in the elderly types.

This paper describes the architecture of on-board SHM and its concept of operation. The work aims to establish a precedent of using this perspective SHM system and its installation on a small commuter aircraft. In particular, SHM system for the L-410 NG is being developing as a part of the aircraft modernization efforts where the damage tolerant design philosophy is applied for specified Principal Structural Elements (PSEs), which are prone to fatigue damage. The damage tolerance design philosophy is based on the scheduled inspection plan for fatigue cracks detection. Analysis, which was done in connection with the aircraft design under Damage tolerance philosophy, revealed advantageousness of the SHM methods application for PSEs with short inspection interval, PSEs with limited life or for PSEs prone to Multi-Site Damage (MSD), i.e. parts with multi-focal cracks growth, typically riveted lap joints in aircraft fuselages or wings.

2. ON-BOARD SHM REQUIREMENTS

The main function of the SHM is the aircraft structure monitoring during the whole aircraft life. This puts several requirements on the on-board SHM system design and installation:

• Minimal impact on the aircraft design and manufacturing. Optimization of the sensor layout and sensor wiring to minimize need for modifications of the

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adjacent structure has to be assured. The sensor installation process should be as simple as possible to minimize influence on the aircraft manufacturing and assembly. Optimally, it should be possible to install sensors on aircraft, which is already in operation. This requirement should be taken into account in design of sensor network distribution, connections, wiring and sensor bonding technology.

- Low weight and small dimensions are the most important requirements on the SHM system design from the point of view of ecomonical utilization of the aircraft. Practical applicability of the SHM system and benefits of the application are strongly dependent on these parameters. Evaluation of SHM benefits against its weight influence on the aircraft payload has to be taken into account.
- System modularity and installation versatility has to be assured due to a variety and high number of monitored aircraft structural areas. These system properties would minimize SHM design and installation costs.
- Long-term system operation without maintenance need is required. The SHM system life has to exceed the life of the monitored structure in case of inaccessible areas monitoring. The system has to be designed with respect to all adverse environmental service conditions and safety requirements. Thus, reliable solution or functional system backup is required.
- Automated operation and integration with overall avionics system is the key factor of its effective and advantageous deployment with regards to all system capabilities and benefits utilization. It includes high frequency/continuous monitoring on the individual aircraft. It results in an increase of safety of the aircraft operation in comparison to current approach. The current scheduled inspection plan is based on the assumed crack growth behavior dependent on supposed typical loading. On the other hand, the SHM provides information about the real state of the monitored structure. Further, high level of automation minimizes impact of human factor on the results of the inspection.

All those described requirements have been considered during the on-board concept development including requirements resulting from standards and regulations related to the commuter category: EASA CS-23, RTCA DO-160, RTCA DO-178 and RTCA-DO 254. Further, the Guidance on Structural Health Monitoring for Aerospace (ARP6461) has been considered and appropriet recommendations have been applied during the SHM concept preparation.

3. SHM SYSTEM ARCHITECTURE

Scheme of the conceptual SHM system architecture is shown in the Figure 1. The system consists of on-board and on-ground parts. Each PSE selected for monitoring of its health is equipped with permanently installed sensor network, which is particularly designed and optimized for the PSE. The sensor network is controlled by SHM hardware (HW). The SHM HW is connected to Central Maintenance Computed (CMC), which controls the SHM system operation, i.e. initiates collection of the data for particular PSE, stores the data, provides indication of correct functionality of the monitoring system for individual PSE and allows transfer of the data to the ground unit for further processing and evaluation. The ground unit consists of a computational device with installed software for the signal processing and evaluation of the health of individual PSE, which includes defect indication, localization, and estimation of severity / size of the defect alternatively PSE Remaining Usage Life (RUL) estimation.



Figure 1. General Concept of SHM system

4. ON-BOARD SHM SYSTEM ARCHITECTURE

The on-board part of the SHM system (Figure 2) can be described as a distributed modular system respecting structural design and PSEs selected for the monitoring. The modularity of the SHM system design allows various numbers of sensors connection in different net configurations. The redesign of elementary system modulus is not necessary in case of its application on different structural parts. The SHM system, for which the architecture is designed, is based on technology of generation / registration of ultrasonic surface waves using simple PZT actuators. However, the architecture is general enough to be implemented with other SHM technologies or their combinations.



Figure 2. On-board SHM System Architecture

Particular application of the SHM on-board architecture consists of local PZT sensor nets, sensor switches and sensor control unit (SCU). Local sensor nets are attached on monitored structural parts and controlled by small lightweight switches localized in the vicinity of sensor nets. A BUS topology is used for the switches connection to the SCU. This topology allows connection of various numbers of sensor switches and sensor network complexity optimization.

The SCU provides several functions. First group of functions relates to sensors signals generation, sensor signal responses registration, temperature measurement and sensor control. The measuring period and other required settings for different PSEs are individually set in dependance on the particular structural element criticality and localization. Further, the SCU performs data pre-processing, temporary storing and transfer/communication to the CMC with usage of a standard communication protocol (e.g. ARINC 429). The SCU is designed for the independent operation (data collection in defined intervals). This operational independence minimizes burdening of the CMC modulus, which main function is initiation and termination of the measurement by the SCU and transfer of measured data from SCU to the on-ground processing.

5. OPERATIONAL CONCEPT

Nowadays, maintenance of the aircraft using damage tolerance philosophy for the structure design is characterized by scheduled structural inspections. General Visual Inspections (GVI) are done and Non-Destructive Testing (NDT) methods are used by maintenance staff to inspect structure in details. Threshold interval of the inspection introduction, interval of inspection recurrence and particular inspection method is defined for all PSEs. Any structural damage has to be detected before its critical level is reached causing aircraft failure.

Certification and operation of the SHM system with deployment of its full capabilities is challenging nowadays. It is caused by no-existence of legislative allowing certification and operation of SHM for continuous on-board monitoring of aircraft structure damage, e.g. aircraft operation with known structure damage is not allowed. Therefore, we choose following strategy for the SHM system transition to real operation on the aircraft.

An operational concept of the parallel periodical maintenance checks related to damage tolerance and SHM system measurements is used in the first phase of SHM implementation into L-410 NG maintenance manual (Figure 3). SHM structural checks are carried out during the aircraft service in the automatic way. Data from sensors are automatically measured and stored on-board for further processing on the ground. The process of data transfer and evaluation is not fully automated. The pilot or maintenance crew assistance is needed for data transfer initialization and execution. The data processing and evaluation is done by maintenance or structure specialist on the ground and results are provided to maintenance staff.



Figure 3. Operational Concept of SHM System in the first phase.

Running SHM system as a parallel / alternative means of inspection to the standard inspection procedures allows for long term data collection and comparison of results provided by SHM to the standard inspection methods. This will allow building confidence in reliability, accuracy and durability of the SHM solution, which is critical from the point of view of qualification of the SHM technology for commercial application. The SHM system has to fulfill same certification requirements and regulations as NDT methods for the damage monitoring, (probability of detection - 90 percent with confidence level of 95 percent). The SHM system on-board installation brings additional requirements on high level of technical durability and functionality (e.g. durability of sensors and wiring > 30years, environmental resistance - meeting RTCA DO-160 standard).

The operational concept of fully automated & integrated SHM system will be implemented in the second phase. Schematic drawing of the concept is shown in the Figure 4.



Figure 4. Operational Concept of Fully Automated & Integrated SHM System

Now the SHM system takes over the full responsibility in the area of the structural damage monitoring. All structural damage related inspections are fully covered by SHM system monitoring. It results in decrease of the burdening structural maintenance time. The life limitation of particular PSE is determined by the instant when a structural damage is detected by the SHM system. The structural health is monitored by the automated SHM system with arbitrary periodicity during all phases of the aircraft service. The periodicity of inspections can be very high resulting almost into continuous monitoring. In this case, the CMC provides automated and seamless data transfer to the ground for the following data processing and evaluation. There are several ways of the data dispatching from the aircraft to the ground: SATCOM (during flight) or WiFi (at the gate).

The on-ground data processing is fully automated. Responsibility for correctness of diagnostic results is on the integrated SHM system, which significantly degrease requirements on expertise of the maintenance staff. This concept opens door for implementation of wide range of various maintenance and logistic support services including deployment of Remaining Usage Life (RUL) estimation for predictive maintenance usage, advanced maintenance and logistic planning, wide-fleet management and others. These services will be used not only by the maintenance organizations but they can be also advantageously used by operators and manufactures of aircraft.

6. CONCLUSIONS

The paper describes an approach to the SHM system application on the small commuter aircraft. Two main topics are discussed: SHM architecture and SHM operational concept.

The most important feature of the proposed on-board SHM system architecture is its modularity. This allows for

monitoring arbitrary PSE on the airframe, minimization of the SHM system weight, optimization of the SHM system architecture and facilitation of its installation and integration with structure. Further, the modular architecture provides scalability of the SHM solution even for large aircraft platforms.

Two operation concept of the SHM system for implementation into the aircraft maintenance plan are discussed in the paper. In the first phase, the parallel SHM system operation to regular structural inspections is utilized for SHM system on-board introduction, installation issues fixing and its operation capabilities testing and verification. All SHM functions are not fully automated in this phase. The data transfer, data processing and heath status assessment requires involvement of the maintenance staff and structural specialist.

The SHM system takes over the full responsibility in the second phase. All structural damage related inspections are replaced by the automated SHM system. Applied automation and integration level increases the SHM application potential. Besides minimization of maintenance tasks done by maintenance staff, it enables other services as fleet-wide maintenance management, advanced maintenance and logistic planning and implementation of predictive maintenance strategies.

The SHM system development is still in progress. It is expected that results of current work will open way to the SHM system operational deployment in serial aircraft production.

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NOMENCLATURE

ARINC	Standard communication protocol
ATA	Air Transport Asociation
СМС	Central maintenance computer
EASA	European agency for civil aviation
FAA	Federal Aviation Administration
FH	Flight hour
FPC	Flexible printed circuit
GVI	General visual inspection
MSD	Multiple side damage
NDT	Non- Destructive Testing
PSE	Principle Structure Element
PZT	Lead Zirconate Titanate
RUL	Remaining Usage Life
SCU	Sensor Control Unit
SHM	Structure Health Monitoring

REFERENCES

- European Aviation Safety Agency (EASA). Part 23 Certification Specification for N, U, A and Commuter Category Aeroplanes
- RTCA DO-160 Environmental conditions and test procedures for on-board equipment
- RTCA DO-178 Software Considerations in Airborne Systems and Equipment Certification
- RTCA DO-254 Design Assurance Guidance for Airborne Electronic Hardware
- SAE ARP6461 Guidance on Structural Health Monitoring for Aerospace

BIOGRAPHIES



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Cure Monitoring of Composite Carbon/Epoxy through Electrical Impedance Analysis

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ABSTRACT

Composite materials are increasingly used in aeronautic; they offer many benefits such as mechanical strength, mass and consumption reduction. However, their process development needs to be known and controlled, in order to adjust the process parameters and optimize the characteristics of structures made from these materials. This paper is focused on impedance spectroscopy measurement and analysis technique to characterize material's properties. In fact, the composites based on carbon fiber have electrical proprieties; therefore a three-dimensional modeling of the electrical conduction in the material is established by using a distributed allocation of an electrical resistance (R_P) in parallel with a capacitance (C_P) . Then, thin electrodes (40 um thick) are inserted inside the material and a specific impedance measurement bench is developed to perform real-time measurements of R_P and C_P on unidirectional (UD) mono-ply and multi-plies samples. During curing (in an oven) the change in values of both R_P and C_P in different stages of the curing cycle is showed. Then, problems that occur during the curing cycle (layup defect, loss of vacuum) were detected by a large gap of the measured electrical parameters in comparison with the ordinary case. Therefore, by this electrical measurement, we present a way to ensure an automated real-time monitoring of the composite curing process.

1. INTRODUCTION

Carbon Fiber Reinforced Polymers (CFRP) are highly used for the high mechanical performances as regards with their low density. An answer in how optimize their properties can be found in the knowledge and the control of parameters linked to the material itself (voids, percolation network, fiber and resin ratios, etc.) and to the cycle (temperature, pressure, vacuum) during curing.

In order to provide more elements to monitor composite cure process, various works have been undertaken by means of dielectric sensors, optical fiber sensors and piezoelectric sensors, etc. These techniques often required sensors to be embedded, thus could affect the mechanical properties of the structure or their use could be tricky. However, another interesting approach is to investigate the behavior of the material by considering the material itself as a sensor and measuring its electrical properties. Some studies are focused on the measurement of the resistance (R) or the capacitance (C) or better still on the measurement of the impedance (Z).

Ryan, Carolyn and Karim (2002) propose to use the measurement of the capacitance as an indicator to reduce the curing time; but notify the need of further studies to determine a relationship between the change of capacitance and temperature or the degree of cure. Inada and Todoroki (2005) use two electrodes placed on the surface of the material. They consider the material as a parallel RC circuit and perform a frequency analysis of the dielectric permittivity to study the change of the capacitance. They established an estimate of the degree of cure, but they talk about errors that are caused by the decision of the end point of perfect cure.

Shoukai and Chung (1999) burn out the ends of the material to expose the carbon fibers for the purpose of making electrical contacts. The exposed fibers are wrapped by pieces of copper foil, with silver paint between the copper and the fibers. They show that the resistance of the material depends on the direction of currant flow, temperature and pressure. Joung-Man, Sang-II and Jin-Ho (2005) for their part, perform resistive measurements on a single carbon fiber embedded in an epoxy resin, they were able to assess the residual stresses and temperature during curing.

The previous works of Marguerès, Camps, Viargues and Olivier (2013) have been show that it is possible to monitor the evolution of the behaviour of the material during its cure

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cycle by using flexible printed electrodes (inserted inside the material) and an associated acquisition system. They also consider the material as a parallel RC circuit and perform the impedance analysis to provide the online change of the resistance and the capacitance during curing. The evolution over time of the measured electrical parameters (R and C) matches the evolution of the rheological parameters studied by standard methods (obtained on a parallel plate rheometer); more than ten points of agreement were established.

Indeed, the purpose of this paper is to continue previous studies of Marguerès et all (2013). The composite material studied is made from T700/M21 prepregs (pre-impregnated plies) used in aeronautic and space industry. This material has conductive and insulating parts (long carbon fiber and epoxy resin) and its electrical conduction properties depend on the fibers orientation. Firstly, a three-dimensional (3D) model of the electrical conduction is made to describe the material's anisotropy. This model consists of a resistance and a capacitance connected in parallel (R_P and C_P). Thin copper electrodes (40 µm thick) inserted in the material, depending on the fiber orientation, serve as measuring elements. A specific impedance measurement bench has been developed to achieve real-time measurements of R_P and C_P. The sensitivity of this R_P and C_P depending on the different stages of the curing cycle to detect a defect is studied here. All this aims to provide a monitoring and possibly to real-time control the curing cycle to obtain the desired properties of the produced CFRP structures.

2. MODELING OF ELECTRICAL CONDUCTION

The used prepregs are unidirectional and 250 μ m thick. The matrix is a M21 epoxy resin. The reinforcement is made of high strength carbon fibers (7 μ m diameter). The studied materials are mono-ply samples but also unidirectional laminates (multi-plies with fibers oriented in the same direction). This unidirectional (UD) orientation confers anisotropic electrical properties.

Thus, this material contains a conductor part (fibers) and an insulator part (resin). So it is suitable to perform impedance analysis using a frequency sweep (here from 10 Hz to 1 MHz). The resistive conduction is linked to the conduction through the fibers and the percolation points, and it is predominant at low frequency. The capacitive conduction (through resin and voids) is predominant at high-frequency. To establish a three dimensional model of the electrical conduction inside the composite material, the axes of the electrical conduction are defined as follows:

1. In the fiber plane (intra-ply): Two types of conduction are possible. A longitudinal conduction in the fibers (intra-fibers intra-ply conduction), and a transverse conduction which is perpendicular to the fibers orientation (inter-fibers intra-ply conduction). The longitudinal impedance measurements are delicate, because the low value of the corresponding resistance induces distortions on capacity measurement. That is why, in our model, only the resistive conduction along the fibers is considered (measured at 10 Hz). The intrafibers conduction corresponds to the current flow in the fibers and through the percolation points. But the interfibers conduction is mainly due to the current flow through the percolation points. At high frequency only the inter-fibers capacitive conduction in the resin is considered and measured at 100 kHz. Finally, the longitudinal conduction is modeled as distributed resistances, while transverse conduction as resistances and capacitances in parallel (figure 1).

2. In the thickness plane (inter-plies): The electrical conduction is considered as the same as the inter-fibers conduction (in red in figure 1).

Finally, the complete electrical model equivalent to a unidirectional multi-plies composite material can be considered as a cascaded structure of hexapole nodes.



Figure 1. 3D electrical conduction model of the multi-plies composite material.

3. EXPERIMENTAL SET-UP

The mono-ply sample is a prepreg placed on an epoxy substrate. The measuring electrodes are inserted between prepreg and substrate (see figure 2.a). The multi-plies samples contain up to 24 plies ($10 \times 10 \text{ cm}^2$). Before curing, thin flexible electrodes (flexe) are inserted between two consecutive plies in order to reduce interfaces resistances (see figure 2.b). A flexe is a copper tape which is 40 µm-thick, 6mm-wide and 20 cm-long. It is covered with polyimide film (kapton, 35 µm thick) at masking areas (outside the material). A frequency sweep of the sinusoidal current at constant amplitude, combined with the alternating voltage measurement (amplitude and phase), allows establishing frequency evolution of complex electrical impedance (Z) for our electrical model, as shown in the following equation:
$$Z = \frac{R \times \frac{1}{jC\omega}}{R + \frac{1}{jC\omega}} = \frac{R}{1 + jRC\omega}$$
(1)

Where : *R* is the resistance ; *C* the capacitance ; *f* the frequency ; ω the angular velocity ($\omega = 2\pi f$).

From this expression, measurement at low frequency allows determination of resistance, while the capacitance measurement is optimal at high frequency. The developed acquisition bench allows real time measurement of the overall electrical impedance parameters R_P and C_P on samples during their curing process.



Figure 2. Mono-ply (2.a) and multi-plies (2.b) samples.

4. PRELIMINARY STUDIES

The post-curing measurements on the composite mono-ply and multi-plies samples were used to validate the model and to bring out the values levels of the measured parameters. The fibers resistivity in the longitudinal intra-ply measurement is $15.10^{-5} \Omega$.m; its determination is difficult because of the presence of significant contacts resistances R_C (1 to 4 Ω) which disrupts measurement. These contacts resistances have random values with a large dispersion (400%) and impose 4-points measurement method. The transverse inter-fibers measurement shows a resistivity about 1.5 Ω .m and the transverse inter-plies measurement shows the higher values of resistances with a resistivity equal to 4.5 Ω .m. In both previous transverse inter-fibers and inter-plies cases, 2 points measurement method is used because contacts resistances effects are negligible.

5. CURE MONITORING

The real-time measurements were achieved during curing, in an oven, using mono-ply samples (for longitudinal intrafibers and transverse inter-fibers conductions) and multiplies UD samples (inter-plies conduction).

The longitudinal intra-fibers measurements show sporadic variations of R_P and C_P ; this is due to the low resistances values and also mainly the preponderance of the contact resistances between fibers and electrodes (as described above). Both transverse measurements show variations of R_P and C_P correlated to the changes in the material state.

The figure 3 shows the results of transverse inter-plies R_P and C_P measurements during curing. The electrodes are inserted between plies 1 and 2, and plies 23 and 24 (figure 2.b). As expected, the resistance R_P decreases over time from 30 k Ω to few hundred ohms (220 Ω). This is due to the contacts improvements between fibers and electrodes and also to the increasing of the percolation network. The changes in C_P during curing show two peaks; the first corresponds to the point of polymer liquefaction and the second to the gel point.



Figure 3. Changes in R_P and C_P during curing.

To prove the advantage of our measurements, we caused vacuum loss when curing. This incident is visible on the values of R_P and C_P (figures 4.a and 4.b). After curing, there is also a large difference between the values obtained in the curing with an incident and those measured under normal curing condition. Thus we have obtained, in the case with an incident, a resistance around 18 k Ω against 220 Ω in ordinary or normal curing.

This loss of vacuum, caused by a bad layup, limits material compaction during liquefaction and it manifests itself by the high value of the resistance (less percolation points) or low value of the capacitance (more polymers between fibers). Therefore, it is possible to make a cure monitoring or to use a standard (benchmark) to determine the quality of a curing cycle.



Figure 4. Loss of vacuum detection using R_P (4.a) and C_P (4.b) measurement during curing.

6. CONCLUSION AND OUTLOOK

Thanks to a simple and robust instrumentation, with flexible thin electrodes, an electrical impedance spectroscopy was carrying out inside of carbon composite material T700/M21. These electrodes associated with an acquisition system allow tracking material's behaviors during curing in an oven. Over time evolution of the measured electrical parameters R_P and C_P is according to different states of the material. Then, a loss of vacuum was detected by a large gap of these electrical parameters. In fact, in manufacturing, incidents during layup or curing can cause errors in the matrix/fibre or voids volume fractions, or even structural defects (delamination, imperfect ply-drop etc.). Therefore this monitoring can be used to control or to optimize the manufacturing processes of composite materials.

Furthermore, after curing these flexible electrodes facilitate access inside of material and can be used, either for monitoring the health of composite material during the phases of conditioning and service, or to access to nanoparticles that can be added in polymer.

REFERENCES

- Ryan, M., Carolyn, P., & Karim, Y. (2002), Insulation Cure Monitoring on Global VPI Large AC Motors. *Proceedings of IEEE Symposium on Electrical Insulation*, April 7- 10, Boston, MA USA. doi:10.1109/ELINSL.2002.995982
- Inada, T., & Todoroki, A. (2005). Smart Cure Monitoring Method of Carbon/Epoxy Laminates using Electric Capacitance Change with Applied Alternating Current Frequency. *Key Engineering Materials*, Vols. 297-300, pp. 2903 - 2908. dio: 10.4028/www.scientific.net/KEM.297-300.2903
- Shoukai, W., & Chung, D.D.L. (1999). Apparent negative electrical resistance in carbon fiber composites. *Composites*, Part B 30, pp. 579 - 590. dio: 10.1016/S1359-8368(99)00021-9
- Joung-Man, P., Sang-II, L., & Jin-Ho, C. (2005). Cure monitoring and residual stress sensing of single-carbon fiber reinforced epoxy composites using electrical resistivity measurement. *Composites Science and Technology*, Vol. 65, pp. 571–580. doi:10.1016/j.compscitech.2004.09.019
- Marguerès, P., Camps, T., Viargues, M., & Olivier, P. (2013). Preliminary experimental study on the electrical impedance analysis for in-situ monitoring of the curing of carbon/epoxy composite material for aeronautical and aerospace structures. *Meas. Sci. Technol*, Vol. 24, 095005 (10pp). doi:10.1088/0957-0233/24/9/095005

Structural Health Monitoring of Composite Structures using embedded PZT Sensors in Space Application

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ABSTRACT

The use of composite structures in the space domain has increased significantly over the past years owing to its high strength to weight ratio. Because of the criticality and huge amount of money associated with these missions, there is an urgent requirement to monitor the structural integrity and its degradation by novel SHM techniques.

In this paper we use ultrasonic guided wave technology and study the different possibilities of embedding piezoelectric sensors (PZT) into the carbon composites made by filament winding. We demonstrate the sensing capabilities of our developed sensor system to damages which can arise due to any accidental low-energy impact. A series of lab test was conducted on composite coupons to inspect the ability of PZT sensors to detect individual damages with high probability based on their distance from the impact location. The results show that PZT sensors are very promising in detecting all the damages caused by impacts with varying energies and can be a possible answer to needs of the structural health monitoring and non-destructive evaluation of advanced space structures.

1. INTRODUCTION

Composite materials are currently believed to be the cutting edge technology for the future space vehicles. There exist many different composite materials and many different ways of their manufacturing (Harris et al., 2002). The main advantage of composites is much lower weight and higher strength than classical metallic structures. Although they are utilized very often, there is still significant lack of understanding of their mechanical properties and related risks (Chiachio et al., 2012). Behavior of the composite materials is very complex and its proper investigation requires many experiments and theoretical modeling (Chiachio et al., 2013).

Composite structures manufactured for space industry must meet strict criteria because their failure could cause fatal damage of the vehicle. Among some of the most critical composite space structures belong pressure vessels, which store propellant. A Composite Overwrap Pressure Vessel (COPV) is a vessel with metallic liner overwrapped by nonmetallic fibers. Maximal operating pressure in standard COPV can reach up to 300-400 Bars and therefore the whole structure must be absolutely flawless otherwise it would cause immediate burst. Details about COPV design can be found in (Ni & Chang, 2012).

Currently, the COPVs for space industry are very carefully tested by various nondestructive techniques (NDT) directly after manufacturing. Apart from visual inspection, the COPVs are usually tested by acoustic emission, eddy currents, thermography, ultrasound, shearography etc. (Ni & Chang, 2012). These methods often require special test beds and highly skilled operators.

However, the flawless state of the COPV after manufacturing does not imply the same flawless state before its final inflation for launching to space. During transportation of COPV from the manufacturer to assembly place and also following installation to the spacecraft (satellite, rocket...) there is a risk of an accidental damage on the tank. Typically, it can be accidental tool impact during installation or collision of the tank with any other object. Although these accidents have quite low energies, their consequences can be fatal. From the security perspective, the COPV should be tested before launching. However, it is not possible by conventional NDT methods because the whole tank's surface is usually not accessible. Currently, this issue is mitigated by designing COPVs with security margins (winding redundant carbon layers ...), which makes tanks more heavy and expensive.

Another way of avoiding this issue is installation of suitable sensor system directly into COPV structure. Data from these

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integrated/embedded sensors can be processed and used for testing presence of defect or damage without any direct access to the tank. This approach is known as Structure Health Monitoring (SHM). There are currently several technologies which are able to monitor COPV directly without human interaction and among some of the most promising ones are Fiber Bragg Gratings (FBG) and Ultrasonic Guided Wave (UGW) method. FBG technology uses sensors embedded in optical fibers and monitor differences in the local stresses. FBG sensors were successfully integrated between metal liner and composite overwrap or directly into the overwrap of COPV for instance by (Grant, 2005) or (Pereira et al., 2013). The UGW uses piezoelectric sensors and propagate ultrasonic waves through the structure. For general review of UGW see e.g. (Raghavan & Cesnik, 2007). This approach has been used for monitoring many different types of structures and damages (e.g. fatigue (Peng et al., 2012) or metallic liners of the COPVs (Ottaviano, 2013)).

The aim of this paper is to describe a series of experiments for detecting damages caused by low energy impacts by piezoelectric sensors (UGW) integrated in carbon fiber composite structures. These tests are designed to provide basic assessment of such detection system and its further possible use for structural health monitoring, condition based maintenance and fault adaptive control of COPVs (forced reduction of internal pressure etc.).

2. COPV DESIGN AND TEST SPECIMENS

Generally, COPVs consist of a metallic liner and a composite overwrap. Space applications usually use titanium liner because of its relative high strength, considerable corrosion and oxidation resistance and good fatigue characteristics. The liner's main purpose is to prevent propellant leakage. The composite overwrap is wound from high performance carbon fibers and coupled by epoxy resin. Usually, there are several layers of winding in two main directions: hoop and helical (Tam & Griffin, 2002). The top layer is sometimes covered by one more additional layer from glass fibers. The glass layer serves for protecting carbon layers and making the visual inspection of the tank surface easier. The proposed experiments were designed for investigating possibilities of embedded sensors between different layers of COPVs.

2.1. Test coupons

The test coupons for laboratory experiments were designed to represent only the carbon overwrap without the metal liner. The piezoelectric sensors have been embedded between various layers and their detection capabilities were verified. All the test coupons were cut out from a composite tube with diameter 226mm (see Figure 1).



Figure 1. General drawing of the test coupon.

Several different composite layouts with different sensors placement were tested. The main differences between the specimens are in different thickness of the carbon layers, presence of glass layer and sensors' placement in between the different layers. Figure 2 shows one of the tested layouts. The bottom part of the depicted coupon consists of carbon helical winding. The top part is a glass layer and carbon layers with hoop winding. There are piezoelectric sensors (mounted on two flexible printed circuits) placed between the top and bottom part of the coupon.



Figure 2. Example of a test coupon.

The manufacturing process of the coupons starts with winding composite carbon fibres T700 with helical layout (4 layers with fibres at 65°) with no metal liner inside and then overwrapping it by radial winding (fibres in 90° with respect to the axis of the tube) in two further layers. The fibre/matrix material for each layer is carbon/epoxy it is additionally covered by glass/epoxy layer to provide protection to the real COPV. The prepared composite tube is cured at 40°C and then it is cut to several pieces which are used as the test coupons.

2.2. Sensor system

The piezoelectric sensors are mounted on a thin flexible printed circuit (Kapton) to make the embedding process easier (replacing cables). The sensors are made of piezoceramic material (NCE51) and their dimensions are $5 \times 5 \times 0.5$ mm. Each coupon contained 5-6 sensors distributed on two flexible strips. The strips are placed between selected layers (see next section) during the manufacturing process and covered by resin. Embedding sensors into carbon layers can significantly decrease strength of the overall composite structure but these experiments were intended mainly for verification of the sensors capabilities. The optimal layout for sensors would be subject of a consequent research and investigation.

3. EXPERIMENTS SETUP

Experiments were designed to investigate capabilities of piezoelectric sensors to detect low energy impacts. The manufactured test coupons went through a series of steel ball impacts with defined energies. Embedded sensors were used to collect signal before the impact and after the impact. The two signals were then compared to each other.

COPVs must withstand very high internal pressure that causes also high stresses in the carbon overwrap. This phenomenon was simulated in the test coupons by introduction of artificial tensile load. Each state of the structure (before and after impacts) was measured under several different tensile load levels.

Sensors are excited by 3 cycles of sinusoidal wave weighted by Gaussian window. Frequency of the wave is 200 kHz. The obtained signals are the values of voltage on the sensors recorded with respect to time. Sampling frequency is 12MS/s.

3.1. Processing of results

The detection is considered to be successful if signals measured under one physical state are similar to each other but different from signals measured under varied physical states.

For the sake of visualization, damage indices are computed for all measured signals by comparing them with the baseline signals. The damage index represents the observed variability (with respect to the baseline) and it is computed as overall energy extracted from Short Time Fourier Transform (window length 0.21ms). The visualization of the damage is consequently based on the computed damage indices and processed by adjusted version of WEMAT algorithm (Hedl et al., 2012). This algorithm triangulates observed damage indices on the whole plane. The extent and severity of the damage is not estimated directly from the data. The only analyzed information is its localization based on intensity of observed variability of the measured signals. Produced visualizations show estimated distribution of damage (source of the observed variability in the signals) in relative scale. Therefore it is possible to estimate position of the damage.

3.2. Experiments description

Three distinct test coupons were manufactured that mainly differ in sensor placement with each other (see description below). Each coupon was artificially damaged by impacts with different energies. Therefore, there is no direct comparison of the results between each specimen. The major outcome of the experiments is to examine how the ultrasonic waves interact with impact damages and what impact energies are provably detectable.

3.2.1. Test coupon 1

The first test coupon does not contain sensors embedded directly in the carbon layers. Sensors are placed below the final glass layer (see Figure 3). The hatched layers represent carbon layers. The top white layer represents glass layer and the two gray rectangles represent piezoelectric sensors. This layout does not affect strength of the composite structure but perhaps the ultrasonic waves cannot reach the underneath deep layers to detect damages.



Figure 3. Schematic composition of the test coupons.

The coupon 1 was tested by two impacts with energy 14J. This energy is approximately related to an accidental impact of a tool with weight 1 kg dropped from a height of 1.4 meter. Each impact was aimed at different location to avoid interactions between the induced damages.

3.2.2. Test coupon 2

The sensors in the test coupon 2 were covered by one layer of carbon fibers and one layer of glass fibers (see Figure 4). This layout slightly changes mechanical properties of the composite structure.



Figure 4. Schema of the test coupon 2 with sensors placed under one carbon layer.

The test coupon 2 was tested by two impacts with the same energy 6J. This energy is approximately related to accidental impact of a tool with weight 0.6 kg dropped from 1 meter height. The impacts were aimed at the same location as before to test the influence of progressively increasing damage.

3.2.3. Test coupon 3

The test coupon 3 has sensors embedded approximately in the middle of the coupon material thickness. The sensors are covered by two layers of carbon fibers and one addition layer of glass fibers (see Figure 5).



Figure 5. Schema of the test coupon 3 with sensors under two carbon layers.

There were tested three impacts to the same location and each impact has twice time higher energy than the previous one. Particularly, the tested energies were 6 J, 12 J and 24 J. This test was designed to investigate influence of rapidly expanding damage.

4. RESULTS

Each of the impact damages was measured by the embedded sensors and visualized by WEMAT approach. The resultant images show intensities of observed signal variability over the test coupons. The red color signifies higher damage than the blue on the scale of expected damage. One test coupon contains 8 sensors and therefore there are 28 different sensor pairs. The WEMAT images are constructed from damage indices calculated for these 28 pairs and interpolated on the whole surface of the test specimen. The white dot represents exact location where the impact took place. It is used for verification of the obtained results.

4.1. Test coupon 1

The sensor system embedded in the coupon 1 was tested by two independent impacts with energy 14 J. The impacts significantly damaged the top glass layer in a way that visual inspection can easily detect it. The sensor system provably detected and localized both impacts and the results can be seen in Figure 6 and Figure 7. Figure 7 represents the observed damage by the second impact only, which means that it does not represent cumulative damage caused by both impacts together.



Figure 6. Test coupon 1 – first impact (14 J).

The observed variability in the signals could be caused only by the damage of the glass layer and therefore it is unclear whether this impact also broke the carbon fibers in the underneath layers. In this application, it is not crucial to monitor defects of the glass layer because it serves only for protecting and inspecting purposes. On the other hand, damages in the carbon layers are critical from the perspective of the overall strength of material and therefore they must be monitored very carefully. Nevertheless, due to significant extent of the damage, it is expected that the carbon layers suffered by damage too.



Figure 7. Test coupon 1 – second impact (14J).

4.2. Test coupon 2

The test coupon 2 contains sensors under the last carbon layer. The energy of impacts was decreased (in comparison to the test coupon 1) to 6 J and the impact was repeated with the same energy at the same location. The result of the first impact can be seen in Figure 8. The result indicates that the biggest damage is located 3 cm from the actual impact location. There are two possible explanations for this fact. The first one is that the impact really caused bigger damage in more distant locations (e.g. debonding of layers), and the second explanation is related with resolution of sensor system itself. It is not possible to perfectly localize all the possible damages by only eight sensors and therefore the obtained results must have some limit resolution. In whichever case, the results can be considered as successful and the detection is provable (if obtained precision is good enough for intended application).



Figure 8. Test coupon 2 – first impact (6J).

On the other hand, the second impact (same place and same energy) was not detectable at all. The damage did not increase its extent and therefore the measured sensor responses are exactly as same as after the first impact.

4.3. Test coupon 3

The third test coupon has the sensors embedded under two carbon layers, which mean that they are located approximately in the middle of the coupon's thickness. The results from the first impact (6J) are comparable with the results from the first impact on the test coupon 2 but with more precise localization.



Figure 9. Test coupon 3 – second impact (12J).

Figure 9 shows results from the second impact 12J (same location as the first impact). The damage is very precisely localized and detection is provable. The results show that the second impact significantly damaged the test coupon (unlike to the test coupon 2) and the embedded sensors were able to detect it even from more substantial depth. The third impact (24J) has the same characteristics but with wider detected extent of the damage. All three impacts were successfully detected and moreover the magnitude of the observed variability in the signals was increasing with increasing energy of impacts.

5. CONCLUSION

This paper summarizes results from conducted experiments on test coupons, which were designed as a simplified representation of the composite overwrapped pressure vessel. These experiments investigate possibility of detecting low energy impacts by embedded piezoelectric sensor system.

In general, pressure vessels operate under very high internal pressures and therefore even very small damage can lead to critical consequences. It was shown that these small damages can be detected and localized by comparing measured ultrasonic signals with their baselines.

The investigated test coupons contain sensors in three different layouts and the main difference between them is in depth of their placement. All the three layouts were able to detect all the tested impacts (from 6J to 24J) but the sensitivity is generally better when the sensors are closer to the surface.

These experiments proved that health monitoring of carbon composites is feasible and they opened a way for developing complete monitoring system. The main advantage of using such system would be obtaining quick and reliable information about current state of the composite structure. This information can be further utilized for condition based maintenance or fault adaptive control. Composites and COPVs are extensively used in space industry, which requires the highest level of intelligent and autonomous systems. Currently, there is no known issue, which would prevent using this technology in space. Therefore, there are several possibilities how to use the collected information for better and safer operations of spacecrafts.

Conducted experiments have demonstrated possibilities of detecting and localizing low energy impact damages. Further research should focus on determining the type and extent of these damages and estimating their severity.

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REFERENCES

- Chiachio, M., Chiachio, J., & Rus, G. (2012). Reliability in composites A selective review and survey of current development. Composites Part B, 43(3), 902–913.
- Chiachio, J., Chiachio, M., Saxena, A., Rus, G., & Goebel, K. (2013). An energy-based prognostics framework to predict fatigue damage evolution in composites. In Proceedings of the Annual Conference of the Prognostics and Health Management Society, 2013 (Vol. 1, pp. 45–49).
- Grant, J.(2005), Optical Sensing using Fiber Bragg Gratings for Monitoring Structural damage in composite overwrapped pressure vessels. Proc. SPIE 5911, Photorefractive Fiber and Crystal Devices: Materials, Optical Properties, and Applications XI. doi:10.1117/12.620528.
- Harris, C.E., Starnes, J.H., and Shuart, M.J., (2002) Design and Manufacturing of Aerospace Composite Structures, State-of-the-Art Assessment, Journal of Aircraft, Vol. 39, No. 4, pp. 545-560.
- Hedl, R. and Finda, J. and Adamek, K (2012), Structural damage index mapping system and method. Patent US 20120330570 A1.
- Ni, Y., & Chang, J. B. (2012). COPV Standard Requirements Implementation Issues, Proceedings of Structures, *Structural Dynamics, and Materials Conference*, 12-15 April, Orlando, Florida.
- Ottaviano, S. & Francesconi, C. (2013), Structural Health Monitoring Demonstration on Propellant Tank. Technical Interchange Meeting on Fracture Control of Spacecraft, Launchers and their Payloads and Experiments 2013, ESA, Netherlands.
- Peng, T., He, J., Liu, Y., Saxena, A., Celaya, J., & Goebel, K. (2012). Integrated fatigue damage diagnosis and prognosis under uncertainties. In Proceedings of the Annual Conference of the Prognostics and Health Management Society

- Pereira, G., Figueiredo, J., Faria, H. & Marques, A.T. (2013), Applicability of optical fiber bragg gratings sensors in the structural health monitoring of composite overwrapped pressure vessels. *Proceedings of the ASME 2013 Pressure Vessels and Piping Conference.*
- Raghavan, A. & Cesnik, C.E.S. (2007), Review of Guidedwave Structural Health Monitoring, *The Shock and Vibration Digest* 2007; 39; 91. doi: 10.1177/ 0583102406075428
- Tam, W. H. & Griffin, P. S (2002). Design and manufacture of a composite overwrapped pressurant tank assembly. *Liquid Propellant Feed System & Tankage*. doi: 10.2514/6.2002-4349

Evolving the Data Management Backbone: Binary OSA-CBM and Code Generation for OSA-EAI

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ABSTRACT

Integrated system health monitoring and management (ISHM) is a field of research and development where both academia and industry is highly focused on. Airbus Defence & Space has recognized that simulation is a key capability for developing ISHM technologies and is therefore in the process of developing a comprehensive simulation framework in that area. One significant building block is to invite 1st class technology providers, e.g. Universities and SMIs, to provide innovative technologies and support their integration into the simulation framework. This paper is a joint presentation of Airbus Defence & Space and Linova Software GmbH, an Airbus Defence & Space preferred software provider. The Open System Architecture for Condition-based Maintenance (OSA-CBM) and Open System Architecture for Enterprise Application Integration (OSA-EAI) are complementary reference architectures and represent an emerging standard for application domainindependent asset and condition data management. The architectures address several challenges in building Prognostic Health Management (PHM) systems, which are commonly composed of disparate and distributed hard- and software components. Therefore, a common challenge to PHM systems is to be confronted with vast amounts of data which are exchanged over a heterogeneous collection of communication channels. Any such system's success depends upon an open, uniform, and performance-optimized solution for data management. A solution that includes: data definition, data communication, and data storage. We will follow up on previous work and report on our experiences from implementing our second generation data management backbone based on binary OSA-CBM transmission. We also aim at implementing a fully OSA-EAI compliant database. We confirmed the general feasibility of OSA-CBM and OSA-EAI by previous work. We have now migrated our

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data management backbone to the current release of OSA-CBM, which includes a standard binary transportation format. We report on our experience from implementing this format and discuss issues regarding message handling and Meta data overhead. In previous work we used a simplified and stripped-down implementation of OSA-EAI and our current goal was to be fully compliant with the OSA-EAI standard. In order to reach this goal, we have created a code generator which receives **OSA-EAI-provided** documentation artifacts as input. It produces compileable source code for a Java-based 3-tier OSA-EAI information system. We have identified issues with the OSA-EAI standard regarding completeness and handling, which we discuss, and suggest means for mitigation or enhancements to the standard. To underline the feasibility of our solutions, we provide empirical evidence drawn from our work. The conclusion is a summary of our experience and the direction of future work in the area of PHM system design for aircraft maintenance. In total, our contribution to the community is best seen from a practitioner's perspective.

1. INTRODUCTION – MIMOSA STANDARDS

The paradigm shift from prevention towards prediction, which PHM systems impose to maintenance and operational processes of technical system, promise higher availability and higher operational capability, coupled with a reduction of overall maintenance costs. The challenges, which programs to introduce PHM systems in any application domain must face, are twofold. The enablers challenge deals with developing enabling technology, such as novel state detection, and health assessment sensors, methodologies and models for determining future life of (possibly deteriorated) components. The data challenge deals with integrating heterogeneous data from disparate and distributed sources into consolidated information and dependable decision support. It has therefore been recognized by the community that efficient data management solutions are crucial to success of PHM. Such

a solution should introduce a commonly accepted framework for data representation, data communication, and data storage. In other words, all solutions should be based on a commonly accepted and open standard in order to allow for seamless integration. In this writing we focus on the data challenge, i.e., the realization of a highly productive and standardized data management middleware

The organization MIMOSA is a "non-profit [...] industry association, focused on enabling industry solutions leveraging supplier neutral, open standards, to establish an interoperable industrial ecosystem for Commercial Off The Shelf (COTS) solutions components provided by major industry suppliers" (MIMOSA). The organization performs standardization work by defining reference architectures for PHM data management, respectively, aspects of PMH data management. We have chosen to base our data management backbone on two of MIMOSA's proposed standards, which are introduced in the following.

1.1. OSA-CBM

The Open System Architecture for Condition-based Maintenance (OSA-CBM) is an emerging reference architecture which has a chance of becoming the de facto standard for exchanging data in a condition monitoring system. Being an implementation of the ISO-13374 functional specification, the architecture defines six functional layers. Each layer is allocated different and unique functions of the data processing chain in a condition monitoring system (see Figure 1).



Figure 1.OSA-CBM Reference Architecture

This architecture focuses on the definition and communication of PHM data. Specifically, on the question as to which data entities and events can be exchanged between the layers during operation and the communication interfaces used for this purpose. The standard recommends the usage of XML messages, which are transported over HTTP, and for this purpose, a thorough collection of specifications for XML messages is provided. Recently, a binary transmission format for OSA-CBM messages has been added to the standard, and it is recommended to be used in embedded systems, or systems with limited computing resources (Löhr, Haines & Buderath 2012). In this writing, we will report about our experience in implementing the binary OSA-CBM format.

1.2. OSA-EAI

The reference architecture OSA-EAI is complementary to OSA-CBM and specifies comprehensive data storage architecture for asset management and configuration management systems. This architecture consists of: a physical relational data model (Common Relational Information Schema, CRIS), a corresponding logical object model (Common Conceptual Object Model), and CRUD interfaces (Create, Retrieve, Update, Delete) for all defined entities, as depicted in Figure 2. The data model is harmonized with OSA-CBM to facilitate storing data coming from all six OSA-CBM layers. Analogously to OSA-CBM, it is recommended that clients exchange XML messages transported via HTTP. For this purpose, the authors of the OSA-EAI standard provide a multitude of CRUD XML message specifications.



Figure 2. OSA-EAI Reference Architecture

The XML message specifications have been provided in XSD format. In this writing, we describe a Java code generator, which processes the XSD files and generates a fully functional client- and application tier upon the CRIS relational data model provided by MIMOSA.

2. Environment

Airbus Defence & Space is developing a comprehensive simulation framework for research in the areas of condition monitoring and prognostic health management. The framework includes airborne functions hosted on embedded systems, as well as ground-based functions hosted on PCbased systems. The primary objective is to interconnect both airborne and ground-based systems using a uniform data management philosophy and, as far as possible, uniform communication protocols. The simulation environment consists of airborne and ground-based functions which are connected by a data management backbone upon OSA-CBM and OSA-EAI.

In the following section, we provide a brief technical overview, whereas a more detailed description can be found in Löhr, Haines & Buderath, 2012. The air segment of the simulation framework models systems and associated sensors for which IVHM capabilities shall be developed. At the core of the framework is a central IVHM data processor to which data gets pushed by OSA-CBM. The IVHM data processor calculates IVHM information according to the OSA-CBM layer specifications, up to the health assessment layer (refer to Figure 3).



Figure 3. Air Segment of Simulation Framework The central data processor supports download of data, which has been collected and calculated on board the aircraft, to the ground-based environment for further processing (e.g. during the aircraft's turnaround). Once downloaded, the data is stored in a central data management component, which we call the CBM data warehouse (refer to Figure 4).



Figure 4. CBM Data Warehouse

The CBM data warehouse is based on the OSA-EAI reference architectures and it serves two major purposes: first, it hosts all current (i.e. short timeframe) and historical (i.e. long timeframe) condition data. Second, it provides services to distributed client applications that are involved in the PHM process.

In our context, data management includes the entire data set life cycle: from initial instantiation of a sensor value, transportation to the IVHM data processor, downloading to the ground-based environment, on through to storage and further processing.

3. OSA-CBM ENCODING IN THE AVIATION DOMAIN

When implementing OSA-CBM for an on-board embedded system one has to consider the software certification context for in-flight software. In this regard, our implementation deviates from MIMOSA's recommendation of transmitting OSA-CBM-encoded messages via a HTTP/TCP stack. Instead, we transport OSA-CBM messages via a UDP/IP stack. In our work we apply OSA-CBM messaging from data acquisition layer up to health assessment layer and in the following sections we report about our experience in implementing the binary OSA-CBM messaging standard in the C programming language under specific restrictions.

3.1. Programming Environment

When fielding OSA-CBM compliant applications on embedded systems certified for in-flight usage, several issues are brought to the fore. Ultimately, two aspects defined the unique structure of our solution: resource limitation and non-dynamism. Computing hardware for avionics, due to qualification requirements, are generations behind present off the shelf computing hardware. Implementation rules for applications hosted on real-time operating systems (such as VxWorks) typically forbid dynamically allocating memory resources, as these operations are potentially non-deterministic and lead to memory leaks if not used carefully. This environment imposes further constraints on the solution space: due to qualification or certification requirements (depending on the risk class of the final system) all embedded code must be written in the C programming language. Furthermore, UDP must be used as the sole protocol for network communication.

3.2. Starting Point

In order to make our current work comparable to prior work, we transmit the same OSA-CBM event instances as described in Löhr, Haines and Buderath 2012. This is, a heavy load data event set which contains four heterogeneous OSA-CBM DMDataSeq events at individual sample rates of 160Hz, 360Hz and 1 kHz (in total 2520 floats which corresponds to 10080 raw bytes). Additionally, we want to transmit a light load data event set, containing a single DMDataSeg event recorded at 20Hz (80 raw bytes). Both data event sets will be transmitted with a frequency of 1Hz. We have previously used these use cases to compare the standard XML-based OSA-CBM messaging protocol against a custom binary OSA-CBM messaging protocol, which we had designed at a point in time, where the standardized MIMOSA binary messaging protocol was not yet available to us. The ratio between transmitted data and usable payload, which shall act as a benchmark for the standardized binary messaging protocol, is given below.

MIMOSA XML Prop. Binary Ratio

Heavy Load	165 345 bytes	40 792 bytes	4.1
Light Load	1 827 bytes	576 bytes	3.2

Table 1. Data Transmission Size Comparison

As seen in Table 1 there is a significant reduction in the volume of data from XML-based transmission compared to binary transmission, ranging up to a factor of four. Also, processing the messages is less costly in binary mode (Swearingen, Kajkowski, Bruggeman, Gilbertson & Dunsdon, 2007).

3.3. Previous Work

For the implementation of our use cases in standardized binary OSA-CBM, we expected no significant deviation from the ratio of transmitted data versus usable payload, as for our custom binary approach. We were however unsure if it would increase or decrease. Our custom binary format is not prepared for all optional or dynamic elements of an OSA-CBM message. We provided maximum boundaries for dynamic elements and implemented the subset of optional elements, which we need, as static fields. In contrast, the standard binary OSA-CBM format can deal with all optional and dynamic fields, but has to include metadata fields which control the interpretation of the byte stream.

In our previous work we modeled OSA-CBM data as structs and captured their memory footprint for direct transmission to the receiver side. An example can be found in Figure 5. We transmitted OSA-CBM messages from a 32-bit Ubuntu sender system on an Intel processor to a 32bit VxWorks receiver system on a PowerPC. In order to overcome the platform differences we worked with artificial padding bytes so that the internal in-memory arrangement of our transmission structs was equal on both platforms. Also, we performed byte-swapping on the receiving platform to deal with high- and little-endian issues. This allowed us to easily cast the UDP package payload into the required structures (including pointer remapping) with a minimum of marshalling and un-marshalling effort.

typedef struct {
 long id;
 Site site;
 OsacbmTime time;
 int alertStatus;
 OsacbmDataType_ENUM osaCbmDataType;
 int noEvents;
 char* events;
} DataEventSet;

Figure 5. Data Event Set as Custom C Structure

However, our approach was highly platform- as well as use case-dependent and did not cater for the full spectrum of OSA-CBM features. The standard OSA-CBM binary protocol is platform independent as it

- defines endianess
- introduces a limited set of primitive data types with specified width and defines signdness
- strictly serializes the OSA-CBM classes into a flat byte stream. Here, it benefits from the fact that no multiple inheritance is used in the OSA-CBM classes

3.4. Design and Implementation

The high level design of our implementation consists of the following three core parts:

- a representation of all OSA-CBM data types, Meta data elements, enumerations, constants, etc. as C language elements, such as enums, structs and defines. We modelled inheritance as already shown in Löhr, Haines & Buderath, 2012.
- an encoder library, which receives an instance of an OSA-CBM data event (struct instances) as input and transforms it into an OSA-CBM-compliant binary byte buffer
- a decoder library, which receives a binary byte buffer as input. It interprets the buffer form left to right, and instantiates and wires respective structs from left to right into an OSA-CBM compliant event structure

We have chosen to not include the actual network transmission layer into our implementation. It depends on the deployment of how the encoded bytes are actually transmitted or the encoded bytes are received. Our C code implementation is subject to the restrictions pointed out in section 3.1, according to which we do not have dynamic memory allocation available. We require that the caller of the decoder or encoder provides a chunk of (statically) allocated memory, on which the en- or decoder operations work. All structs will be allocated within this static piece of memory, of which the allocation we assume to be external to the library.

We model OSA-CBM data elements as C structs an enums, and have restricted the scope of implementation to OSA-CBM data event elements. Other elements, such as Configuration, can be implemented analogously. Having the user of our library modifying the data event struct and its children directly is possible, but error prone. Meta data fields could be missed, or the structure might simply be incomplete or incorrect. To avoid such errors, we provide a comprehensive set of wrapper functions for creation of events in the correct structure and for setting attributes on this structure. The creation functions operate on the preallocated static buffer. With these functions the user can create and populate an OSA-CBM data event set without having to deal with implementation details (such as pointer handling or OSA-CBM Meta data management). Also, the functions assure that the event is in a valid state at any time. An example will be given in the following.

- 1. osacbmCreateNewDataEventSet: provided with a chunk of statically allocated memory, the function will create an empty OSA-CBM data event and return a handle for further manipulation
- 2. addDMRealToDataEventSet: provided with a handle to an existing data event set, the function will add a new DMReal event to the given event set, hereby hiding all memory handling details. Also, the function returns a handle to the new

DMReal event for further manipulation (i.e., setting its value).

- addDMDataSeqToDataEventSet: analogously, this function will add a new DMDataSeq event to a given data event set. Using the returned handle, the DMDataSeq can be populated
- addValueToDMDataSeqEvent: given a handle to a DMDataSeq event, this function can populate the DMDataSeq event with a potentially infinite number of values
- 5. setNumAlertsForDMDataEvent: example for one or many functions which set specific attributes on a given event structure

Having constructed the required event structure as described above, the actual encoding is just one additional function call. Additionally to the actual data event that should be encoded, our encoder's entry function takes a pre-allocated buffer to which the resulting encoded byte stream shall be written. The encoder inspects the given struct and serializes it to the byte buffer. This approach is straight forward as it means implementing the pre-defined OSA-CBM specification.

The resulting binary and OSA-CBM compliant content can then be transmitted with any medium, such as UDP/Ethernet, a serial line or AFDX, to only name a few examples. On the receiver side, the decoding process is essentially the inverse of the encoding process. The function osacbmDecodeOSACBMBinaryDataPacket receives the transmitted bytes and a handle to a statically allocated working buffer. Additionally to the decoded data even struct, the function returns a handle to an object modeling the OSA-CBM message properties. Using our wrapper functions, the user can inspect the content of the just received data event set; for example, for passing the data into a state detection or health assessment layer.

3.5. Discussion of Results

As described in section 3.2, we transmit a data event set containing four heterogeneous OSA-CBM DMDataSeq events at individual sample rates of 160Hz, 360Hz and 1 kHz. The overall data event set has a frequency of 1Hz. The resulting data push represents 2,520 individual measurements being sent across the system every second. The second sample is a light load data event set, containing a single DMDataSeq event recorded at 20Hz; the corresponding overall data event set has a frequency of 1Hz. The heavy load event transmits 10080 raw bytes and the light low data set transmits 80 bytes.

Prop.	Std.	Ratio gross/	Delta
Bin.	Bin.	net Std.	Prop.

Heavy Load	40 792	16 972	1.7	58%
Light Load	576	568	7.2	-1%
	1 0 0 0	6.0		D) (

Table 2. Performance of Binary OSA-CBM

The figures in Table 1 illustrate the performance of our binary OSA-CBM implementation. For the heavy load event a reduction of 58% of total raw bytes has been achieved. For the light load data event set the number of raw bytes increased by 1% -- obviously, Meta data has less impact for large payloads than for small payloads. We explain the significant reduction for the heavy load data event by the possibility to allocate dynamic data sections in the binary OSA-CBM protocol. Our custom implementation used fixed blocks with a maximum length for dynamic data fields (e.g., strings, arrays) and left unused space populated with initialization data, whereas in binary OSA-CBM the length as well as the actually transmitted number of bytes may vary.

4. OSA-EAI-COMPLIANT CBM DATA WAREHOUSE

The ground segment of our simulation framework includes a central repository for data and information, called *the CBM data warehouse*.

4.1. Motivation

Design of the CBM data warehouse was driven by the following high-level requirements.

- 1. act as a central information system
- 2. provide a uniform and standardized interfaces
- 3. maintain full traceability for in-service data

The MIMOSA reference architectures define a uniform data management philosophy that allows for full traceability of virtually any sensor value and its derived information. Earlier work (Gorinevsky, Smotrich, Mah, Srivastava, Keller & Felke, 2010, and others) demonstrated the feasibility of using these architectures as a reference to build a comprehensive information system for the aerospace domain. We consequently considered the selection of OSA-EAI and OSA-CBM as guidelines for the design of our CBM data warehouse as a promising approach to satisfy our high level requirements.

4.2. Previous Work

We have implemented a subset of the OSA-EAI standard for our initial version of the CBM data warehouse, as described in Löhr, Haines & Buderath, 2012. The subset was derived with the aim of providing data management for diagnostics and prognostics on our candidate systems. We concentrated on the ability to express system breakdowns (Assets, Segments, and Parent/Child relations) and the ability to associate data from the data acquisition, data manipulation, and state detection layers. Additionally, each asset was to have an active history of health assessments and remaining useful life estimates. We customized the utilized OSA-EAI tables in a way that would simplify the generation of test and reference data. We made further customizations to map specific features of the aerospace domain and stripped the composite primary keys of each entity down to a single dataset id, allowing us to strip down foreign keys as well. This approach was shown to be feasible by Mathew, Zhang, Zhang and Ma Lin (2006). Finally, we only considered those columns of any table which we really required. As a result, our CBM data warehouse was fully compatible to OSA-EAI, as it represented a subset of the standard. However, it was not compliant to OSA-EAI and we began work towards implementing the OSA-EAI standard to its full extent.

4.3. Approach and Architecture

The OSA-EAI standard defines a magnitude of documents and IT-specific artifacts of which the core artifacts – at least for our work – are briefly described here:

- CRIS: Common Relational Information Schema, a heavily normalized relational database schema. The standard provides CREATE statements for Oracle and other databases in the form of text files
- XML Request Specification: a set of XSD document type definitions which represent the entirety of XML-based requests that a client can send to an OSA-EAI compliant database. Also, the responses are defined.

The information sources above are the technical entry point for implementing an OSA-EAI database. Considering the proposed architecture from Figure 2 the implementation effort can therefore be summarized as follows. Instantiate the provided CREATE statements (porting the statements to the utilized RDMBS might be necessary). Create a server application which consists of a top layer listening for incoming XML messages via HTTP. The next layer inspects the parsed XML and routes the request to a more specific request processor. The request processor translates the XML content into an SQL statement (SELECT, INSERT or UPDATE) and executes the SQL statement against CRIS. Then, the result form the SQL statement, if any, is captured again by the request processor. If there is resulting data, the result set is worked off and the data it is wrapped into an XML document according to the XSD specification that corresponds to the initial request. The resulting XML response is finally serialized and appended to the output stream of the originating HTTP request - and as such received by the client.

The implementation of the server application cannot be done without significant effort by boldly implementing the partially very complex XML request for up to 300 XSD documents, which have to be mapped against up to 400 individual tables from CRIS. Instead of implementing the server application "by hand", we thought of a tool that would generate the source code for the server application from the available artifacts (CRIS CREATEs and XSD documents). The architecture of such a tool is depicted in Figure 6. The code generator receives all available XSD documents as well as the CRIS description as input, parses and analyzes them, and finally generates code for any layer of the described server application. Also, the code generator is able to generate unit tests for the server.



Figure 6. Code Generator for OSA-EAI

4.4. Realization

The OSA-EAI XML request specification is roughly grouped into the following three categories:

- Tech-Doc: facilitate data exchange between an application with information which it needs to publish periodically
- Tech-CDE: entity-centered, simple CRUD (create, update, retrieve and delete) operations
- Tech-XML: region-centered complex query, update, and create operations

For our work we initially focused on Tech-CDE and Tech-XML because our motivation was to create the required services for managing the information content in the database. For this purpose, CRUD operations only are required. We started with an analysis of the XSD documents provided in order to infer the required steps and architecture of the code generator. Both request groups provide a central XSD file which defines all XSD types referenced by the request definitions. In addition, Tech-CDE provides one file which contains all available retrieve requests (Tech-CDE Query) as well as one file which contains all available create, update, and delete requests (Tech-CDE Write). In contrast, Tech-XML provides a magnitude of files for each specific Tech-XML request. In total, there are 256 request files, of which the majority is Query definitions, followed by a few Create and Update definitions. The core difference between Tech-CDE and Tech-XML is that a Tech-CDE request is focused on one specific entity only. Relations to other entities are only considered by the respective foreign keys and entity-references are not fully resolved. It can therefore be seen as a relation-centric way of interacting with the database - just that one is not talking SQL, but XML. In contrast, Tech-XML defines requests which are based on a core entity upon which all provided filter parameters shall be applied. In addition to Tech-CDE the Tech-XML requests also resolve the entities which are referenced form the core entity. A response to a query request therefore not only contains the core entity's data, but also the resolved attributes of any referenced entity. As a result from this analysis we chose to focus on Tech-XML only, at least for the first iteration, since we believed Tech-CDE being a virtual subset of Tech-XML - at least from the perspective of what is required to talk to the underlying database. A significant result of our analysis was - as we hoped to confirm in the first place - that the request/response definitions all follow a common structure. This was the key prerequisite for designing the code generator. For the first iteration we made an important assumption: our aim was to only query or manipulate the core table that a specific Tech-XML is directed to. Although foreseen by the standard, we did not intend to resolve foreign key relations and thus we treated Tech-XML like Tech-CDE. We considered foreign key resolution as just an implementation effort.

Our code generator produces Java code: a server application which performs the XML request handling and the mapping of XML to SQL and vice versa, and a Java client library which provides an interface for client applications. The client library encapsulates the XML-messaging and leaves transparent that the client is actually talking to a remote database via the network. We will describe the four major phases of code generation:

Phase 1: Generate Model Classes

In this phase, the code generator parses the XSD files and generates Java POJO (plain old java objects) classes which correspond to the type hierarchy imposed by the XSD definitions. These classes do not implement any business logic and act as model objects for marshalling and unmarshalling XML or SQL result sets. For this task, we utilized the JAXB framework (refer to JAXB in the references section) which is an implementation of the Java API for XML Binding. The framework was able to create respective Java POJO code from the XSD files provided by MIMOSA. The generated model classes will both be utilized by the client library as well as the server application and thus act as common interface between the two parties. For example, from the XSD type <code>asset_healthTYPE</code> the class as depicted in Figure 7 will be generated (getters and setters have been omitted in the figure).

Phase 2: Generate Client and Server Interfaces

The interface that the client library exposes is not explicitly defined by the provided MIMOSA artifacts. We therefore chose to infer suitable method names from the request types as provided in the Tech-XML XSDs. For example, using the inherent substructure of the request element mim_6002, the interface method for this request type can be generated as follows:

public Mim6002Ack query(Mim6002Req query);

Phase 3: Generate Client/Server XML Transmission Code

In this phase the generator "implements" the client interface methods by generating code that serializes the given request object to an XML string, wraps the string into an HTTP POST request and opens the server URL. At this stage, the client instance can already perform request validation based on the multiplicity and optionality information declared in the XSD.

	< <java class="">></java>
	AssetHealthTYPE
	(default package)
4	lcinfo: Lcinfo
4	assetOrgSite: byte[]
4	assetId: long
4	gmtAssessment: XMLGregorianCalendar
4	byAgentSite: byte[]
\$	byAgentId: long
4	locHrDelta: Short
4	locMinDelta: Integer
4	healthLevDbSite: byte[]
4	healthLevDbld: long
4	healthLevTypeCode: long
4	healthScalePrecise: Double
4	kelihoodProb: Double
4	gmtCreated: XMLGregorianCalendar
4	crLocHrDelta: Short
4	crLocMinDelta: Integer
4	chPattDbSite: byte[]
4	chPattDbld: Long
4	chPattTypeCode: Long
4	gmtAudited: XMLGregorianCalendar
4	audLocHrDelta: Short
<	audLocMinDelta: Integer
4	audQualityCode: Integer
4	audByOrgAsite: byte[]
4	audByAgentId: Long
4	userTagldent: String
4	name: String
4	gmtLastUpdated: XMLGregorianCalendar
4	lastUpdDbSite: byte[]
4	lastUpdDbld: Long
	rstatTyneCode: Integer

Figure 7. Example Generated POJO Class (getters and setters have been omitted for clarity)

For the server side, the generator creates code which receives the incoming HTTP POST request from a HTTP server socket, inspects the XML prefix in order to instantiate the correct XML parsing method (specific to the Tech-XML request type) for obtaining an object tree corresponding to the request. At this stage, the generator also produces code which serializes the object tree of the response into XML and streaming it to the output stream of the incoming request.

Phase 4: Generate Database Queries

The request object tree is inspected for the purpose of generating an SQL SELECT, INSERT or UPDATE statement depending on the content of the request. The type information of the objects themselves as well as Java annotations provided by JAXB provided enough information, to create syntactically and semantically valid SQL. For SELECT-type queries, the code generator produced code which inspects the result set from the database and – again, by utilizing the POJOs type and Meta information – which is able to translate the result set into a Tech-XML response object tree. As already explained in phase 3, this response object tree can then be serialized to XML and pushed to the requesting client.

4.5. Discussion of Results

The generation of POJOs was done by hooking up a single file into the JAXB framework. All dependent types and files were well referenced. We noticed however that the resulting class naming is somewhat odd – as already seen in Figure **7** all POJOs have a *TYPE postfix, which is introduced by JAXB. We found this issue to be of cosmetic nature only. The generation of interface method names seemed straight forward at first. The multitude of method names however made the client interface rather confusing as the request number (e.g., 6002) has to be mapped mentally to what the request is actually doing (e.g., asset health).

Compared to Tech-CDE it is not clear how the current catalog of Tech-XML requests was motivated. During the utilization of our generated application we were missing several request types for accessing specific areas of the OSA-EAI database model, such as the steps of solution packages. We were able to work around the missing requests by adding to the catalog following the already existing philosophy. We do not see this as a significant drawback of the OSA-EAI standard as the requests which are missing in Tech-XML can be found in Tech-CDE. It is however a strong indication that a productive application should implement both Tech-XML and Tech-CDE requests. We encourage the standardization committee to include the possibility of defining customer Tech-XML requests on the basis of standardized XSD request specifications.

Tech-XML requests provide support for equality filtering ('=') on the attributes on an entity. It is also possible to get

the N latest (chronologically) instances of an entity, which is necessary for PHM applications, e.g., the latest asset health assessment of a specific asset. What's missing is support for filtering beyond attribute equality. We were missing the general possibility for range filtering (left-, right- and left-right-bounded) on numeric or date attributes (range filtering is possible for specific date attributes), and filtering by regular expressions on character attributes, or at least wildcards. The latter is a matter of interpreting the already existing search criteria on the server-server side, and does not require structural modification, but explicit conventions of how to populate the search criteria. The former can be realized by enhancing Tech-XML XSDs to include optional left and right bounding attributes for each Tech-XML search criteria. A negative filter ("get all entities which do not match") is missing, but can be integrated analogously.

We were also missing the possibility for grouping, or ranking, and aggregation within a single query. Our application requires retrieving the latest health and RUL for each asset and both information types are stored as time series per asset in respective tables. It is possible to write a single SQL query on table asset_health which returns the latest health grade per asset. In Tech-XML this is currently not possible, and one has to make one Tech-XML query per asset. Again, a solution to this issue is the enhancement of the Tech-XML query XML to include indicators on a search attribute, whether the result should be grouped or ranked by this attribute, and which aggregation functions should be used on the result columns.

The "core" table of a Tech-XML request, i.e., the entry point into the data, is not highlighted in the request specification and cannot be uniquely inferred from the list of parameters. However, for the majority of requests, the first entity of the response specification corresponds to the core table that shall be queried. Here, we suggest a more explicit way of specifying the request parameters, i.e., which entity should actually be queried.

For SQL code generation, the mapping between entity names to table names as well as entity attribute names to column names is not 1:1. For our generator we exploited the fact that both XML elements and database elements followed a specific naming schema that could be used for a bidirectional mapping - however, the naming schema is not documented, thus, subject to be changed (accidentally). We suggest to standardize a bidirectional mapping function (e.g., the current pattern) for entity/table and attribute/column names. We found that for the sake of request validation the consideration of the CRIS CREATE statements was needed for synchronizing multiplicity information from the XSD with primary and foreign key definitions on the database level.

4.6. Summary & Outlook

Assuming that any graphical user interface will take the role of a client application we have shown that a fully functional OSA-EAI information system for Tech-XML requests can be generated from the provided MIMOSA documentation as is. The compiled system is able to run the entire requestresponse cycle, starting from the assembly of the request on the client side, transmitting the request, issuing SQL against the CRIS database and sending back the results. Our implementation does not yet resolve foreign key relations but provides the foreign keys themselves for later referral. Since Tech-XML provides a different focus than Tech-CDE we conclude that a productive application must provide both Tech-XML and Tech-CDE interfaces to provide access to the full information content. Tech-CDE provides CRUD access for every entity and can therefore be considered as the "Swiss Army Knife" for OSA-EAI interaction. Tech-XML provides convenience functions and the ability to resolve dependent entities in a single request. In further work we will extend our code generator to Tech-CDE request types. Given the more complex nature of Tech-XML, we do not expect any significant issues for this endeavor.

5. CONCLUSION

We presented our experience from the realization of our next generation data management backbone for a simulation framework for PHM systems in the aerospace domain. For the airborne segment OSA-CBM-based communication was chosen. From previous work, where we evaluated XMLbased transmission, we were motivated to use binary transmission and defined a custom protocol. Recognizing the drawbacks of our approach we switched to the new available binary transmission standard of OSA-CBM 3.3.1. We have shown that the standard can be implemented in the C programming language under the restrictions of airborne software development. Furthermore, for this special environment, we have suggested a layered approach which provides simple creation as well as manipulation functions for OSA-CBM data, which hide the details of the underlying implementation. The ratio of transmitted event size to usable payload is about 25% of the XML-based approach (overhead for HTTP and TCP not included).

The ground-based part of our data management backbone is centered on an information system, which we call the CBM data warehouse. It is designed compatible to the OSA-EAI reference architecture. Confirming the feasibility of OSA-EAI by a prototype implementation of a stripped-down instance of OSA-EAI in previous work we describe here our experience from realizing a Java code generator for a fully functional OSA-EAI client-server application system. We could successfully show that the MIMOSA-provided artifacts provide enough suitable information to generate executable code in an automatic way. We further found that Tech-CDE and Tech-XML should be both implemented in a productive information as both request categories cover different aspects (however, they also have common areas). During the implementation of our code generator we found several issues regarding object naming and object mapping which we do not consider critical. We found that the request specification lacks comprehensive support for extended filtering and aggregation when assembling a request. By providing such support in a standardized way the response times and the network traffic could be reduced significantly.

REFERENCES

- Dunsdon, J. & Harrington, M. (2008). The Application of Open System Architecture for Condition Based Maintenance to Complete IVHM. *IEEE Aerospace Conference*, March
- Gorinevsky, D., Smotrich, A., Mah, R., Srivastava A., Keller, K., &Felke, T. (2010). Open Architecture for Integrated Vehicle Health Management. AAIA Infotech@Aerospace Conference, April20-22
- JAXB. JAXB Project Website. https://jaxb.java.net/
- Löhr, A., Haines, C., & Buderath, M. (2012). Data Management Backbone for Embedded and PC-based Systems Using OSA-CBM and OSA-EAI. AAIA Infotech@Aerospace Conference, April20-22
- Mathew, A. D., &Ma, L. (2007). Multidimensional schemas for engineering asset management. *Proceedings World Congress on Engineering Asset Management*, Harrogate, England
- Mathew, A. D., Zhang, L., Zhang, S., & Ma Lin (2006).A review of the MIMOSA OSA-EAI database for condition monitoring systems. *Proceedings World Congress on Engineering Asset Management*, Gold Coast, Australia
- MIMOSA. Mimosa Organization Website. http://www.mimosa.org
- Swearingen, K., Kajkowski, W., Bruggeman, B., Gilbertson, D., &Dunsdon, J. (2007). Multidimensional schemas for engineering asset management. *Proceedings IEEE Aerospace Conference*

BIOGRAPHIES

Matthias Buderath Aeronautical Engineer with more than 25 years of experience in structural design, system engineering and product- and service support. Main expertise and competence is related to system integrity management, service solution architecture and integrated system health monitoring and management. Today he is head of technology development at Cassidian. He is member of international Working Groups covering Through Life Cycle Management, Integrated System Health Management and Structural Health Management. He has published more than 50 papers in the field of Structural Health Management, Integrated Health Monitoring and Management, Structural Integrity Programme Management

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Data Acquisition and Signal Analysis from Measured Motor Currents for Defect Detection in Electromechanical Drive Systems

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ABSTRACT

This paper presents the development of a diagnostic method which uses the measurement of motor currents in order to detect defects in electromechanical systems. It focusses on two main topics: the acquisition of experimental data, and the development of the diagnostic method. The data acquisition was crucial for the successful development of a dedicated signal analysis method. For this purpose, a test rig for generating experimental training data was created. The rig provides the ability to simulate a wide range of defects experimentally. Different types of artificial defects, such as bearing damage or misalignments, were used; these are described in detail in the second section of the paper. The experimental data was obtained under varying operational conditions. Using all possible settings of operational parameters for data generation would mean excessive experimental time and effort. Therefore, a special approach using the theory of "Design of Experiments" was applied. By using a fractional factorial design based on orthogonal arrays, the number of experiments could be reduced significantly. Details of this approach are given in the third section. The main ideas of the classification algorithm, including some of the results, are summarized in the fourth section. A special method using a combination of Principal Component Analysis and Linear Discriminant Analysis was designed for the correct detection of damage or misalignments. With this method, a successful classification of the systems' health state could be obtained.

1. INTRODUCTION

Electric motors are usually inexpensive in comparison with

the equipment of the powered process (e.g. a conveying system, a machine tool, or an assembly line). This is especially true for small engines with a power consumption below 1 kW. The use of additional sensors for such a motor increases the price of the component significantly. Therefore, such an approach to defect detection seems practically unfeasible in many cases. That is why monitoring the health conditions of electric motors is uncommon for industrial applications. However, in the case of a motor standstill, a stop of the entire process, for example a production line, may be required. In such a case, the monetary cost is usually significant. The problem may be prevented by collecting information about the motor condition and the dependent process from the motor's internal physical quantities. Much research has been done on the development of methods for condition monitoring using motor currents. Stack, Habetler, and Harley (2004), for example, focus on categorizing bearing faults as either single-point defects or generalized roughness; they describe the detection fault signatures by investigating machine vibration and shaft current. Widodo, Yang, Gu, and Choi (2009) apply discrete wavelet transform to transient current signals, followed by a component analysis as well as a support-vector-machine-based classification. Tran, AlThobiani, Ball, and Choi (2013) use a decomposition of current signals via a Fourier-Bessel expansion and classify the features with a special class of neural networks. Zhen, Wang, Gu, and Ball (2013) present the application of socalled "dynamic time warping", a special time-domainbased method, to motor current signals to detect common faults. In all these contributions, application-specific features are considered. However, in contrast to previous research, a generic approach to feature extraction using phasor description of motor current signals is pursued in the present paper (see Section 4).

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For synchronous motors, the electric phase currents are measured to enable correct control of the motor operation. Hence, all currents are already known; they could thus be used to determine the current motor condition and its trend over time, offering the possibility of detecting defects with minimum resources by reusing these currents and without requiring additional sensors. The proposed method uses the motor's phase currents for the detection of faults and damaged components, such as e.g. rolling bearings in the electric motor itself or in the powered equipment.

To develop this diagnostic method, experimental data was required. The generation of suitable experimental data is a complex task, especially when the investigation focusses not on one specific type of damage, but rather on different types of defects in different components, as well as on combinations of such defects. The long-term aim is to integrate the proposed method into drive systems by using existing current measurements within frequency inverters in industrial applications. Therefore, systematically generated data of relevant damage and operational conditions must be available to develop the required diagnostic methods.

This paper will describe the necessary test setup, the design of experiments, and the development of the algorithms to detect defects in commonly used machine components, such as rolling bearings and gears. It will focus especially on the creation of a sophisticated database, which is essential for the development of the diagnostic method.

2. DEFECT SIMULATION VIA TEST SETUP

To generate experimental data, a specific test rig was developed and constructed. The test rig is a modular system to ensure flexible use of different artificial defects (or inaccuracies). A defect is a "non-fulfilment of a requirement related to an intended or specified use" (DIN EN ISO 9000, 2005). In this paper, defects are divided into two groups: damage and faults. Damage is constituted by defects which arise in a technical system after a period of time. They appear as a change in the shape of one or more components, e.g. fractures or pitting in gear wheels or bearings. The term fault is used for any defect that exists in a technical system from the start, such as assembly defects, as well as for any reversible defect which is forcibly introduced by the operational conditions, such as shaft deflection under high loads.

The basic components of the test rig are the drive motor, a torque-measuring shaft, the test modules, and a load motor (see Figure 1). Different types of faults and damage could be generated using the test modules. An implementation of several defects in combination was also possible. The detection of defects was carried out using measured motor current signals from the test data.



Figure 1. Modular test rig for generation of experimental data: drive motor (1), torque-measuring shaft (2), rolling bearing module (3), gear module (4), flywheel (5), load motor (6)

2.1. Test Rig

As described above, the test rig consists of different modules. The motor is a 425 W Permanent Magnet Synchronous Motor (PMSM) and is operated by an inverter with a switching frequency of 16 kHz. This inverter has a sensorless closed-loop structure. The motor phase currents were measured by a current transducer of the type MCTS 60/ IT60-S with a conversion ratio of 1:600. The signals are filtered by a 12.5 kHz low-pass filter and converted from an analogue to a digital signal with a sampling rate of 100 kHz. These devices were used for proof-of-concept instead of the inverter's internal ammeters because of their higher sampling rate and accuracy.

In industry, power inverters with pulse-width modulation are commonly used for driving synchronous motors. Therefore, all experiments described in this paper were performed using an industrial power inverter, even though the motor current signals show significant noise because of the disturbances from the pulse-width modulation. In previous experiments, better defect detection results were obtained with an alternatively used sine-wave generator (Lessmeier, Piantsop Mbo'o, Coenen, Zimmer, & Hameyer, 2012). Nevertheless, it was determined that it is possible to detect the defects despite noisy signals; thus, the noisy signals were chosen because of the prevalence of power inverters in industry. This practice-oriented selection ensures that an industrial application of the method developed here will be as easy as possible.

To record the operational conditions and to have the possibility of supplementing the diagnosis with additional information, the following parameters were measured: the radial force on the rolling bearings, load torque, rotational speed, surface acceleration of the housing, and the temperatures of both oil and housing.

The torque-measuring shaft has a nominal torque of 2 Nm and an accuracy of ± 0.1 % of the nominal torque. It was used to measure and to record the torque synchronously to the motor currents.

The rolling bearing module provides the possibility of using a specifically prepared test bearing under continuously adjustable variable radial loads and shaft tilting. The assembly group consists of an outer and an inner housing. Only the inner housing with additional components is shown in Figure 2. The test bearing (1) is installed in a spherical bearing (2) to allow tilting of the outer ring in relation to the shaft. This tilting is forced by tilted discs (3) and pressure rings (4) on the outer ring of the test bearing. The self-aligning ball bearings (5) compensate force and deflection of the shaft by diverting it into the outer housing. The radial force on the test bearing is generated by tightening a screw between the outer housing and the thread (6). This force is measured and recorded by a load cell. The housing is sealed by radial shaft seals (7) and filled with oil through an inlet (8).



Figure 2. Shaft and inner housing of the rolling bearing module

In total, the following experimental conditions were implemented to generate faults in the rolling bearing test module under different conditions:

- Tilting of the shafts (vertical or horizontal) to 0.1°, 0.2°, 0.3° or 0.5°;
- 2. Different types of mechanical damage in the rolling bearings;
- 3. Different rolling bearing types (6203 ball bearing, N203 and NU203 cylindrical roller bearings); and
- 4. Different lubricants and lubricant filling levels.

The gear module (Figure 3) consists primarily of a set of gear wheels (1) with a gear transmission ratio i = 1, each of them on a shaft (3) in a housing (4). The gear wheels can be changed for damaged ones, and can be tilted by changing the spacer ring (2) to an angled one. With different spacer rings, the housing of the second shaft can be tilted horizontally or vertically.

The shaft offset because of gear and tilting is compensated by moving the subsequent modules of the powertrain. The positions are held by fixing and adjusting elements. So a change between different testing setups is easily possible without losing the alignment of the powertrain.



Figure 3. Sectional drawing of the gear module

The following experimental conditions were implemented to generate faults in the gear module:

- 1. Tilting of the shafts and gear wheels due to loads by external forces as well as manufacturing inaccuracies (vertical [y-axis] or horizontal [z-axis]) to 0.5°.
- 2. Different mechanical damage (e.g. wear, pitting, fracture).
- 3. Different lubricants and lubricant filling levels.

The flywheel and the load machine simulate the inertia and the load of the driven equipment, respectively. The load motor is a PMSM with a nominal torque of 6 Nm (Power of 1.7 kW).

Moreover, there are further test modules available for the test rig, such as a gearbox with planetary gears or an electromagnetic brake. These modules allow for follow-up investigations, which are, however, not in the focus of the present paper.

2.2. Defects: Faults and Damage

Before designing the test rig, the relevant defects were identified by a failure mode and effects analysis (FMEA) of a real system. Such a system may, for example, consist of a drum motor (Enge-Rosenblatt, Bayer, & Schnüttgen, 2012), and a conveyor belt. The failures identified as most relevant, which were therefore used for the experiments, are types of damage to bearings and gear wheels, as well as misalignments of the shafts due to loads or manufacturing inaccuracies.

To reduce the number of experiments, the defects were selected based on the resulting values from the FMEA. These values indicate the defect importance in combination with a factor related to the chance of detection. The following defects were selected:

Rolling bearing module:

- Tilting around the horizontal axis (y-axis)
- Damage in cylindrical roller bearing N203

Gear module:

- Tilting around the horizontal and vertical axis

Based on these evaluations, three levels were defined for each tilt defect (see Table 1).

Table 1. Tilt levels of bearings and gear wheels

Tilting of		Tilting of gear wheel		
bearing		[tilting axis]		
Name	Angle	Name	Angle	
AN0	0	WF0	0	
AN2	0.2°	WF1 [z-axis]	0.5°	
AN5	0.5°	WF2 [y-axis]	0.5°	

Special artificial damage preparation is particularly necessary for the bearings in order to obtain reproducible test conditions. The types of damage were selected based on the completed FMEA while respecting the technical possibilities of their manufacturing.

For the experiments, four cylindrical roller bearings with different levels of damage, which represent pitting, were selected (Figure 4). The damage was limited to the cylindrical roller bearings, with severe damage at the outer ring. These simplifications were chosen, because a better possibility of detection and therefore an easier development of the classification method was expected. One bearing without damage was used as a reference (numbered LS0). The damage type denoted by LS1 was manufactured manually using an electric engraver and is 2 mm long in the rolling direction over the entire width of the outer raceway. The damage types denoted by LS2 and LS3 were manufactured using a wire-cutting electrical discharge machine. LS2 is a cylindrical groove (radius = 8 mm) and a depth of 0.2 mm at the centre. The last type of damage is a repetition of LS2 at irregular intervals, covering 120° degrees of the outer ring. These damaged bearings were used in the rolling bearing module in the high-load zone of the outer ring.

The damage introduced is based on investigations of damaged bearings from industrial applications. In particular, damage types LS1 and LS2 have a similar shape and size as the ordinary pitting of investigated bearings. Damage type LS3 is a severe damage type similar to the advanced damage caused by high numbers of cycles after the start of pitting. Because of this geometric similarity between the artificial defects and real bearing defects, it is assumed that a sufficient equivalence has been achieved in emulating real damage.



Figure 4. Outer rings of the prepared cylindrical roller bearings

For future experiments, more damage types in bearings have been generated, including bearings from an accelerated lifetime test. These damage types are equivalent to damaged bearings from industrial applications. However, the artificial damage types were used for developing the diagnostic methods because they could be generated easily and quickly. In future experiments, the corresponding impact on the physical quantities of artificial and real damage has to be proven.

2.3. Operational Parameters

The test rig can be operated under different operational conditions (described by corresponding parameters of the test rig e.g. speed or load torque). To develop a detection method which is robust in the face of different operational conditions, it is also necessary to vary these parameters.

The main operational parameters are the rotational speed of the drive system, the load torque, and the radial force on the test roller bearing. To ensure constant boundary conditions and comparability of the experiments, three fixed levels were defined for each parameter (Table 2). All three parameters were kept constant for the measurement time of each data set.

Table 2. Levels of operational parameters

Rotational speed		Load torque		Radial force	
Name	[rpm]	Name	[Nm]	Name	[N]
N04	400	M01	0.1	F04	400
N09	900	M04	0.4	F10	1000
N15	1500	M07	0.7	F20	2000

Another parameter is the temperature, which was kept constant at roughly 45°C during all experiments after warming the test rig before every measurement.

3. DESIGN OF EXPERIMENTS

The test rig was used to generate data experimentally for the purpose of distinguishing several defect phenomena from healthy system behaviour. For this purpose, an algorithm was developed and tested as described in Section 4. This algorithm must be robust and able to decide correctly under different operational situations. Hence, such an algorithm must be developed based on a broad data set, considering all defect phenomena in question as well as a variety of operational situations.

In a real system, each of the defect phenomena (see Section 2.2) and each of the operational parameters (see Section 2.3) can change any number of times. Each defect phenomenon would have to be investigated under different operational conditions in order to determine whether such a situation could be detected using only signals from electric phase currents. To consider the problem to its full extent, multiple measurements would have to be performed for all defect phenomena, in combination with all possibly occurring operational conditions. This would lead to an enormous number of experiments. A way around this dilemma is described in this section. It is based on completing a comparatively small number of experiments while still gathering all relevant information.

From the mathematical point of view, two groups of input parameters must be distinguished when simulating different situations using a test setup. First, there is the group of defects. The main attribute of this group is that there is exactly one level of every input parameter which corresponds to a functioning system, while all other levels of the input parameters belong to a damaged system. This group of input parameters describes the health conditions of a system. Secondly, there are the operational parameters. These parameters can vary between different levels during the operation of a system.

In Section 2.2, the most important levels of defect phenomena are described. This leads to a minimum of 4 levels of pitting in bearings, at least 3 levels of shaft misalignment, and 3 levels of gear wheel misalignment. Taking only these levels into account for investigation, it results in 36 possible combinations. In Section 2.3, some carefully selected levels of operational parameters are defined, leading to 3 different levels for each of the parameters revolution speed, load torque, and radial force on the main bearing. This gives additional 27 combinations. In total, 36 * 27 = 972 different experiments would have to be performed to examine all possible combinations. Hence, despite taking into account only the most important levels of

input parameters, the number of possible combinations is still too high.

In order to significantly reduce the amount of work necessary for the experiments, the theory of Design of Experiments (DoE) was applied. This theory offers a broad range of approaches for carrying out experiments in a scientifically well-founded way (Box, Hunter, & Hunter, 2005), (Dean & Voss, 2008), (Wu & Hamada, 2009). In this context, several assumptions are made concerning particular linear and non-linear relationships between the input variables and the (usually just one) output variable. Using such assumptions, it is possible to deduce the complete results logically from a few – well-chosen – experiments, with a very high degree of confidence. Often, a so-called fractional factorial design based on orthogonal arrays is used for this purpose.

An example of such an approach is shown in Figure 5. It is assumed that there are 3 input parameters (x_1, x_2, x_3) . Each parameter can take 2 different values, one lower value (denoted by -1) and one higher value (denoted by +1). The 3D representation on the left side of Figure 5 shows $2^3 = 8$ different combinations, represented by the 8 corners of the cube. All of these combinations have to be investigated to generate a complete statement about the parameter's influence on an output variable. But using an orthogonal array OA (4,2³) as shown on the right side of Figure 5, the effort can be reduced to 4 experiments. These experiments are represented by the 4 rows of the matrix. The disposition in 3D space can be seen on the left side, shown by the 4 dots at the cube's corners.



Figure 5. Fractional factorial experiment schema for 3 parameters: representation in 3D space (left), orthogonal array OA (4.2^3) of parameter values (right)

In the context of generating an appropriate experimental data set using the test rig, the DoE approach is used to select a well-suited set of combinations of defect phenomena and operational parameters. This procedure was applied in two separate steps. First, an orthogonal array for all possible combinations of defect phenomena was determined. Because the levels to be investigated were assumed to be 4 by 3 by 3, the OA $(12,4^{1}3^{2})$ was found to be suitable,

resulting in 12 combinations of defect phenomena. The OA $(12,4^{1}3^{2})$ is shown in Figure 6. It consists of the lines 1 to 12 of the left array.

In a second step, an orthogonal array for all possible combinations of operational parameters was determined. In this case, each parameter was assumed to have 3 different levels. Hence, the OA $(9,3^3)$ was found to be suitable, resulting in 9 combinations of operational parameters. The OA $(9,3^3)$ is shown in Figure 6. It consists of the lines 1 to 9 of the right array. These two steps lead initially to a total of 108 necessary experiments.



Figure 6. Results of Design of Experiments application: orthogonal array OA $(12,4^{1}3^{2})$ for defect phenomena (left), orthogonal array OA $(9,3^{3})$ for operational conditions (right)

The possibility of using only one DoE design for all 6 input parameters was also considered, but quickly rejected. Using the same numbers of levels introduced above, this would have led to an orthogonal array OA $(12,4^{1}3^{5})$. A number of 12 experiments did not seem to be an appropriate investigation for such complex physical interrelations as those in the present case.

From the mathematical point of view, the two DoE designs shown in Figure 6 were found to be suitable. However, for a good understanding of the physical interrelations, there are some slight disadvantages to these two designs. All phenomena appear solely in combination; thus, there is no phenomenon for which its influence can be investigated singly. Hence, for a better understanding of the influence of varying a single phenomenon, the idea of including 3 additional experiments for the 3 defects and 3 additional experiments for the 3 operational parameters arose. Such additional experiments have no influence on the results of the two suitable DoE designs, as DoE theory was only used for decision support while planning the experiments.

As additional experiments, the edges of the parameter space were used, meaning the maximum parameter level in each case. The 3 additional experiments for defect phenomena are shown in the last 3 rows (numbers 13 to 15) of the left table in Figure 6. The last 3 rows of the right table in Figure 6 (numbers 10 to 12) show the additional experiments for operational parameters. Thus, 15 * 12 = 180 experiments were finally found to be necessary in total as a result of a DoE-based selection.

All 180 experiments were carried out repeatedly, leading to at least 5 data sets of phase currents for each experiment. Based on these measurement results, a well-organized basis for development of an appropriate classification method could be established.

4. CLASSIFICATION ALGORITHM AND RESULTS

The goal of the research project was to find an algorithm which is able to distinguish between different defects (or health states) and operational conditions solely from measured electrical currents. For this purpose, two of the three phase currents of the synchronous motor were evaluated. For the classification approaches presented, all states and conditions found by DoE as well as the measurements from the test setup mentioned above were used.

Since the motor investigated was a synchronous machine, the phase currents are directly related to the angle of rotation of the device. Therefore, it is useful to relate the currents measured to this angle as well. Two of the currents behave as a rotating phasor with an elliptical shape of the amplitude trace, due to the 120° relative phase shift. Figure 7 shows the ideal trace as a dotted line. However, this trace will vary in real applications with the condition of the system and even with every cycle of rotation. During each experiment, a number of cycles were measured for each state and condition and each cycle was added to the phasor plot. Afterwards, the continuous angle of rotation α was divided into uniformly distributed sections in the range $[0,2\pi]$ leading to intervals $[\alpha_i, \alpha_{i+1}]$ with a certain number of measurement samples in each interval. These sample groups are suitable for statistical analysis. As a result, a modified phasor is obtained which has only one data point within each interval. A combination of statistical values can be used to obtain an artificial phasor, as shown in Figure 7 (solid line). This is simply derived using the mean value of all single phasors within one angular section. The amplitude of such a phasor with respect to the intervals can be used as a feature for classification purposes. This means n sections within $[0,2\pi]$ yield *n* features which characterize the phasor and its corresponding measurement.



Figure 7. Ideal rotating phasor (dotted line) and artificial phasor determined using the mean value of original phasors within each section (solid line).

The complete experiment evaluates different health states and operational conditions where each state is measured multiple times. This leads to a large number of feature sets, as each measurement corresponds to one set of features. Each set can be arranged in a feature vector. The number of features, i.e. the length of such a vector, is typically too large for complete classification or visualisation and may contain redundant information. Therefore, two approaches were applied to reduce the number of features, which are described in detail by Bayer, Bator, Enge-Rosenblatt, Mönks, Dicks, and Lohweg (2013), or by Paschke, Bayer, Bator, Mönks, Dicks, Enge-Rosenblatt, and Lohweg (2013).

Principal Component Analysis (PCA), as discussed by Dunteman (1989) or Jolliffe (2002), and Linear Discriminant Analysis (LDA), as discussed by Mardia, Kent, & Bibby (1979) or Duda, Hart, & Stork (2000), were used to find structure in the data. Both methods lead to a reduced mathematical basis, which can be used to represent the original feature vectors by a linear combination. The related coefficients form a new and significantly reduced feature set, which can then be used for classification. The methods were examined separately to show different aspects of their usability. PCA turned out to be suitable for the recognition of unusual states throughout the entire test system.

The PCA may be used to find any similarities in the data. The idea is to represent each state, i.e. the respective feature vector, by a linear combination of typical states. These states are equivalent to the first few principal component vectors provided by performing a PCA of all available measurement data. The vectors then span a new sub-space, which the feature vectors are projected into. The coordinates of projected feature vectors form the final, reduced feature set. If the conditions of the system are similar, data points will accumulate in the projected feature space and build clusters. Different health states as well as operating states will form independent clusters. Figure 8 shows the clustering for a particular health state class under different operating conditions, such as rotational speed or load. There were 12 operating states in total, of which at least 8 can be seen in the figure. The remaining 4 states overlap with existing clusters, as only two axes of the feature space were used for visualisation. The results indicate that, in general, different states can be distinguished using the PCA approach. The variation within each cluster is sufficiently small, which is mandatory for reproducibility.



Figure 8. Clustering of operational condition states within a health state class after performing PCA: The features 1 and 2 are the first two of the reduced feature set. They already allow for the separation of at least 8 of 12 states measured in total.

However, the clustering of operational states prevents a good classification of actual health states. Each health state would consist of sub-clusters produced by different operating conditions; hence, a health state cannot be described by a single cluster function, e.g. multivariate normal distribution. In reality, only health states as actual "classes" to be distinguished from each other are relevant here. The LDA provides a method of producing coherent health state clusters in the feature space independently of operational conditions. However, sample measurements from each class are required for LDA, which is usually a problem in practical applications. Since the experimental setup used here allows for damage and fault emulation, different health states are known from the measurement procedure. LDA offers a reduced mathematical basis for data representation, which ideally separates known and predefined classes in the present application. For different health states, the results are shown in Figure 9.



Figure 9. Separation of health state classes after LDA: The features 1 and 2 are the first two of the reduced feature set. The notations of the health states are declared in Table 1 and Figure 4.

Here, the clusters are independent of operation conditions. The separation of classes is not ideal for two reasons. First, at least 5 features are necessary to separate the 6 classes safely, but only two of the features, i.e. two axes, are used for visualisation. Second, some states may not be different enough for reliable classification. The LDA approach works quite well, but requires comprehensive knowledge about the system. In general, the results show that distinguishing health states would be possible. The classification itself is typically carried out using a fuzzy pattern approach. For example, the clusters may be described by particular multivariate normal distribution functions, which yield fuzzy membership values with respect to all known states. From this result, the most likely class membership can be determined for each measured state.

In many practical cases, there is no reference data for predefined health states. Even the consideration of operating conditions might be too costly in terms of effort. Therefore, the classification was restricted to the recognition of a previously trained, "good" state, regardless of operating conditions. The proposed method uses self-learning techniques and is based on PCA. The goal is to automatically find system states that are unusual and may represent arbitrary failures or defects. The challenge is to avoid false alarms caused by varying operating conditions. It must be assumed that the system is in a healthy condition during the learning phase and that all relevant operating conditions have appeared in the past. From the data gathered, one can construct a reduced mathematical basis using PCA. This basis spans a subspace that contains approximately all the measured data from the past. Any data measured in the future that lies outside this subspace represents an unknown state. This new state is then generated either by new operating conditions or by some defect or failure of the system. The geometric distance of a measured state to the known subspace was regarded as an error indicator. In Figure 10, the result obtained from the experimental setup is shown. The reference state LS0 AN0 WF0 has no artificial defects, and represents the system in good condition. Regardless of the operating conditions, the state is identified correctly. All other states shown are characterized by introduced defects, whereas the set of operating conditions was the same as for the reference state. The dashed line is determined by the variance of the error indicator produced using the reference state. It separates healthy states from defective states. This classification method works quite well and is mostly suited as an additional indication for maintenance service. However, it may not expose the actual defect or source of deviation.



Figure 10. Indicator for unknown states of the system: LS0_AN0_WF0 is the reference health state, which also contains different operating conditions.

To verify the robustness of the algorithms developed here, signals gathered directly from the frequency inverter were also evaluated. Typically, these signals exhibit more noise and the sample rate is reduced. However, the data analysis approach also proved to be effective under these circumstances. This provides the basis for a possible integration of the algorithms into the motor control or the automation system.

5. CONCLUSION

The paper presents the main steps in the development of a diagnostic algorithm for defect detection in technical systems driven by electric motors. For this purpose, only measurement signals from the motor's electric currents are used. Additional sensors were applied to the system in order to obtain the process parameters, but were not used for detection of defects. Following this idea, the complete system of defect detection becomes a complex one in a

mathematical sense. However, such a system can be realised at low expense because of the absence of additional sensors. Often, the mathematical algorithms can be executed on the existent control unit of the motor.

This paper focusses on three steps which are necessary for a successful preparation of such a complex algorithm for signal analysis. Firstly, a sufficient basis of measurement data is needed. This data was obtained using a test setup designed for this special purpose. The capabilities of this setup in mimicking particular defects are described in detail in the paper. Secondly, all possible operating conditions of such a motor have to be considered. This leads to enormous effort in order to measure all possible combinations of defects and operating conditions. Hence, specific methods for reducing this effort without risking loss of information have to be employed. Finally, a complex combination of different signal analysis methods has to be applied. Two of these primary methods are mentioned in the paper. Particular results of signal analysis and classification are shown. In doing so, the paper demonstrates that the method developed here works correctly under a broad range of circumstances.

The present work focuses on synchronous motors. An expansion to other types of electric motors is part of planned future research. Furthermore, a combination of sensor-based information about the industrial process and the method discussed here, which is based on measurement of electric currents, is also worth being investigated. Last but not least, improved methods of introducing artificial damage in bearings are in progress. The defects are expanded to the inner rings and to ball bearings. Moreover, real damage from accelerated lifetime tests will be used to examine the impact of artificial bearing damage on the physical quantities as compared to real damage. The creation of a database with experimental data for a wide range of different bearing defects is another goal for future work.

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NOMENCLATURE

DoE	Design of Experiments
FMEA	Failure mode and effects analysis
i	Gear transmission ratio
LDA	Linear discriminant analysis
OA	Orthogonal array
PCA	Principal component analysis
PMSM	Permanent magnet synchronous motor

REFERENCES

- Bayer, C., Bator, M., Enge-Rosenblatt, O., Mönks, U., Dicks, A., & Lohweg, V. (2013). Sensorless Drive Diagnosis Using Automated Feature Extraction, Significance Ranking and Reduction. 18th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA 2013), September 10-13, 2013, Cagliari, Italy.
- Box, G.E., Hunter, J.S., & Hunter, W.G. (2005). *Statistics* for Experimenters: Design, Innovation, and Discovery. Hoboken, NJ: Wiley & Sons.
- Dean, A., & Voss, D. (2008). *Design and Analysis of Experiments*. Springer Texts in Statistics. Berlin, Germany: Springer.
- DIN EN ISO 9000 (2005). European Committee for Standardization: Quality management systems – Fundamentals and vocabulary. Brussels, Belgium.
- Duda, R.O., Hart, P.E., & Stork, D.H. (2000). Pattern Classification. Wiley Interscience.
- Dunteman, G.H. (1989). Principal Component Analysis. Sage Publications.
- Enge-Rosenblatt, O., Bayer, C., Schnüttgen, J. (2012). Modeling a drum motor for illustrating wearout phenomena. 9th International Modelica Conference – Modelica'2012, (pp. 889-896), September 3-5, 2012, Munic, Germany.
- Jolliffe, I.T. (2002). Principal Component Analysis. Springer.
- Lessmeier, C., Piantsop Mbo'o, C., Coenen I., Zimmer, D., & Hamever. K. (2012): Untersuchung von Bauteilschäden elektrischer Antriebsstränge im Belastungsprüfstand mittels Statorstromanalyse, 9. Aachener Kolloquium für Instanthaltung, Diagnose und Anlagenüberwachung (pp. 509-521), November 14-15, Aachen, Germany. Aachener Schriften zur Rohstoffund Entsorgungstechnik, Band 81, Stolberg, Germany: Verlag R. Zillekens.
- Mardia, K.V., Kent, J.T., & Bibby, J.M. (1979). Multivariate Analysis. New York.
- Paschke, F., Bayer, C., Bator, M., Mönks, U., Dicks, A., Enge-Rosenblatt, O., & Lohweg, V. (2013). Sensorlose Zustandsüberwachung an Synchronmotoren. 23. Workshop Computational Intelligence, (pp. 211-225), December 5-6, 2013, Dortmund, Germany.
- Stack, J. R., Habetler, T. G. & Harley, R. G. (2004): Fault classification and fault signature production for rolling element bearings in electric machines. *IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives* (pp. 172– 176), August 24-26, Atlanta, GA, USA. DOI 10.1109/DEMPED.2003.1234568.
- Tran, V.T., AlThobiani, F., Ball, A. & Choi, B.-K. (2013): An application to transient current signal based induction motor fault diagnosis of Fourier–Bessel expansion and simplified fuzzy ARTMAP. *Expert*

Systems with Applications 40 (13), pp. 5372–5384. DOI: 10.1016/j.eswa.2013.03.040.

- Widodo, A., Yang, B.-S., Gu, D.-S., & Choi, B.-K. (2009): Intelligent fault diagnosis system of induction motor based on transient current signal. *Mechatronics*, 19, 680–689.
- Wu, C., & Hamada, M. (2009). Experiments Planning, Analysis and Optimization. Probability and Statistics. Hoboken, NJ: Wiley & Sons.
- Zhen, D., Wang, T., Gu, F., & Ball, A. D. (2013): Fault diagnosis of motor drives using stator current signal analysis based on dynamic time warping. *Mechanical Systems and Signal Processing* 34 (1-2), pp. 191–202. DOI: 10.1016/j.ymssp.2012.07.018.

BIOGRAPHIES



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Key factor identification for energy consumption analysis

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ABSTRACT

Nowadays the economic, environmental and societal issues concerning energy consumption require a deeper understanding of the factors influencing it. The influencing factors could concern the technical characteristics of the systems, the operational conditions and usage of equipment, the environmental conditions, etc. To understand the main contributing factors a knowledge model with the influencing factors is formalized in the form of an ontology. This ontology model allows to distinguish in a general way the main concepts (i.e. factors) that show higher consumption trends. This way, a preliminary analysis reflecting the key influencing factors could be perform in order to focus later on a deeper analysis with data mining techniques. This paper focuses on the formalization of an ontology model in the marine domain for energy consumption purposes. Then, the approach is illustrated with an example of a fleet of diesel engines.

1. INTRODUCTION

Managing energy consumption has become a key factor in enterprise concerns (Saidur, 2010), (Abdelaziz, Saidur, & Mekhilef, 2011). Indeed, it impacts not only from an economical point of view but from societal and sustainable development point of view as well (Hepbasli & Ozalp, 2003). Indeed, energy consumption:

- Increases in the price of energy,
- Carbon impact taxes,
- Environmental impact...

Hence when designing new systems, engineers aim at optimizing and decreasing energy consumption. However, many "old" systems are still in used and require attention for decreasing their energy consumption. Toward this aim, one solution is to bring new technologies to "old" systems. For instance, in the building domain, one has seen outer insulation, heat pump as new technologies available for upgrading old buildings. Nevertheless, such way is slowed down because of:

- The upgrading cost may be too high regarding the price of the "old" system or the economical capabilities of the owner;
- The ratio number of old systems by upgrade providers is always very high when a new technology emerge and makes the time to upgrade all "old" system very long.

When regarding quality management in enterprise, it preaches to learn from mistakes and to pool and share best practices. From this last idea, one can think to apply it to energy consumption reduction. Indeed, such a way does not suffer from both drawbacks outlined earlier. It cost almost nothing to apply new procedures since they do not require hardware upgrade and they can be widely spread using information technologies. However, it requires tools in order to support the determination of the best practices. Such tools have to deal with large/huge amount of data, multi-dimensional data, heterogeneous data, business knowledge structuring". One way is to use data mining techniques in order to highlight those best practices. However, data could be heterogeneous since it can come from different units with different characteristics. Then the use of data mining techniques alone may provide poor results, since they are only based on data. Moreover, data mining always requires pre-analysis in order to structure data and ease the search. Another way lies in using data

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structuring techniques through knowledge modeling in order to help expert to detect those best practices. The paper proposes to explore this second way. It shows how an expert can use an ontology to analyze from several points of view the energy consumption "trajectory" in order to detect what are the key factors impacting the reduction or increase of energy consumption. The purpose of this approach is not to replace data mining techniques, but to provide an overview of the factors affecting power consumption in order to help data miners and statisticians identifying the relevant data that require deeper analysis. This paper focuses on the formalization of an ontology model in the marine domain for energy consumption purposes. Then, we show on an example how the analysis can be conducted.

2. TOWARDS A SEMANTIC MODEL FORMALIZATION

To identify the factors that impact energy consumption one common approach is data mining where artificial intelligence, statistics and machine learning techniques helps to explore and discover knowledge from data. However, some drawbacks of data mining techniques is the time and efforts required to treat real process data due to:

- the noise and outliers values in the signals,
- the synchronization between the multiple data sources,
- the heterogeneity of signals since systems evolve in different environments, with different missions and thus monitored signals show significant variations (Voisin, Medina-Oliva, Monnin, Léger, & Iung, 2013).

To facilitate the work of data miners and statisticians and to overcome some oh these drawbacks, we propose to use semantic models that integrate the knowledge from experts of a domain and provide common semantic to data. In that sense, semantic models, such as ontologies, structure information from a common understanding of experts. The structured knowledge is based on the definition of the main concepts related to a domain and on the relationships among those concepts.

This paper focuses on the formalization of knowledge in the marine domain for energy consumption purposes. To provide the structure to the energy consumption of diesel engines in the marine domain, an ontology model is used. An ontology determines formal specifications of knowledge in a domain by defining the terms (vocabulary) and relations among them (Gruber, 2009). Ontologies are composed of classes, properties of the classes and instances:

 Classes describe concepts in the domain. In the marine domain, examples of classes are "components" or "diesel engines". Subclasses represent concepts that are more specific than the superclass (mother class). When a superclass has a subclass, it means that they are linked by a subsumption relation, i.e. "is a" relation, allowing a taxonomy to be defined. Hence, a hierarchy of classes is established, from general classes to specific ones.

- Properties are contained in a class definition and describe relationships among the classes. For example, the class "component" has property called "is monitored by" with the class "performance indicator". The property "is monitored by" links the individuals of the class "component" with the individuals of the class "performance indicator".
- Instances are the set of specific individuals of classes. For example, the engine "Baudouin 12M26.2P2-002" is a specific individual that is part of the class "diesel engine".

Ontologies define through concepts or classes, the characteristics of similarities among units and contexts, for instance, by defining common characteristics in the operational and contextual domains. The ontology gathers knowledge which is shared on one hand by the Condition Monitoring/ Prognostics and Health Management (PHM) community and on the other hand by the naval community. Some of the capabilities provided consist in (Noy and McGuinness, 2001): sharing common understanding of the structure of information among people or software agents, making domain assumptions explicit, defining concepts and knowledge and making domain inferences to obtain non-explicit knowledge.

The ontology model was built through experts interviews leading to the identification of the concepts to be considered and of the relationships among those concepts.

3. ENERGY ORIENTED SEMANTIC MODEL

The main factors that impact energy consumption are classified in:

- Maintenance factors
- Operation factors
- Environmental factors

An ontology model is formalized in order to structure knowledge and relationships among concepts coming from experts. The semantic model allows grouping data, building clusters and making them comparable. The different clusters will allow to detect differences between the groups and to identify specific directions for deeper investigation. A brief explanation of the factors that were integrated in the ontology model is presented in the following.

For the maintenance factors, it is well known that some degradation modes imply higher energy consumption. So a classification of degradation modes is included in the ontology model. The classification is built from the norm IEC 60812 (Analysis techniques for system reliability – Procedure for failure mode and effects analysis (FMEA), 2006) (Figure 1). The type of maintenance that is performed affects the energy consumption trends of equipments as well. Hence, it is included and built from the norm EN 13306 (*Maintenance terminology*, 2001) (Figure 1).

The operational context integrates the operational conditions to which the units are exposed to. Operational conditions usually lead to different units' behaviors (Medina-Oliva, Voisin, Monnin, & Léger, 2014). In the naval domain, operational context is break up into (Figure 2):

- *The operation conditions* (Figure 3): which include the speed of the engine, torque as well as the engine operation temperatures, such as the engine outlet water temperature. Moreover, engine speed are classified according to expert's rules into "low", "medium" and "high" speed engines. This rule is coded in the ontology; for instance, the "low speed" engine are those whose speed is lower than 200 rpm.
- *The operation modes* enumerate the working modes of the machine. For instance, steady state during constant speed or transient state during the acceleration/braking phases, etc.
- *The production conditions* include how the user maintains and uses the equipment. For this reason, the type of machine-operator is included (e.g. rough, smooth and regular driving), as well as the number of stops made. The lubrication and coolant consumption and types are included as well, since they affect the engine performances.
- *Machine configurations* corresponds to the arrangement or structure of the equipment. It can be in series or in parallel. This factor is formalized in order to differentiate behaviors of the power consumption evolution. Material and performances will depend if the machine is used in series with high demand (constantly) or if they are used with a lower load in a parallel configuration.
- *Mission* of the engine depends on its usage. This factor is quantified either by the distance travelled or by the working time. Also the usage of the engine will depend on the mission of the ship. This is why different types of ships were included (non-exhaustive list).

The environmental context describes the surrounding environment of the engines as a third class of influencing factors. The environment takes into account the weather conditions, the chemical composition of water (pH, salinity), the environmental temperature, water turbulence, etc. (Figure 4) which might impact units functioning behavior.

Hence, the main classes of factors that influence power consumption are formalized. This formalized knowledge is used with the gathered data in order to understand the power consumption behavior.



Figure 3. Part of operation conditions: speed classes.



Figure 4. Part of environmental factors.

4. ENERGY ORIENTED CAUSALITY RELATIONSHIPS

Once an ontology model is built, it allows querying on the data stored in the database. The user (e.g. statistician) is able to have a first approach suggesting plausible explanations of some behaviors. To do that, one must first classify the studied scenarios in two clusters: Low Consumption (LC) or High Consumtion (HC) individuals. As a first approach the median value of the power consumption indicator was used allowing to divide the scenarios in two clusters. In Figure 5 the LC individuals are colored in green and the HC individuals in red.

After, the number of occurrences found for each concept are counted. For example, if an instance has ran 50% of the working time in "low speed", then 0.5 of individual is counted for that concept. Once the occurrences of every individual are counted for all the concepts in the ontology, bar charts repre-



Figure 5. Definition of two clusters of individuals.

senting the differences trends of LC and HC individuals are shown (Figure 6). These bar charts reflect the most important factors influencing energy consumption at a first sight. This way a pre-analysis tool to data mining is proposed. Such tool helps to:

- search meaningful comparisons though the definition of clusters,
- identify possible causality relationships through comparisons,
- identify where to investigate further.

To illustrate the added-value of this approach a case study of a diesel engine used in the marine domain is studied.

5. CASE STUDY

To illustrate the feasibility of the proposed approach as well as the added-value, a scenario is proposed. This scenario shows how the ontology model is useful for statisticians before a deeper analysis for energy consumption purposes. The scenario contains 33 identical individuals exposed to different operational conditions. As a first step, the two clusters of individuals are presented in Figure 5: *LC* and *HC* individuals. The objective is to identify the key factors that influence the most the power consumption. To do such analysis, the impact of the concepts described in the ontology are investigated.

5.1. Speed classes (Figure 3)

According to the different speed classes defined by the experts, a bar chart is built showing the number of individuals belonging to each class (Figure 6). The chart uses the ratio of time spent in each speed class. For example if one individual spent 50% of time in the class "stopped", 25% in the class "low speed" and 25% in the class "medium speed", then the corresponding fraction of the individual is associated to each class. Finally all the fractions of individuals are summed for each class.

As a result we can see that the HC individuals spent more time in the medium and high speed classes (Figure 6). Deeper analysis is needed in that sense.



Figure 6. Bar chart with the distribution of individuals according the different speed classes.



Figure 7. Bar chart with the distribution of individuals according the different speed direction classes.

5.2. Speed direction classes (Figure 3)

The speed direction was also considered. In Figure 7, it can be seen that there is a slight difference between the LC individuals running in the positive direction and the HC ones. The same behavior is found for the negative direction concept. However there is few difference so it can be possible to conclude that this concept is not interesting for further analysis.

5.3. Torque classes (Figure 2)

From the torque classes' analysis, it can be noticed that the individuals that belongs to the very high torque classes have a higher power consumption (Figure 8). Deeper analysis is needed to understand the relation between the increment of torque and power consumption.

5.4. Machine-Operator classes (Figure 2)

There are two types of machine-operators for the engines. With this approach it is possible to notice a significant difference between both machine-operators (Figure 9): Machineoperator Y produces higher power consumption. This factor is interesting for further analysis.



Figure 8. Bar chart with the distribution of individuals according the different torque classes.



Figure 9. Bar chart with the distribution of individuals according the different operator classes.

5.5. Operation modes (Figure 2)

The effect of the engine operation mode is also addressed. As expected, individuals that are more in operation mode (and thus more loaded) require more power (Figure 10).

5.6. Transient mode classes (Figure 2)

The analysis of the time spent in transient modes (acceleration and braking) was also studied (Figure 11). Such operations modes are listed in the ontology (Figure 2). It is possible to observe that LC individuals spent more time in acceleration and braking modes. It is also known that the acceleration and braking phases demand more load (regarding the inertia). So such result is surprising. For this reason and in order to understand better the effect of the acceleration/braking modes, this factor needs to be further studied. For example the number of acceleration/braking, the speed delta among the accelerations/braking, etc. Maybe some correlated factors exist and should be investigated such as the waiting/moving factors.

5.7. Operation condition - engine exhaust gases temperature (Figure 2)

Concerning engine exhaust gases temperature, it can be seen a slight trend of more power consumption when the exhaust gases temperature is very high (class 380-400°C) (Figure 12).



Figure 10. Bar chart with the distribution of individuals according the different operation modes classes.



Figure 11. Bar chart distribution with the distribution of individuals according the acceleration/braking time.

However, this trend is not clearly established and thus with the existing information, it is not possible to draw conclusions.

5.8. Environmental temperature class (Figure 4)

A final factor that was study was the effect of the environmental temperature on the power consumption (Figure 13). It can be noticed that for lower temperature classes ($_{L}25$ "éC and 25-28 "éC), the power consumption is higher and for the higher temperature classes, the power consumption is reduced.

With this preliminary analysis based on a semantic model it is possible to focus the attention on the more relevant factors that affect the power consumption. In this case-study some factors were irrelevant such as the speed direction, the operation modes classes, and the exhaust gases temperature. On the other side, factors that require deeper analysis are: the speed and torque classes, the operator, the transient mode classes and the environment temperature.



Figure 12. Bar chart with the distribution of individuals according the engine exhaust gases temperature.



Figure 13. Bar chart with the distribution of individuals according the environment temperature.

6. CONCLUSIONS

The proposed approach provides the basis for the analysis of the influencing factors on performances. In this paper the target performance is the power-consumption. To do such analysis, an ontology model is formalized. The ontology contains expert knowledge which is introduced as a part of the classes (concepts) in the model. The classes allows to make cluster to bring information for engineers/statisticians. Moreover, the ontology model contains contextual information about the operational and environmental conditions of the engines, allowing to understand better some behaviors.

The influence of each cluster (represented as classes in the ontology) on the power consumption can then be visualized. This way, data-mining time and efforts are reduced. Moreover, the semantic model could integrate causality links that could not always be explained with data.

Some experimentations have already been done as shown in this paper. However, further experimentations have to be conducted to show the feasibility and the added value of this methodology. Moreover embedded knowledge could be refined while implementing this solution to different industrial systems.

As a future work, the analysis must take into account several

factors at the same time. Hence, we propose to use 3D bar chart to show correlated influences of 2 factors. Moreover, a semantic model to deal with the technical characteristics of different units will be integrated, in order to use it from a fleet-wide perspective (Medina-Oliva et al., 2014).

REFERENCES

- Abdelaziz, E., Saidur, R., & Mekhilef, S. (2011). A review on energy saving strategies in industrial sector. *Renewable* and Sustainable Energy Reviews, 15(1), 150–168.
- Analysis techniques for system reliability procedure for failure mode and effects analysis (fmea) (Tech. Rep. No. IEC 60812). (2006). International Electrotechnical Commission (IEC).
- Gruber, T. (2009). Ontology. In *Encyclopedia of database systems* (p. 1963-1965).
- Hepbasli, A., & Ozalp, N. (2003). Development of energy efficiency and management implementation in the turkish industrial sector. *Energy Conversion and Management*, 44(2), 231–249.
- Maintenance terminology (Tech. Rep. No. EN 13306). (2001). Association Française de Normalisation (AFNOR).
- Medina-Oliva, G., Voisin, A., Monnin, M., & Léger, J.-B. (2014). Predictive diagnosis based on a fleet-wide ontology approach. *Knowledge-Based Systems*(0), To Appear.
- Saidur, R. (2010). A review on electrical motors energy use and energy savings. *Renewable and Sustainable En*ergy Reviews, 14(3), 877–898.
- Voisin, A., Medina-Oliva, G., Monnin, M., Léger, J.-B., & Iung, B. (2013, Oct). Fleet-wide diagnostic and prognostic assessment. In Annual Conference of the Prognostics and Health Management Society 2013. New Orleans, États-Unis.

BIOGRAPHIES



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Figure 1. Part of the maintenance factors.


Figure ? Dort of the operational factors

Data quality and reliability: a cornerstone for PHM processes

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ABSTRACT

In most of industrial processes, the measurement are central to the process control and quality management. This become even truer when measurement data are used to develop and support PHM strategies. In this context, many software are installed in order to collect data for providing quality assessment at each step of the manufacturing process. However, measurement error or drift are not considered leading to downgrading / rejected products / suboptimal running conditions that comes from measurement drift not detected on time. In concrete, these lead to bigger penalty than losses of production due to stopping time for repairing sensors. Indeed, generally speaking, process data is the "raw material" for many business processes, starting from process control strategy, PHM strategies to Business Intelligence. Thus being able to ensure data quality and reliability is of first importance. Towards this end, methods and tools are required to support online measurement monitoring, predictive diagnosis and reliability enhancement.

In this paper, a dedicated approach developed in collaboration with ArcelorMittal Research is presented. It consists in the development of intelligent software that would enable sensor measurement validation taking into account process parameters and operational conditions. An illustrative case study is extracted from an ongoing application developed for the finishing line in ArcelorMittal plant at Florange in France. Results regarding measurement reliability assessment as well as sensor failure anticipation will be described.

1. INTRODUCTION

Today, industrial measurement reliability is essential to answer the big challenges of European industries: improving product quality, creating high-added value products and improve process control. Indeed, industrial measurements are used to feed databases and then analyzed in order to improve process control. Therefore, the process control strongly depends on the reliability of measurements.

Usually, measurements devices are monitored thanks to quality assurance and preventive maintenance. However this is not satisfying since it relies on punctual verifications of measurements reliability that covers only a fraction of instruments (less than 10%), and because controls are isolated. Such an approach does not guarantee full-time measurement reliability.

Besides, many sensors management software and process monitoring software are available on the market, such as CompuCalTM/CompucalTM Plus, GESSICA, OPTI MU, HASTING, DECA, SPLI 4M, Wonderware Archestra IDE, which are mainly dedicated to:

- management of instruments' calibration and maintenance actions (planning, monitoring, cost evaluation, definition of procedure, assistance on calibration, etc),
- database of instruments' measurements (report on deviation, definition of uncertainty and capability, audit trail, etc),
- process performance monitoring solutions based on Data Reconciliation and Validation, which enables to rely on reliable and accurate information. Measurements errors are highlighted, corrected. Such system computes a series of unmeasured data that are

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often key for performance improvement. These systems however do not run in real-time and in closed loop with control systems.

In many cases such an approach does not allow identifying immediately a sensor drift. For example, during rolling, an out of gauge information does not allow discriminating a sensor drift from other causes such as rolling actuator failure or a problem linked to the metallurgical feature of the rolled product. These systems do not allow distinguishing individual sensor drift from the process, actuators and control systems behaviors.

Lots of examples can be quoted to illustrate the damages caused by this lack of measurement reliability. In particular, changes in the condition of use of the sensors can influence the sensor measurement accuracy and have important consequences if they are not detected. For instance:

- distance between the sensors and the target;
- alignment of the temperature sensors in an oven can influence the measurement and consequently lead to over-heating;
- dirtying of the sensor optic can lead to an abnormal measurement.

These issues are encountered not only in steel industry but also in many other industries (glass production, polymer production, etc). That makes the challenges of ensuring the reliability of industrial measurements even more important since it will enable the rationalization of both energy and raw material use as well as maintenance costs. In particular, it will have the following impacts:

- increase productivity (by decreasing unintended production line stoppage),
- rationalize maintenance costs leading to a decrease of 15% of maintenance time,
- decrease non-conformity of final products and increase process control,
- decrease energy consumption of production lines (by avoiding over-heating due to non-reliable temperature measurements),
- decrease the early wear of tools (for instance an excessive roll force due to a faulty measurement can induce damage of the work rolls , mechanical transmission , ...)
- optimizing the maintenance actions through the availability of a dedicated tool for anticipating and rationalizing the service operations of sensors.

In parallel, sensor and measurement fault detection and diagnostic have rather constant interest in literature in various industrial domains. One can refer to (Samy et al. 2011), (Reppa et al. 2012), (Lee et al. 2011), (Zhang et al, 2012) for relevant and recent work focused on sensors and measurement fault detection and diagnostic. However, most

of the results rely on complex modelling, or have been developed on top of simulation model (not reflecting fully industrial constraints) and for which the need on computer infrastructure to apply the approach (Miletic et al. 2008) is not fully addressed.

All in all, since industrial measurements are used not only to feed database but also for supporting condition monitoring and analysis in order to improve process control, the reliability of measurements is still a key issue.

Today, maintenance team does not dispose of tools allowing anticipating sensors failures. This means that those failures are discovered during the analysis of incident on production lines or during the analysis of out-of-specification products. For example in the hot strip mill of Seremange, 28% of production line stoppages are due to sensors failures (this represents more than 200000 Euros for only one production line in Seremange).

However, as described in the European Factories of the Future 2020 Roadmap¹, three of the six Research and Innovation Priorities are the creation of high-added value products, Adaptative and smart manufacturing systems – including control and monitoring – and Digital virtual & Resource efficient factory – including Prognostic and Health Management (PHM).

Thus the enhancement of industrial measurement reliability is a sine qua none condition for industries to be able to improve product quality, create high-added value products, improve process control and enhance performance through PHM deployment.

To tackle such issue and further develop and deploy PHM system, intelligent information technologies are required in order to enable sensor measurement validation taking into consideration steel process parameters correlation and operational conditions. To this aim, an integrated software platform is currently developed under the umbrella of the PRIME project (ERA-Net / Manu-Net program) in order to enhance the reliability of on-line and real-time industrial measurements. This innovative solution based on the CASIP/KASEM® platform integrates both an individual monitoring of sensors measurements and intermeasurements consistency monitoring.

Section 2 presents the scope and framework of the project. In section 3, the case study is introduced and the proposed method is presented along with its application. Finally section 4 concludes the work.

2. PROJECT CONTEXT AND FRAMEWORK

2.1. Outlook of the developed approach

The PRIME (ERA-Net / Manu-Net program) project, aims at developing an integrated software platform in order to

¹ http://www.effra.eu/attachments/article/129/Factories%20of%20the%20F uture%202020%20Roadmap.pdf

enhance the reliability of on-line and real-time industrial measurements.

The project objectives follow a PHM approach in that sense that it aims at:

- detect in a short delay and anticipate sensor failure
- detect and localize abnormal measurements,
- set a diagnosis and propose a solution to correct or compensate failures in a short delay;
- propose, whenever it is possible, an alternative measurement solution to ensure service continuity;
- Enhance the accuracy of production database

Towards this end, a specific approach is developed in order not only to focus on measurement individually but also to enable a global and consistent consideration of measurement behavior.

In concrete terms, the integrated platform will gather:

- A toolbox for individual monitoring of sensors measurements: enabling the real-time, in situ monitoring of individual sensors measurements.
- A toolbox for inter-measurements consistency: it will use physical relations between measured parameters as well as models in order to improve the intermeasurement consistency, to identify confidence interval and to propose replacing measurements.

The framework of the project comes from industrial statement and consideration. Sensors are not followed form a continuous point of view in spite of the impact of false measurement or drift measurement can affect the whole product quality. Furthermore, depending on the part of the inter-measurement relationships process, becomes mandatory to distinguish between sensor and process degradation. As results, the innovation of the project is based on the consideration of operational conditions and on the combination of these two complementary toolboxes that will enable to enhance measurement reliability through failure anticipation and dynamic corrective strategies application. Indeed, considering operation condition brings the necessary segmentation of data that enable process behavior to be compared over time since the condition of comparisons are known and well defined. This approach falls within the whole methodology developed at PREDICT.

The toolbox for individual monitoring of sensors measurements enables a local approach of data validation. It integrates operational conditions in the validation process in order to provide on-line confidence value to raw data and allows early drift or abnormal value detection. The toolbox for inter-measurements consistency will thus benefit from the individually validated data and will concentrate on interrelationship between measurements.



Figure 1. Framework of the proposed approach.

Moreover inter-measurement validation will improve to distinguish between individual sensor drift from the process, actuators and control systems faulty behaviors since it relies on interrelation linking different measurements.

As shown in Figure 1, on top of that, it is also expected to investigate a fleet-wide dimension for sensor measurement. The objectives of investigating the fleet dimension is to enlarge knowledge about sensors behavior in order to share this knowledge by means of the software platform. As a consequence solutions to fix problem can be more easily and quickly deployed over all the process measurement. The fleet dimension rely on the capacity to deal with similar/heterogeneous equipment (from sensor to large and complex equipment (e.g; engine...)), taking benefit form already developed approaches (Monnin et al. 2011a, Voisin et al. 2013).

2.2. Software platform foundations and features

In addition to the structuration of the underlying approach, a key success factor relies on the ability to provide within an integrated platform, the data processing means that will run on-line in an industrial environment with a smooth integration in the existing architecture and infrastructure. Towards this end, the project platform is based on the CASIP/KASEM® software platform designed and developed by PREDICT (Leger 2004, Monnin et al. 2011b). The platform has been designed to support Asset Health Management (AHM) including Condition Based Monitoring (CBM), Predictive Diagnostic, Prognostic & Health Management (PHM), Fault-Tolerant Control (FTC) and Proactive Therapy. Towards this end, the platform is built on top of a knowledge-based system. The database formalizes information and knowledge and makes it more synthetic and shareable between users (experts, technicians, and operators).

For supporting the toolboxes, the platform is not limited or constrained by particular modelling techniques and integrates a programing environment. That allows to develop and execute algorithms and gather datadriven/statistics based algorithms as well as models (physical models, setting-up models...). Specific algorithm can be directly coded within the programming environment of KASEM®, while existing one can be integrated in the toolbox as DLL to be further used. Thus, starting from process raw data acquisition, algorithms are structured by means of sequence of treatments in order to provide realtime and on-line monitoring (e.g. drift indices monitoring and detection).

3. APPLICATION CASE AND RESULTS

In this section, the proposed approach and technique for the individual monitoring toolbox is described along with their implementation within the KASEM® platform. In order to progress in the development of the toolboxes, the production site of ArcelorMittal in Florange has provided a data set reflecting the current situation in order to develop early demonstrator to show the potentiality of the supporting tools and techniques and highlight the added value of the approach with regard to the current situation. Focused on the application and capability of existing tools and methods, this paper does not deal with a strict comparative study. The presented results are evaluated with regard to the existing alarm system implemented on site.

3.1. Hot strip mill case study

The study takes place with the hot strip mill (Figure 2) of the production site which produces high-performance steel mainly for the automotive industry.



Figure 2. Hot Strip Mill at Florange

The proposed case study was concentrated on the finishing part of the process and more precisely on the finishing scale breaker (FSB) (Figure 3). Indeed the efficiency of the descaling directly impact the end product quality. Thus the descaling process is monitored thanks to the pressure measurement of the water supply circuit. Actually, a sensor failure can be detected by means of thresholds within the PLC.



Figure 3. FSB supervision system screenshot

The descaling process is controlled by means of the water supply circuit configuration according to the opened/closed valves and the outlet pressure is acquired and stored every 3ms seconds. In normal condition when the valve is open the pressure in the corresponding line is around 10 bar and null when the valve is closed. Currently, a quality alarm is triggered by the PLC when the mean pressure on 1 second is less than 7 bar.

In Figure 4, the red signal corresponds to the opening command of the valve and in black the corresponding pressure measured from line E_i (see Figure 3). Here, the last period before the sensor replacement is shown. It corresponds to one day of data and around 2 million of values for the pressure.



Figure 4. Pressure signal from the KASEM visualization tool

In this context, the work was focused in the scope of individual measurement monitoring in order to develop the first tool within the toolbox for individual measurement monitoring. In the next section the method applied and the corresponding results of monitoring and early detection are presented.

3.2. Individual measurement monitoring and detection

In order to develop monitoring and detection tool for the individual measurement, the proposed approach relies on 3

majors steps. First the operating conditions are determined. Then abnormal behavior are investigated and condition monitoring indices are defined and finally detection process is developed.

According to the circuit presented in Figure 3, 7 binary signals are available (one for each valve and draining). Based on that, 34 combinations have been identified in the dataset and ranked according to (i) their duration time and (ii) their occurrence number. The 2 combinations with the highest duration where E_i is opened and E_i is closed are kept for further analysis. In spite of the applicability of the proposed approach in each of the combination, the highest duration combinations represent the most "current" process behavior and then the combinations in which the probability of encounter problem increase. Moreover, the corresponding amount of data provides more accuracy in the statistical approach to assess thresholds for detection.

Even in normal conditions, the transient behaviors of the pressure can affect the detection. It becomes necessary to consider the pressure value in reliable open or close mode in order to avoid for instance peaks or delay when the valve opening or closing and concentrate on real expected value. Towards this end the opening and closing modes are re-evaluated. In Figure 5 an example is provided where the new stopping condition (in blue) is evaluated to avoid, in this case, oscillations.



Figure 5. Example of stopping condition recalculation

In order to propose an accurate and robust monitoring and detection tool, statistical approaches have been used both for monitoring and detection.

The statistical approach combines the evalutation of median and confidence interval. Given the high sample rate and pressure behavior, it is important to provide accurate and consistent indicators. Indeed, due to its easy computation and robustness property the median is a efficient way to summarize such time series data. In addition the confidence interval calculation allows to assess accurate threshold to built detections. Working with the median for each opening and closing sequence reduces effect of signal noise since it acts as a sliding median filter and allow to reduce fasle alarm and missed alarm. Thus for each conditions (i.e. valve opening and closing) theses statistical indices are computed. An example for 2 valve opening sequences is provided in Figure 6.



Figure 6. Example of statistics calculation

In this example, the upper level is set at 90% and the lower level is set at 10%. In order to provide generic toolbox, each of these parameters for the statiscal indicators can be tuned.

From these indicators, it is possible to defined the detection thresholds and algorithms. Indeed, by statistically summarising the behavior it allows to provide more robust and efficient detection.

Towards this end, the upper and lower thresholds for detection have been defined according to the upper and lower confidence level obtained from the data set (Figure 7).



Figure 7. Example of the evolution of the upper and lower levels in functioning mode (i.e. valve open)

Thus, the threshold obtained, as median of the upper and lower levels considered, are 8 bar for the lower threshold and 12 bar for the upper threshold. Since the thresholds are determined, the abnormal behavior detection can be set up. Given this process, only two steady states are achieved for the pressure (namely opening and closing) leading to fix upper and lower thresholds for each mode. In case of more complex process with different steady states, adaptatvies thresholds would have been defined and applied.

For the detection, a first approach relies on considering the median of the pressure value as shown in Figure 6 and to trigger alert when the upper or lower thresholds are overpassed. The results of the simple approach are shown in Figure 8. For the period considered (~1,5 month) before the sensor replacement, the pressure signal leads to 17063 values of median (i.e. 17063 valve opening sequences) and in that case, 370 detections have been triggered for both the upper and lower thresholds.



Figure 8. Example of statistics detection

Even if the median calculation for the detection can be setup on-line for real-time detection, another approach have been investigated to get closer to the process and sensor behavior.

A moving window detection approach has been defined. Given that one valve opening sequence corresponds to around 2500 pressure values, a moving window of 300 points have been defined. If 200 points in the window exceed the threshold then a alert is triggerd. Finally, given the process dynamic, there are around 50 valve opening sequences per hour. Then in order to avoid untimely alarms, we consider a consolidated detection that delivers the number of triggered alert (based on the moving window detection) every 50 opening valve sequences.

3.3. Comparative results

As stated in the introductory part of section 3, the purpose of this work within the project context was to show the potentiality of the supporting tools and technique and highlight the added value of the approach with regard to the current situation.

Towards this end, the existing alarm rule (i.e. "alarm is triggered if mean pressure on 1 second is less than 7 bar") was also integrated in the KASEM® platform in order to compare the detection. Additionally we also setup the consolidated detection every 50 opening valve sequences for the detection rule. The results are highlighted in Figure 9.



Figure 9. Detection results comparison over a 2.5 month period

The proposed approach has highlighted several benefits and improvements. The statistical evaluation of thresholds has permits to increase the lower threshold from 7 to 8 bar when valve is open. As a consequence, the early detection is greatly improved. Furthermore, by coupling the moving window detection with the consolidation per every 50 functioning sequence that allows to reduce untimely alarms without loss of accuracy and consistency. All in all, by considering only the detection of the same abnormal behavior as the existing one, i.e. the loss of pressure when the valve is open; the proposed approach with the consolidated detection provide an efficient mean to continuously follow-up the sensor behavior. Given the process dynamic, by considering that 10 detections per 50 opening valve sequences becomes critical, the implemented detection approach is able to early detect the sensor fault with around one month of anticipation compared to the existing alarm (cf orange arrows in Figure 9). From Figure 9, the data set start in middle of March, since we haven't get much data from early period, we were not able to assess if the proposed approach was able to provide much more early results.

3.4. Generic and modular toolbox

The approach has been developed in a generic way allowing to deploy the same detection method for the different operating modes and abnormal behaviors presented by the sensors. Indeed, for the closing valve sequence the same approach was applied. Upper and lower thresholds was identified by means of confidence level method. And the same detection method was deployed. Additionally, the peaks of pressure at opening were also studied as well as opening delays. Thus various monitoring indicators are now available for monitoring the sensor behaviors and included in the toolbox for individual monitoring of sensors. These indicators will also contribute to enhance the diagnosis capabilities of the platform. Figure 10 provides an example for the valve closing sequence. In this operating mode the upper threshold has been determined to 1 bar (by means of the confidence level approach as previously). The detection method presented here is the moving window on 300 points. The pressure signal is in black, the valve command in red and the detection in blue



Figure 10. Example of moving window based-detection for the closing mode.

4. CONCLUSION

In this paper, a robust and efficient detection approach for sensor monitoring has been presented. The statistical approach makes the detection more robust and consequently more meaningful by reducing false alarm. In addition the consolidation and frequency approach avoid untimely alarm without making the system too less sensitive. The implementation within the KASEM® platform has allowed a generic and modular toolbox to be developed. Each step of the method has been easily deployed to the other signals considered in the application (i.e. 6 pressure signals of the FSB system) and for the 2 operating modes.

The efficiency and accuracy of the method has been assessed in real condition by comparison of the results with the existing alarm system running at the plant.

Based on that, future work will investigate on the one hand, how this approach could contribute to the toolbox for intermeasurements consistency. Especially when several indicators can be defined for the same sensor. In addition, inter-measurement methods could also allow to assess behavior within the confidence interval. For instance if a sensor start to tangent the higher or lower confidence level it could have impact on other measurement (in case of control loop for instance). On the other hand, other methods will be investigated thanks to different measurement sensor type with a focus on torque and force sensors.

Thus, the combination of consistent continuous follow-up indicators, early detection and diagnostic features, the toolboxes within the platform will directly contributes the reliability enhancement of sensor measurement.

REFERENCES

Lee, B. H., Jeon, N. J., & Lee, H. C. (2011, October). Current sensor fault detection and isolation of the driving motor for an in-wheel motor drive vehicle international conference on control, automation and systems (ICCAS 2011). In *Control, Automation and Systems (ICCAS), 2011 11th International Conference* on (pp. 486-491). IEEE.

- Léger J-B. (2004). A case study of remote diagnosis and emaintenance information system, *Keynote speech of IMS'2004, International Conference on Intelligent Maintenance Systems*, Arles, France.
- Miletic, I., Boudreau, F., Dudzic, M., Kotuza, G., Ronholm, L., Vaculik, V., & Zhang, Y. (2008). Experiences in applying data-driven modelling technology to steelmaking processes. *The Canadian Journal of Chemical Engineering*, 86(5), 937-946.
- Monnin, M., Voisin, A., Leger, J. B., & Iung, B. (2011a). Fleet-wide health management architecture. In *Annual Conference of the Prognostics and Health Management Society.* September, Montreal, Quebec, Canada.
- Monnin, M, Leger, J-B., Morel, D. (2011b). KASEM®: e-Maintenance SOA Platform, in Proceedings of 24th International Congress on Condition Monitoring and Diagnostics Engineering Management, 29th May – 1st June, Stavanger, Norway.
- Reppa, V., Polycarpou, M. M., & Panayiotou, C. (2012, August). Distributed sensor fault detection and isolation for nonlinear uncertain systems. In *Fault Detection, Supervision and Safety of Technical Processes* (Vol. 8, No. 1, pp. 1077-1082).
- Samy, I., Postlethwaite, I., & Gu, D. W. (2011). Survey and application of sensor fault detection and isolation schemes. *Control Engineering Practice*, *19*(7), 658-674.
- Voisin, A., Medina-Oliva, G., Monnin, M., Leger, J. B., & Iung, B. (2013, October). Fleet-wide Diagnostic and Prognostic Assessment. In Annual Conference of the Prognostics and Health Management Society 2013.
- Zhang, Y., Bingham, C., Gallimore, M., Yang, Z., & Chen, J. (2013, July). Sensor fault detection and diagnosis based on SOMNNs for steady-state and transient operation. In *Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), 2013 IEEE International Conference on* (pp. 116-121). IEEE

Poster Papers

Synthetic Data for Hybrid Prognosis

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ABSTRACT

Using condition-based maintenance (CBM) to assess machinery health is a popular technique in many industries, especially those using rotating machines. CBM is relevant in environments where the prediction of a failure and the prevention and mitigation of its consequences increase both profit and safety. Prognosis is the most critical part of this process and the estimation of Remaining Useful Life (RUL) is essential once failure is identified. This paper presents a method of synthetic data generation for hybrid model-based prognosis. In this approach, physical and data-driven models are combined to relate process features to damage accumulation in time-varying service equipment. It uses parametric models and observer-based approaches to Fault Detection and Identification (FDI). A nominal set of parameters is chosen for the simulated system, and a sensitivity analysis is performed using a general-purpose simulation package. Synthetic data sets are then generated to compensate for information missing in the acquired data sets. Information fusion techniques are proposed to merge real and synthetic data to create training data sets which reproduce all identified failure modes, even those that do not occur in the asset, such as Reliability Centered Maintenance (RCM), Failure Mode and Effect Analysis (FMEA). This new technology can lead to better prediction of remaining useful life of rotating machinery and minimizing and mitigating the costly effects of unplanned maintenance actions.

1. INTRODUCTION

The use of Condition-Based Maintenance (CBM) has increased rapidly over recent years, largely because CBM can predict failure in such a way that the profit and safety of the asset are increased. Once failure occurs, however, it is crucial to continue the prognosis process, estimating the Remaining Useful Life (RUL) of the asset.

Physical or theoretical models can be used for this purpose. Theoretical models are determined from the physics of the system and expressed by means of equations (Isermann & Münchhof, 2011). These equations, either ordinary or partial differential equations, can be classified as the following:

- Balance equations (i.e. chemical reactions)
- Physical or chemical equations of state (i.e. equations that relate state variables)
- Phenomenological equations (e.g. Fourier's law of heat conduction)
- Interconnection equations (e.g. Kirchhoff's current law)

Once a set of equations is obtained, the theoretical model is defined. Complex equations are simplified by means of linearizations, approximations with lumped parameters, and order reductions, among others (Isermann & Münchhof, 2011), making mathematical treatment feasible.

These models are very useful for describing the behaviour of time-varying systems, taking into account different operating modes, transients, and variability in environmental conditions. The greater the complexity of the model, the greater the effort required to develop and validate it (Galar, Kumar, Villarejo, & Johansson, 2013). This calls for more computational resources. Thus, a limit in the complexity of the physical model should be defined.

There are many physical models used for rotating machinery. (Qiu, Seth, Liang, & Zhang, 2002) simplify a bearing as a single Degree-of-Freedom (DOF) model using a massspring-damping system. (Harsha, 2006) and (Purohit & Purohit, 2006) take a 2 DOF approach when modelling a bearing

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to study the motion of the shaft in the plane of the bearing. Other authors such as (Jain & Hunt, 2011) consider the dynamics of the rolling elements of a bearing by using a 3 DOF model for the shaft and a 2 DOF model for each ball.

(Sawalhi & Randall, 2008) develop a 5 DOF model for a rolling element bearing in which they consider the rolling elements as angularly equidistant; they also propose a 6 DOF model for a gear, and use the model to obtain the response of a gearbox test rig. The work of (Baguet & Jacquenot, 2010) combines a shaft-gear model and hydrodynamic journal bearing model. In this case, a pinion-gear pair is represented by means of two shaft finite elements with two nodes each; the stiffness is calculated taking into account the tooth deflection and the foundation flexibility. (Abbes, Hentati, Maatar, Fakhfakh, & Haddar, 2011) present a model that combines the dynamics of a ball bearing and a gear transmission. They introduce a time-varying stiffness matrix, where the number of teeth in contact and the variability of periodic and meshfrequency based mesh stiffness are considered as varying parameters.

In all these approaches, a system model is at the centre of the development process, from requirements analysis, through design, implementation and testing. Today, nevertheless, the model-based approach is also designed for maintenance purposes, especially condition monitoring. The main advantage of these approaches to CBM over data-driven approaches is their ability to incorporate a physical understanding of the monitored system (Luo et al., 2003). Data-driven models miss the link between data and the physical world, thus questioning the reliability of the algorithm, but physical models make the prediction of results intuitive because of their use of case-effect relationships. Their main drawback is the effort required to develop them. Moreover, they require assumptions regarding complete knowledge of the physical processes; parameter tuning may require expert knowledge or learning from field data. Finally, high fidelity models may be computationally expensive to run.

2. MODELLING FAILURES

Physical models are used to estimate the response of systems in both healthy conditions and failure conditions. The models can be used to simulate component or system failures, and with adequate modelling of the failure modes, the model can be adjusted. In other words, different system responses can be obtained, with and without failure, using the equation set forming the physical model.

The literature notes several ways of modelling failure in the field of rotating machinery. For example, (Rafsanjani, Abbasion, Farshidianfar, & Moeenfard, 2009) reproduce the transient force that occurs when a rolling element bearing comes into contact with a defective surface creating a series of impulses that repeat the characteristic frequencies of the ele-

ments of the bearing. (Kiral & Karagülle, 2003) amplify the contact forces using a predefined constant when the bearing contact is produced in a damaged area.

(Nakhaeinejad, 2010) proposes modelling faults as surface profile changes instead of introducing mathematical impulse functions based on fault frequencies. (Tadina & Boltežar, 2011) develop a 2D model of a bearing in which defects are modelled as geometric changes. In this case, a fault in a race is modelled as an ellipsoidal depression whereas a fault in a ball is modelled as a flattened sphere.

For fault modelling of gears, (Chen & Shao, 2011) develop a mesh stiffness model in which a gear tooth is divided into thin pieces; the stiffness of each piece is calculated taking into account bending, shear and axial compress (function of fault properties). Then, the whole tooth stiffness is obtained by integrating the stiffness of each slide. (Jiang, Shao, & Mechefske, 2014) introduce spalling faults in a gear model as a variation in the mesh stiffness of the teeth contact. The length of the contact line is modified to change the value of the stiffness.

However, it is difficult to predict the RUL once there is a spall in the system. Thus, failure evolution and how some failure modes initiate or aggravate others should be defined. Crack propagation failure modes are the most commonly developed behavioural models for prognostics (Sikorska, Hodkiewicz, & Ma, 2011). For example, the Paris-Erdogan law (Paris & Erdogan, 1963) can be used to define the evolution of the growth of a sub-critical crack under a fatigue stress regime and is expressed as:

$$\left(\frac{da}{dN}\right)_{n+1} = C \cdot \left(\Delta K\right)^m \tag{1}$$

where a is the crack length, N is the number of load cycles, n is the current iteration, ΔK is the range of the stress intensity factor, and C and m are material constants. Following this theory, as well as Forman and NASGRO 2/3 laws, (Drewniak & Rysiński, 2014) provide an analytical gear teeth fatigue life estimation. (Li, Kurfess, & Liang, 2000) use a stochastic defect-propagation model to calculate the RUL of a bearing.

3. CREATION OF DATA SETS

System prognosis requires data which can be obtained from two sources: an operating system using different sensors or a physical model. In certain cases, the latter source has some advantages, as for example, the case of an aircraft.

Data from an aircraft system can be recorded when the asset is healthy, but once the Key Performance Indicator (KPI) of the system reaches the maintenance threshold limit, maintenance processes are carried out. Thus, data can only be acquired until near time t_m , the time when the limit is crossed, taking into account some tolerance, as shown in Figure 1. The asset



Figure 1. Trend analysis for the remaining useful life

will never be allowed to exceed the predefined safety threshold limit (reached at an unknown time t_s) for the following reasons:

- Security: some faults put both the asset and the people using it at risk.
- Cost: the development of a fault in a component of an aircraft can be very expensive.
- Environmental issues: the effect of a fault can be detrimental for the environment.

Consequently, faulty conditions cannot be recorded from the real system. However, such data can be created with a physical model. Failure modes can be defined using Reliability Centred Maintenance (RCM) and Failure Mode and Effect Analysis (FMEA), among others. When these failure modes are modelled, the data generated are called "synthetic" data.

In conclusion, the final data set is formed by data generated from both real systems and a physical model of the system. As both physical-model and data-driven approaches are used, a hybrid model is formed, as illustrated in Figure 2.

3.1. Semi-supervised learning

Classification techniques are divided into three groups: unsupervised, supervised and semi-supervised learning. Unsupervised classification or cluster analysis consists of a set of techniques used to group individuals in unknown groups. The objective is to relate p individuals to q groups in such a way that each element is associated with only one group and the distribution of each group is internally homogeneous. Supervised learning, also known as machine learning, begins with data that belong to 2 or more groups. The objective is to obtain a relationship between the inputs (data) and the outputs (groups) in such a way that it is possible to assign a group to a new data case.



Figure 2. Hybrid model approach

Semi-supervised learning falls between the two other methods. Looking again at the aircraft, data can only be recorded when the system is healthy. Figure 3 shows some healthy data taking into account two features. Newly acquired data near the individuals in Figure 3 will belong to the healthy case, but if not they will belong to a faulty case. Therefore, only healthy and faulty cases can be distinguished.

Faulty data cannot be captured from the aircraft because of the reasons already presented. When synthetic data are generated by a physical model, however, different failure modes can be recognized besides the healthy case. This improves the initial classification criterion. Data belonging to healthy (H) and some faulty cases (F_1 , F_2 and F_3) can be seen in Figure 4. Newly acquired data will belong to any of these cases.

Once the data set is created, semi-supervised learning is carried out using such techniques as Support Vector Machine



Figure 3. Learning using healthy data recorded from the real system



Figure 4. Learning using both healthy data acquired from the real system and synthetic data generated by the physical model

(SVM), k Nearest Neighbour (kNN) and Neural Networks (NN), among others.

4. TUNING PROCESS

When the learning process is completed, newly acquired data can easily be classified using the aforementioned methods. However, data that do not fit into any of the clusters defined in the learning process can also appear. This state in which an abnormal or unknown fault is produced is known as No-Fault-Found (NFF). A graph illustrating this is shown in Figure 5. Here, the new data do not belong to any of the predefined groups (H, F_1 , F_2 and F_3) are labelled NFF. There are two main reasons for the appearance of NFF data:

- The physical system is not sensitive to one of the studied failure modes, and the acquired data do not reflect the response of the physical system.
- The acquired data belong to a failure mode not previously identified.

The appearance of this kind of data must be used to update the already established classification criteria. They are considered data related to another failure mode, and the semisupervised learning is repeated. The process of automatically updating the classification criteria is called the tuning process. A scheme of this process appears in Figure 6. New data acquired from the real system are considered input data and are classified according to the clusters previously obtained using synthetic and raw data. The output is used to retrain and improve the classification method.



Figure 5. No-fault-found case

Once the tuning process is developed, it gives a better understanding of failure evolution; consequently, the prognostics process is more easily carried out.

5. CONCLUSIONS

The main purpose of the hybrid model is to compensate for the weaknesses of data driven and physical models. Datadriven techniques are based on complete data sets that do not usually cover all the identified failure modes because of economic, security or environmental reasons. Additional data are needed from models based on knowledge to fill the gap. Physical models are able to represent the response of a system in



Figure 6. Tuning process of the classification method

normal operating conditions and include fault modelling with the objective of determining the behaviour of the system in different faulty cases detected by different failure mode analyses. It is not new to get data from physical models, but the way these data are integrated in the system and how the physical model is tuned to increase the accuracy of these synthetic data are certainly new. In addition, the system must be able to produce data for all the failure modes identified by means of FMEAs and other failure analysis techniques.

As a consequence of this interaction, "synthetic" data sets are created. These, in combination with raw data acquired from the real system, can be used in semi-supervised learning to improve the accuracy of estimations using only the real data. When newly acquired data suggest the presence of a failure that has not been considered, the data are used to update the learning process. The goal is to create the most complete date sets covering all relevant failure modes to obtain better remaining useful life estimation.

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REFERENCES

- Abbes, M. S., Hentati, T., Maatar, M., Fakhfakh, T., & Haddar, M. (2011). Dynamic analysis of helical gears supported by rolling element bearings. *Journal of Theoretical and Applied Mechanics*, 41, 33-50.
- Baguet, S., & Jacquenot, G. (2010). Nonlinear couplings in a gear-shaft-bearing system. *Mechanism and Machine Theory*, 45(12), 1777-1796.
- Chen, Z., & Shao, Y. (2011). Dynamic simulation of spur gear with tooth root crack propagating along tooth width and crack depth. *Engineering Failure Analysis*, *18*(8), 2149-2164.
- Drewniak, J., & Rysiński, J. (2014). Model of fatigue damage accumulation. *Key Engineering Materials*, 598, 51-56.
- Galar, D., Kumar, U., Villarejo, R., & Johansson, C.-A. (2013). Hybrid prognosis for railway health assessment: an information fusion approach for PHM deployment. *Chemical Engineering Transactions*, 33, 769-774. (PHM 2013 Special Issue)
- Harsha, S. P. (2006). Nonlinear dynamic analysis of rolling element bearings due to cage run-out and number of balls. *Journal of Sound and Vibration*, 289(1-2), 360-381.
- Isermann, R., & Münchhof, M. (2011). Identification of dynamic systems An introduction with applications.

Springer Berlin Heidelberg.

- Jain, S., & Hunt, H. (2011). A dynamic model to predict the occurrence of skidding in wind-turbine bearings. *Journal of Physics: Conference Series*, 305(1), 012027.
- Jiang, H., Shao, Y., & Mechefske, C. K. (2014). Dynamic characteristics of helical gears under sliding friction with spalling defect. *Engineering Failure Analysis*, 39, 92-107.
- Kiral, Z., & Karagülle, H. (2003). Simulation and analysis of vibration signals generated by rolling element bearing with defects. *Tribology International*, 36(9), 667-678.
- Li, Y., Kurfess, T. R., & Liang, S. Y. (2000). Stochastic prognostics for rolling element bearings. *Mechanical Systems and Signal Processing*, 14(5), 747-762.
- Luo, J., Namburu, M., Pattipati, K., Qiao, L., Kawamoto, M., & Chigusa, S. (2003). Model-based prognostic techniques [maintenance applications]. In AUTOTEST-CON 2003. IEEE Systems Readiness Technology Conference. Proceedings (p. 330-340).
- Nakhaeinejad, M. (2010). Fault detection and modelbased diagnostics in nonlinear dynamic systems (Unpublished doctoral dissertation). The University of Texas at Austin.
- Paris, P., & Erdogan, F. (1963, December). A critical analysis of crack propagation laws. *Journal of Basic Engineering*, 85, 528-533.
- Purohit, R. K., & Purohit, K. (2006). Dynamic analysis of ball bearings with effect of preload and number of balls. *International Journal of Applied Mechanics and Engineering*, 11(1), 77-91.
- Qiu, J., Seth, B. B., Liang, S. Y., & Zhang, C. (2002). Damage mechanics approach for bearing lifetime prognostics. *Mechanical Systems and Signal Processing*, 16(5), 817-829.
- Rafsanjani, A., Abbasion, S., Farshidianfar, A., & Moeenfard, H. (2009). Nonlinear dynamic modeling of surface defects in rolling element bearing systems. *Journal of Sound and Vibration*, 319(3-5), 1150-1174.
- Sawalhi, N., & Randall, R. (2008). Simulating gear and bearing interactions in the presence of faults: Part I. the combined gear bearing dynamic model and the simulation of localised bearing faults. *Mechanical Systems and Signal Processing*, 22(8), 1924-1951.
- Sikorska, J. Z., Hodkiewicz, M., & Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, 25(5), 1803-1836.
- Tadina, M., & Boltežar, M. (2011). Improved model of a ball bearing for the simulation of vibration signals due to faults during run-up. *Journal of Sound and Vibration*, *330*(17), 4287-4301.

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A multivariate statistical approach to the implementation of a health monitoring system of mechanical power drives

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ABSTRACT

The implementation in service of accelerometric health monitoring systems of mechanical power drives has shown that a considerable number of false failure alarms is generated. The paper presents a combined application of several multivariate statistical techniques and shows how a monitoring method which integrates these tools can be successfully exploited in order to improve the reliability of the diagnostic systems.

1. INTRODUCTION

Failure diagnostics via condition monitoring on mechanical systems and components is a broad and very relevant topic. Different approaches based on the development of specific sensors and data-driven methods have been applied. For example in (K. Liu, 2013) is described the construction of a composite health index through the fusion of multiple sensor data. In many cases the calibration of reliable data-driven models is obstructed by the lack of data regarding the failure modes of the mechanical system. In such circumstances sophisticated anomaly detection and decision mechanisms might be required (see for example (Ramasso & Gouriveau, 2010)).

Our activity was performed under research contract granted by AgustaWestland. It was focused on monitoring the health conditions of mechanical power drives of helicopters. Accelerometric monitoring systems have been previously installed on several types of helicopters produced by AgustaWestland. The adopted vibration monitoring methods are based on analyzing analog signals provided by a set of accelerometers (we refer the reader to (Randall, 2011) and especially (CAA- PARER-2011/01, 2012)). Each power drive is monitored by a single accelerometer. The accelerometric outputs undergo Fourier spectral decomposition and the description of the local (not global) properties of the energy distribution through the spectrum of vibrational modes leads to a set of scalar health indicators, which are supposed to detect specific damages. For example relevant physical indicators represent the energy of the spectral components corresponding to the main rotational frequency and its multiples, the energy contained in a localised energy bands etc. Other indicators, obtained from the second-level signal analysis, are related to local variations, correlations between specific spectral channels, local shape factors and signal standard deviations. The monitoring methodology of the health state of a component is based on fixed critical thresholds for the values of each condition indicator and damage alerts are generated when any of the indicators exceeds the threshold for certain number of measures. In other words the adopted monitoring method concerns a univariate (independent) interpretation of the health indicators.

The implementation of this health monitoring system on power drives in actual service has shown that a considerably high number of false alarms is generated, thereby requiring additional troubleshooting workload.

The purpose of our research is to develop a health monitoring method able to reduce to the very minimum the false positives. The efficiency of the existing diagnostic systems has been improved via third-level multivariate treatment of the condition indicators. A monitoring method which integrates several multivariate statistical techniques has been developed and implemented. The method is able distinguish with very high level of statistical confidence true failure situations and false anomaly alerts if these have been previously observed and diagnosed on any other aircraft of the same type.

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2. EXPERIMENTAL SETUP

Our research was focused on mechanical power drives of helicopters which consist of an assembly of several gears rotating on shafts supported by ball and roller bearings. AgustaWestland provided a large amount of data collected on sixteen aircrafts of the same type flying in different conditions. Our experimental data set consists of several thousands of measurements of the condition indicators of each mechanical component and was collected over a period of several months and hundreds of flight hours. Our study mainly concerned the following set of power drives in which true (confirmed by inspection of the power drive) and false alerts were detected: TTO Pinion, characterised by twelve condition indicators (CI), IGB Pin (12 CI's), TGB Gear (12 CI's), TRDS (2 CI's), 2nd Stage Pin RH Brgs (6 CI's), Oil cooler Brg (6 CI's), Hangar Ball Brg (9 CI's).

In some cases (TRDS and the Hangar Ball Brg) the singlevalued thresholds of several health indicators were strongly exceeded in a false alert state and a true damage provoked a more moderate reaction of the monitoring system. These cases were considered as particularly "critical" as the monovariate evaluation of the damage appears to be misleading.

In the rest of the article the set of N health indicators of a mechanical power drive will be interpreted as an element in a real N-dimensional vector space and called the *vector state* of the power drive.

3. MULTILINEAR RE-CALIBRATION AND ANOMALY DE-TECTION

The values of the standard health indicators, which characterise the normal operational regime of a mechanical component vary quite consistently between different aircrafts of the same type. If compared to each-other, the vector states of the same component in ordinary regime on different helicopters form well-distinguished clusters inside the vector space of indicators (a striking illustration is given on Fig. 1).

The fact that ordinary operational states of a power drive installed on different aircrafts cannot be compared, makes impossible the calibration of any sort of statistical model, based on historical collection of vector states measured on a fleet of helicopters. Moreover the mechanical components selected for our investigation are typically subject to a very low number of failures. A calibration and a validation of a reliable multivariate model on *each single aircraft* appears therefore as extremely unrealistic.

Besides the set of component vector states, a historical collection of simultaneous measurements of the following parameters of operational condition of each aircraft was available: Engine 1 Torque, Engine 2 Torque, Rotor Speed, Roll Angle, Pitch Angle, True Airspeed, Radio Altitude, Vertical Speed, Normal Acceleration, Density Altitude, Tail Rotor Torque,



Figure 1. PCA scores of normal operational states of TRDS component on different helicopters (the marker is the "helicopter number").

Main Rotor Torque, Roll Rate, Pitch Rate, Yaw Rate, Longitudinal Acceleration.

It has been hypothesised that the accelerometric measurements are influenced by the environmental state of the aircraft. In order to test that hypothesis, *canonical correlation analysis* has been applied on the available data set. It has been observed that many components are characterised by three or four canonical correlations with considerably high values (over 0,5). This fact is quite relevant with respect to the interrelations between the environmental vector state and the component vector state. Unlikely in some cases (Hangar Ball Brg) the canonical correlation profile is characterised by high first (considered as accidental) and very low second canonical correlation.

The established multi-correlation between the aircraft states and component states led us to the construction of the following linear filter. A liner map $f : \mathbb{R}^{17} \longrightarrow \mathbb{R}^N$ (where N is the dimension of the component vector) which provides a "predicted" component vector state in correspondence to each environmental state has been calibrated. The k-th row of the matrix associated to this linear map represents the coefficients of a multiple liner regression of the k-th component of the power drive vector over the set of environmental parameters.

If we compare Fig. 1 to Fig. 2, we observe that as a consequence of re-calibration, scores of normal operational states measured on different helicopters slightly concentrate and mix together quite uniformly. Furthermore the shape of the cluster of projections on the space generated by the first two principal components becomes more ellipsoidal. This means that



Figure 2. PCA scores of normal operational states of TRDS of different helicopters after linear re-calibration.

the linear re-calibration procedure filters the deterministic impact of the general state of the aircraft onto the accelerometric measurements. Once filtered the influence of the specific exploiting regime of the aircraft, the variability of the normal operational states of each mechanical component can be attributed to a random noise process. In other words, the filtered normal operational states of each power drive fit with a multidimensional Gauss distribution. This fact was verified by various multivariate normality tests like Kolmogorov-Smirnoff, Jarque-Bera etc. (see (Kolmogorov, 1936; A. Justel, 1997; C. M. Jarque, 1987)). It has been observed that both the distributions of filtered normal operational states of a component of a single helicopter and the filtered normal operational states of a component installed on different helicopters can be considered as Gaussian with a very high level of statistical confidence (p-value around 2×10^{-15}).

Similar effects are observed for all the mechanical components, for which the canonical correlation analysis reveals considerable level of linear correlation. Linear re-calibration makes vector states measured on different helicopters of the same type *comparable*. A specific situation on an aircraft can be compared to analogous situation on another aircraft.

The fact that filtered normal operational states of the power drives are normally distributed, enables us to implement a standard anomaly detection method based on the Mahalanobis distance, i.e. the multidimensional Shewhart control chart (see (Shewhart, 1931) and (Shewhart, 1986)).

A Shewhart control chart has been calibrated on the set of ordinary operational states of each mechanical component on a single helicopter. A small portion (less than 2%) of ordinary vector states exceed the control limit. The same control chart was applied to normal operational states of the same power drive, installed on other helicopters and bigger portion of states was judged out of control (15% for the Hangar Ball Brg). This means that even though linearly filtered data are used, there are still residual differences in the ordinary regime of mechanical components of different aircrafts. The same control chart has been also validated in the context of anomalous situations occurred on the same helicopter with very good results. In the case of Hangar Ball Brg roughly 73% of the states were judged as anomalous.

In conclusion, anomaly detection method based on a Shewhart control chart must be calibrated on each single helicopter. A software tool implementing a multivariate *selflearning* Shewhart control chart, which calibrates itself automatically on the ordinary regime of a single mechanical component and highlights anomalous states, has been produced. The program computes automatically the upper control limit by means of a Gaussian approximation of the Fisher-Snedecor distribution.

In many cases (especially TRDS and Hangar Ball Brg) the Mahalanobis distance between states corresponding to false alerts and the mean value of the normal regime exceeds the distance of the true damage states. For this reason the multivariate self-learning Shewhart control chart is an excellent tool for the detection of anomalous situations, but it is not sufficient for the discrimination of true failure states and anomaly alerts which do not correspond to a failure. Thus, additional discrimination statistical tools, as described later, have been applied.

4. METHOD

The linear re-calibration strongly reduces the differences between the normal operational regime of power drives installed on different aircrafts. This fact enables us to apply a set of standard multivariate statistical methods on a historical database of a fleet of helicopters. For a detailed description of those techniques we refer the reader to the following texts (Ferrell, 1979; Rencher, 2002; Timm, 2002; W. K. Härdle, 2012; Izenman, 2008).

We adopt a geometric viewpoint on multivariate statistics, since in our study an Euclidean approach provides some very useful intuitions on multivariate methods (see, on this aim (Wickens, 1995) and (Epps, 1993)). See also (Tyurin, 2009), where is presented a more intrinsic (coordinate free) geometric prospective on multivariate statistics. In this context we developed our analysis in terms of projections onto relevant subspaces. Our approach interprets (analogously but independently on (Gniazdowski, 2013)) correlations as angles and further radicalises this viewpoint by identifying statistical variables in terms of real projective classes in the space of random vectors.



Figure 3. PCA scores of the states of a 2nd Stage Pin RH Brgs.



Figure 4. LDA scores of TGB Gear.

4.1. Structure of variance

The complete set of available states (normal, true failures, false alerts) of each mechanical component was processed by Principal Component Analysis (PCA). This technique high-lights existing spontaneous clusterings in the variance structure of the data set. On Fig. 3 is displayed an example of scores of complete data sets on the subspace generated by the first three principal components. In this and in each of the following figures green dots represent scores of normal operational states, yellow orange and blue dots represent scores of false alert states and red dots - true failure vector states.

In the "critical case" of Hangar Ball Brg the projections on the subspace generated by the second and the third principal components reveal a relevant spontaneous clustering of the vector states.

PCA leads to a consistent dimensional reduction in the space of states. Equations of linear and quadratic separation surfaces between the projections of the group clusters have been easily worked out and simple control methods can be based on the spontaneous clustering.

The structure of variance in the data sets has been further explored by applying multivariate discrimination methods like Liner Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA)(see (W. K. Härdle, 2012)). The set of component state vectors has been divided into three groups, ordinary operational states, false alerts and true failures.

On Fig. 4 are displayed projections of TGB Gear states onto the subspace generated by the first three linear discriminant

Table 1. Leave-one-out LDA re-classification of 2nd Stage Pin RH Brg vector states

real \setminus classified as	false alert	normal	true failure
false alert	74	0	0
normal	1	1869	0
true failure	8	67	495

functions.

The calibrated linear discriminant models were validated by standard leave-one-out procedure using the complete data set of the fleet. On Table 1, and Table 2 are displayed some examples of LDA re-classification results.

There is a well-known quadratic classifier based on the minimisation of the Mahalanobis distance (with some corrections) (see (Rencher, 2002)). On Table 3 and Table 4 ere displayed some examples leave-one-out quadratic discriminant validation results.

The results obtained by both LDA and QDA leave-one-out cross validation are quite encouraging, especially because of the small portion of miss-classified true failure states. In the "critical" case of the Hangar Ball Brg both methods provide statistically significative number of correctly classified true failure states. This means that true failure can be unambiguously detected.

4.2. Failure detection via canonical correlation

Canonical correlation analysis can be employed for detecting anomalies. Suppose that the ordinary operative regime of a process is characterised by a strong correlation between vector variables X and Y. In such case one estimates the values of Y starting from known values of X by a suitable linear

Table 2. Leave-one-out	LDA re-classifi	cation of Hangar	Ball
Brg vector states		C	

real \setminus classified as	false alert	normal	true failure
false alert	54	6	4
normal operat.	29	1513	20
true damage	5	49	117

Table 3. Leave-one-out QDA re-classification of 2nd Stage Pin RH Brg vector states

real \setminus classified as	false alert	normal	true failure
false alert	74	0	0
normal	0	1860	10
true failure	0	0	570

model. If Y assumes "unexpected" values i.e. its behaviour contrasts with the established correlation, this fact can be considered as a manifestation of some anomaly.

In our study, has been tested the hypothesis that anomalous behaviour of a mechanical component is uncorrelated with the environmental data. We would expect that the linear correlations between the environmental parameters and the components health indicators should decrease in presence of anomalous behaviour of the component. Therefore the data sets of normal states and data sets containing anomalous states have been compared in order to establish whether the relevant (high) linear correlation coefficients decrease.

The situation which emerges from this procedure appears slightly chaotic. For the TRDS the linear correlation is very strong and the values of the coefficients drastically drop in mixed regime which contains true failure states. For the IGB pin the linear correlation is strong, the correlations in mixed regime get certainly worse, but monitoring of that component did not give evidence for real failures, so the measured anomalies correspond to false alerts. The TGB gear is characterised by relatively high values of the significant correlation coefficients and its mixed regime contains a true failure, but it seems that the second canonical correlation slightly improves in mixed regime.

In conclusion, for components for which the linear correlation with the environmental states is particularly high our theoretical hypothesis is confirmed. This means that for those components the canonical correlation method can be considered as a supplementary anomaly detection resource.

4.3. Structure of covariance

In our study, a particular behaviour of the covariance matrix of the vector states of some mechanical components in case of anomalous measurements has been observed. The states of true damage are often characterised by increased correlation of certain vector components. The behaviour of the correlation matrix appeared slightly different in the case of false

Figure 5. Bartlett factor scores of the 2nd Stage Pin RH Brgs.

anomaly reports.

A possible explanation of this phenomenon could be given if in the case of true failure, different health indicators react simultaneously in a consistent and correlated way (failure states provoke an enhancement of certain elements of the correlation matrix). On the contrary false alerts can be interpreted as anomalous measurements not necessarily induced by a consistent reaction of the monitoring system.

Canonical factor models have been calibrated on the set of state vectors. Typically the calibration of factor model based on two factors was possible, but in some cases (Hangar Ball Brg) the iterative procedure does not converge with two but with three factors.

In terms of projections onto the space generated by the principal factors, our hypothesis translates in the following way. We expect that the projections of the normal operational cluster (near by the origin) and true failure cluster (away from the origin) onto the subspace generated by the principal factors show different characteristic profiles. The direction in which failure states projections spread away from the origin is indicative regarding the correlation modifications introduced by the simultaneous reaction to a damage. The shape of the cluster of ordinary operational states characterises the intrinsic covariance structure of the component. In this context we

Table 4. Leave-one-out QDA re-classification of Hangar Ball Brg vector states

real \ classified as	false alert	normal	true failure
false alert	60	2	2
normal operat.	63	1430	69
true damage	2	33	136



Figure 6. Bartlett factor scores of TGB Gear.



Figure 7. Bartlett type scores of unit states of a 2nd Stage Pin RH Brgs.

expect that anomalous or false alerts should reveal some sort of irregular behaviour.

On Fig. 5 and Fig. 6 are shown the projections of the states of the 2nd Stage Pin RH Brgs and the TGB gear. Clustering is present in both cases. Projections (factor scores) of true failure states spread away from the origin in a direction, which is characteristic for the modified covariance structure. Our study substantially confirmed our theoretical hypothesis. It is easy to work out linear or quadratic decision boundaries on factor scores.

In the case of Hangar Ball Brg the factor scores of the ordinary operational states concentrate again near by the origin and the anomalous states spread far from it. Nevertheless these projections do not reveal a striking separation between true and false alert states.

We conclude that for some mechanical components, the covariance structure of the vector data set provides further resources for defining discriminant procedures.

5. SPHERICAL STRUCTURE OF DATA SETS

Since (latent) variables was considered as real projective classes, we have hypothesised that the correlation structure of the data set can be better understood in terms of directions of the state vectors. In this context the module of a vector state plays a minor role as direction in a vector space can be identified by a unit vector. In order to test our hypothesis, an original "experiment" has been performed. Normalised state vectors states has been considered, the set of N-dimensional vector states arranges over an (N-1)-dimensional sphere and factor models on the set of unit vector states have been calibrated.

An obvious effect of our spherical re-definition is a sort of compactification of the operational state clusters (Fig. 7). Our hypothesis on the characteristic variations of the covariance structure appears rather plausible. In fact points representing ordinary operational states and true damage situations form well-defined compact clusters.

Remarkably, as a result of our original approach, in this case the discrimination between true and false alerts becomes much more striking (compare Fig. 7 to Fig. 5). In this new situation the definition of the linear discriminant conditions appears even easier and precise with respect to the previous factor models.

The typical behaviour of the unit states of a power drive is that true damage states condense in a compact region inside the scatter-plot cluster of states. It is often easy to work-out a discriminant condition based on the affinity to that specific compact region. On Fig. 8 is shown the case of a TGB Gear.

Other advantage of the normalisation of the vector states is the elimination of the large spreading of false anomalous alerts far from the mean value of the normal operational regime. In this context LDA leads to precisely the same classification results, but remarkably QDA of the unit vector states of the "critical case" Hangar Ball Brg produces a slight improvement (compare Table 5 to Table 4).

In conclusion, our mathematical experiment led to interesting and in some cases unexpected, potentially useful results. The principal factor analysis on unit states gives further, often relevant, information on the anomalous behaviour of some mechanical components, and can be therefore integrated in a control procedure.

real \ classified as	false alert	normal	true failure
false alert	60	2	2
normal operat.	63	1432	67
true damage	2	33	136

Table 5. Leave-one-out QDA re-classification of Hangar Ball Brg unit vector states



Figure 8. Bartlett type scores of unit states of a TGB Gear.

6. INTEGRATED CONTROL PROCESS, IMPLEMENTATION AND RESULTS

The statistical techniques tested over the available vector data set are based on different mathematical constructions and therefore provide different results. For this reason the above techniques have been combined in a software implementation of an integrated control process in the following way:

1. Anomaly detection by means of a self-learning control chart. A problem highlighted by the experts of AgustaWest-land consists of the fact that the normal operational regime of some power drives on certain helicopters is characterised by very high values of the health indicators. Such values would be considered as anomalous if compared to other helicopters or to some a priori fixed threshold values. This ambiguity is completely removed by the self leaning individual calibration of the control chart. Any vector state judged in control contributes to the real time re-calibration of the control chart i.e. the control chart keeps learning.

2. Anomaly classification based on discriminant methods calibrated and validated over the entire fleet. A vector state judged as anomalous undergoes evaluation based on a set of distinguished discriminant techniques which can regard both the variance and the covariance structure of the calibration

data sets (PCA, LDA, QDA, factor scores). A state classified as false alert does not generate an alert.

3. Evaluation. For different power drives, distinguished discriminant methods appear as more efficient. A pre-alert status is produced by a suitable combination of discriminant outputs. Such a combination is chosen in order to maximise the efficiency of the control system.

The integrated control process was then applied on a series of real cases contained in the historical database of AgustaWestland. In the case of the TGB gear and 2nd Stage Pin RH Brgs the integrated discriminant method judges a state as true failure i.e. generates a pre-alert if each discriminant method classifies it as a true failure. With this requirement only 3% of the measured states were miss-classified. In the most difficult case of Hangar Ball Brg a pre-alert is produced in 13% of the normal states, in 28% of the previous false alerts and in 65% of the true failure states. The current univariate version of the control system generates an alert if the values of the health indicators exceed the alarm thresholds in a fixed proportion (usually 2/3) in a number of consecutive measurements. In the integrated method these proportions can be deduced directly from these last results. For example, in the case of Hangar Ball Brg a suitable proportion appears 1/2.

An engineering software tool which implements both the control process and the calibration of the parameters of the control routine for each of the monitored power drives has been produced.

7. CONCLUSION

Our considerations have highlighted the advantages of our third-level multivariate approach. An efficient control process is based on an integration of several classification techniques. Even in those cases in which true failures and false alerts show misleading univariate profiles, multivariate techniques are able to distinguish them with very high level of statistical reliability.

The elimination of the deterministic influence of the environmental states of the helicopter, gives the possibility to compare rigorously states measured on different helicopters in different flight regimes. Once guaranteed this possibility, one can calibrate classification and discriminant models on historical data obtained from many helicopters and apply them in a future control process. When relevant new data are collected, the statistical models can be updated and improved by re-calibration on a larger and more detailed data set. Once a precise anomaly gets observed and diagnosed on one aircraft of the fleet, it can be diagnosed elsewhere by means of its specific multivariate health profile.

The results obtained by our research appear therefore as quite positive and encouraging.

REFERENCES

- A. Justel, R. Z., D. Pena. (1997). A multivariate Kolmogorov-Smirnov test of goodness of fit. *Statistics and Probability Letters*, 35(3), 251259.
- CAA-PARER-2011/01. (2012). Intelligent management of helicopter vibration health monitoring data (Vol. 01 Based on a report prepared for the CAA by GE Aviation Systems Limited; Tech. Rep. No. ISBN 978 0 11792 403 1). Civil Aviation Authority - Safety Regulation Group.
- C. M. Jarque, A. K. B. (1987). A test for normality of observations and regression residuals. *International Statistical Review*, *55*(2), 163172.
- Epps, T. W. (1993). Characteristic functions and their empirical counterparts: Geometrical interpretations and applications to statistical inference. *The American Statistician, DOI:10.1080/00031305.1993.10475930, 47*(1), 33-38.
- Ferrell, B. L. (1979). *Multivariate analysis*. Academic Press (Probability and Mathematical Statistics).
- Gniazdowski, Z. (2013). Geometric interpretation of a correlation. Zeszyty Naukowe Warszawskiej Wyzszej Szkoly Informatyki(9, Rok 7), 27-35.
- Izenman, A. J. (2008). Modern multivariate statistical techniques: Regression, classification, and manifold learning. Springer (Springer Texts in Statistics).
- K. Liu, J. S., N. Gebraeel. (2013). A data-level fusion model for developing composite health indices for degradation modeling and prognostic analysis. *IEEE T. Au*-

tomation Science and Engineering, 3(10), 652-664.

- Kolmogorov, A. (1936). Sulla determinazione empirica di una legge di distribuzione. *G. Ist. Ital. Attuari*(4), 83-91.
- Ramasso, E., & Gouriveau, R. (2010). Prognostics in switching systems: Evidential Markovian classification of real-time neuro-fuzzy predictions. In *Ieee international* conference on prognostics and system health management, macau, hong-kong, jan. 12-14.
- Randall, R. B. (2011). Vibration-based condition monitoring
 industrial, automotive and aerospace applications.
 John Wiley and Sons, Ltd. Publications.
- Rencher, A. C. (2002). *Methods of multivariate analysis*. Wiley Interscience (Wiley Series in Probability and Statistics).
- Shewhart, W. A. (1931). *Economic control of quality of manufactured product*. David Van Nostrand.
- Shewhart, W. A. (1986). *Statistical method from the viewpoint of quality control.* Dover Publications.
- Timm, N. H. (2002). *Applied multivariate analysis*. Springer (Springer Texts in Statistics).
- Tyurin, Y. N. (2009). Multivariate statistical analysis: A geometric perspective. *arXiv:0902.0408*.
- Wickens, T. D. (Ed.). (1995). *The geometry of multivariate statistics*. Lawrence Erlbaum Associates, Incorporated.
- W. K. Härdle, L. S. (2012). *Applied multivariate statistical analysis 3rd ed.* Springer.

Study on Condition Based Maintenance Using On-Line Monitoring and Prognostics Suitable to a Research Reactor

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ABSTRACT

The purpose of this paper is to look into a more effective way for how condition based maintenance using on-line monitoring and prognostics can be applied to the components/systems in the field of a research reactor, which has been demanded to upgrade or modify the existing MMIS. The requirements of the contemporary diagnostics and prognostics herein are briefly introduced and then an assessment of the actual application to a research reactor is reviewed.

1. INTRODUCTION

The requirements for equipment qualification applied to the nuclear industry have been getting stricter and more challenging in particular since the Fukushima accident. This also strongly influences Research Reactors (RRs) as well as Nuclear Power Plants (NPPs). Most RRs have been recently forced to be modernized or refurbished for lifetime extension or uprating. On the other hand this demand could provide a great opportunity to realize the Condition Based Maintenance (CBM) where the diagnosis and prognosis technique is applied to the upgraded Human-Machine Interface (HMI) system. The health monitoring for the component and system is definitely considered important but the CBM using a suitable prognostic technique should be established in the RR in the near future as found in (NUREG/CR-6895, 2006).

The advantage of CBM is its direct contribution to minimize the cost and prevent unnecessary downtime compared with regular based maintenance. In addition, it also helps to minimize the risk of radiation exposure as low as reasonably achievable owing to less frequency of access to radiation zones and gain invisible benefit such as reducing public anxiety caused from a reactor shutdown. If only utilization of the on-line monitoring technology for system health and prognostics can be maximized, it will be readily possible to predict the estimated Remained Useful Life (RUL) to set up the optimized conditional maintenance plan using an on-line monitoring technique and verified prognostics.

The most remarkable feature in a RR is to have different aspects from a NPP in the case of the operating conditions such as a specific temperature and pressure boundary. The condition in the RR is considerably moderated owing to lower temperature and pressure compared with the NPP case, and it is literally interpreted that the environmental conditions are not severe and therefore so many parts of requirement are under discussion in order to apply to the graded approach. These points are expected to make it easier for the RR to have more various experiments and available application.

2. PROGNOSTICS AND CONDITION BASED MAINTENANCE

Prognosis can be defined as the prediction of future health states and failure modes based on current health assessments, historical trends and projected usage loads on the equipment and/or process according to recent trends as shown in (Singer, R.M., K.C. Gross, J.P. Herzog, R.W. King, and S.W. Wegerich, 1996). These prognostics are inevitable factor to realize the CBM because the CBM is developed by considering the degradation progression. The main idea of CBM is to utilize the system's or component's degradation information extracted and identified from on-line monitoring instruments to minimize the system downtime by balancing the risk of failure and achievable profits. The decision making in CBM focuses on how effectively the predictive maintenance is performed as shown in (IAEA-TECDOC-1625, 2009).

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2.1. Diagnostic-Prognostic Process

As mentioned above, the current failure mode, its cause and effect as well as its extent of degradation are very important for exact prognostics. To determine the RUL of a component, it is inevitable to know and understand the following necessary information in advance: (a) degraded state of the component, (b) cause of initiating the degradation, (c) severity level of the degradation, (d) degradation progress speed from its current state to functional failure (e) method to classify novel events related with degradation, and (f) other factors (e.g. measurement noise) affecting the estimate of the RUL as found in (ISO 13381-1, 2004). If these prerequisites are well prepared, it will be followed by a diagnosticprognostic process. It is significant to classify several steps into the diagnostics with using data preprocessing and prognostics with the RUL determination as shown in Figure 1.



Figure 1. Process step of diagnostics and prognostics.

In diagnosis stage, faults including novel events are detected and abnormal operating conditions are reported upon fault detection. After fault isolation a specific component which is under failure is identified at the stage of fault identification, the extent and nature of the fault is estimated. In the prognosis stage, a time to failure is evaluated based on the fault identification and the appropriate confidence limit is calculated.

2.2. Selection of Suitable Prognostic Model

The CBM program is determined by decision making subject to the operating goal and management plan. The prognostic model should be carefully selected to take the characteristics of the system into account especially for the actual operating conditions. For this reason we have to consider the prognostics in detail and how to implement the prognostics model in a case by case manner.

2.2.1. Prognostics Types by Implemented Sequence

The prognostics type can be classified by three different activities such as existing failure mode prognostics, future failure mode prognostics and post-action prognostics, which are called steps 1 through 3 prognostics, respectively, as they involve an increasing level of modelling and implementation complexity. Step 1 provides estimates for the RUL of components subject to how each diagnosed failure mode is going. Step 2 evaluates the postulated effects of identified failure mode on other potential failure modes in order to evaluate the worst case scenario for the affected components/systems. Step 3 assesses how aforementioned models are affected by maintenance actions at last. As each prognostic level requires the accurate and reliable outputs from the preceding step the likelihood of success is sure to increase. This approach increases a potential enhancement to prognostic capability.

2.2.2. Implementing Prognostics Model

A modified classification approach is proposed here that was specifically designed for the RUL prediction as shown in Figure 2, which is categorized into four main groups and a few numbers of subgroups. Knowledge-based models assess the correlation between observed measurements and a databank of previously defined failures using an expert system or a fuzzy rule as mentioned in (G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess and B. Wu, 2006). The determined life expectancy models literally estimate the RUL of components based on the deterioration under known operating condition using a stochastic model and statistical model such as an auto-regressive moving average and proportional hazards model. Artificial neural networks compute an estimated output for the RUL from a mathematical representation, which has been derived from observation data rather than through a physical understanding. Finally, the physical model represents the behavior of the degradation process based on physical laws as remarked in (G. Vachtsevanos, F. L Lewis, M. Roemer, A. Hess and B. Wu, 2006).



Figure 2. Main model categories for RUL prediction

Ultimately a model selection requires that all advantages and weak points be understood and more importantly how well the actual system operating condition is reflected in the process of model selection.

3. APPROACH FOR APPLICATION TO RESEARCH REACTOR

There are a number of approaches to realize the optimal condition based maintenance, and among them, an on-line monitoring instrument channel calibration is a very simple but effective way to adjust the maintenance term, although it is not exactly the tracking system condition. It is used to identify invalid sensor data that seem faulty due to zero readings, missing data, jump, noise, etc. In addition, sensor anomalies, such as drift and a slow response can be accounted for in validating an array of raw data. Three channels of data from the pressure transmitter are herein introduced, which are used for measuring the hydrogen of the cold neutron source system in a RR.

3.1. On-line Monitoring Data Analysis for the CNS

These pressure transmitters in the CNS of an RR have three redundant sensors, which it means it can perform calibration monitoring, consistency checking, and signal validation. In addition, with redundant sensors, calibration monitoring can be performed using simple averaging techniques as proposed in (M.carnero, 2006). The deviation from the holistic mean among groups of transmitters can be monitored online, and upper/lower limits can be set to trigger alarms if the deviation exceeds that expected for drift candidacy. The signals are subject to pre-set limits of operation. If a value were to exceed these limits, an alarm would be raised, thus indicating the drift.

When analyzing the regularly sampled data through six months, as shown in Figure 3, each channel has shown the hydrogen value staying within a normal range through the whole duration except for certain outliers. There is a just a little deviation between the holistic mean and all channels of values.





The most important thing is to identify how much the drift of the instrument is in progress, and a drift analysis shows that the results from on-line monitoring are better than one from an off-line data analysis. This implies that the maintenance plan and period for a relevant sensor can be adjusted only if the uncertainty on this instrument is fully considered, which can affect both the performance and accuracy of on-line monitoring technique, which utilize the data gathered using the instrument channels as introduced in (A. Yamada & S. Takata, 2002).

3.2. Diagnostics and Prognostics Applied to RR

In a research reactor the critical rotating machines such as a Primary Cooling System (PCS) pump are monitored either continuously or by periodic vibration measurements. This is to monitor the shaft displacement and the vibration level of the PCS pump frame. The Vibration Monitoring System (VMS) is designed to provide an alarm signal to the Main Control Room when the vibration level exceeds the allowable limit as commented in (W. Wu, J.Hu and J. Zhang, IEEE, 2007). It also provides information to be used in analyzing the status of the PCS pump, which incorporates the electrical, mechanical, operational, and environmental condition for detecting the symptom of the shaft crack, and misalignment and rotor balancing, as shown in Figure 4.



Figure 4. VMS principle and configuration

The change in the internal characteristics of a motor(eg. Short winding) will cause the real motor transfer function to change. In the case of mechanical fault detection, if it is assumed that an unbalance occurs, it causes the rotating rotor/stator gap to change, which will make the amplitude modulation shown in the sidebands appear around the line frequency in the spectrum, as shown in Figure 5. For more accurate fault detection, sufficient terms of the learn phase are needed, and after this initial learning, the VMS begins to be monitored as found in (S.J. Engel, B.J. Gilmartin, K. Bongort and A. Hess, IEEE, 2000). Through this VMS, we can recognize the symptoms of the component failure in advance before the fault is worse to exceed the tolerance. However, it was actually found to be a little difficult to predict the RUL in the only this manner. This results in difficulties to confirm the maintenance schedule which has to be estimated upon the system performance. This is because the prognostics in an RR currently depend on a knowledgebased system such as an expert system.



Figure 5. Anomalies estimated from PSD

3.3. Comparison of Prognostics Candidacy

There are many prognostics available to the system in the RR, as aforementioned here, which has an advantageous condition of relatively low temperature, pressure, and radiation level. This enables us to have a large number of opportunities to try in the application of advanced prognostics. This is because the structure of the RR is simpler, which makes it easier for a design change than an NPP. To summarize this, the environmental condition is more moderate in an RR, and a simplified system, components, and structure for the experiment is considered the optimal conditions for testing and verifying whether the prognostics is available in various actual operating conditions.

Prognostics	Anticipated	Anticipated
Model	Advantage to RR	Disadvantage to RR
Knowledge Based Expert System	Easy to develop and understand	 High dependency on experts No confidence limit Not possible to predict exact RUL
Reliability Function	 Numerous software option Confidence Limit available 	 Demand of too big sample size Not possible to prior to actual failure
Artificial Neural Networks	 Available under large noises RUL model is available 	 Data is complex or symbolic Temporal input is not available due to learning period
Physical Models	High accuracy in RUL prediction	1. Physical model is hardly available

Table 1. Comparison between prognostics models.

Table 1 shows a comparison of the prognostics model, which is narrowed down as suitable to apply to the system in the RR. From the viewpoint of RUL, it is the best way to adapt the Artificial Neural Network (ANN) or physical model, but in terms of cost and benefit, an expert system or reliability function is a good alternative to prognostics as proposed in (J. Lee, J. Ni, D. Djurdjanovic, H. Qiu, and H. Liao, 2006).

3.4. Consideration of Uncertainty

The obvious obstacle of acquiring the exact prediction of RUL as well as accurate diagnosis is the inherent uncertainty of the objective. In order to establish the condition based maintenance (CBM) with elegance, it is required to analyze uncertainty associated with the deterioration process and ambiguity of future operation. However it is a difficult task to deal with this uncertainty because it arises from a variety of sources, and is filtered through complicated non-linear system dynamics. In order to find out the resolution, several uncertainty representations such as interval mathematics, and fuzzy have been already introduced.

4. CONCLUSION

On-line monitoring for redundant instrument channels is applied to the CNS of a research reactor for hydrogen trip parameters, and it shows the contribution of this result to adjust the maintenance schedule more efficiently. The aforementioned vibration monitoring system is used for a kind of prognostics suitable to a research reactor, and prominent prognostics models suitable to the research reactor were proposed to exploit this application, and consideration of the uncertainty was shortly addressed. Thanks to the high performance of new prognostics methodology, the application of the on-line monitoring and prognostics to the research reactor seems to be very bright in the near future.

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REFERENCES

- NUREG/CR-6895, Technical Review of On-Line Monitoring Techniques for Performance Assessment, Volume1: State-of-the-art, 2006
- Singer, R.M., K.C. Gross, J.P. Herzog, R.W. King, and S.W. Wegerich, "Model-Based Power Plant Monitoring and Fault Detection: Theoretical Foundations," Proc. 9th Intl. Conf. on Intelligent Systems Applications to Power Systems, 1996
- IAEA-TECDOC-1625 Research Reactor Modernization and Refurbishment, 2009
- ISO 13381-1, Condition Monitoring and Diagnostics of Machines-prognostics – part1: General Guidelines: International Standards Organization, 2004
- G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, B. Wu, Intelligent Fault Diagnosis and Prognosis for

Engineering Systems, John Wiley and Sons Inc., Hoboken, New Jersey, 2006.

- G. Vachtsevanos, Lewis, F. L., Roemer, M., Hess, A. & Wu, B. (2006). Intelligent Fault Diagnosis and Prognosis for engineering system, Hoboken, NJ: John Wiley & Sons, Inc
- M.carnero. An evaluation system of the setting up of predictive maintenance programs, Reliability Engineering and System Safety, 2006
- A. Yamada, S. Takata, Reliability improvement of industrial robots by optimizing operation plans based on deterioration evaluation, Annals of CIRP 51/1 (2002) 319–322.
- W. Wu, J.Hu, J. Zhang, Prognostics of machine health condition using an improved ARIMA-based prediction method, IEEE, Harbin, China, 2007, pp. 1062–1067.
- S.J. Engel, B.J. Gilmartin, K. Bongort, A. Hess, Prognostics, the real issues involved with predicting life remaining, in: Aerospace Conference Proceedings, vol. 6, IEEE, 2000.
- J. Lee, J. Ni, D. Djurdjanovic, H. Qiu, H. Liao, Intelligent prognostics tools and e-maintenance, Computers in Industry 57 (6) (2006) 476–489

BIOGRAPHIES



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Expert Guided Adaptive Maintenance

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ABSTRACT

The heavy truck industry is a highly competitive business field; traditionally maintenance plans for heavy trucks are static and not subject to change. The advent of affordable telematics solutions has created a new venue for services that use information from the truck in operation. Such services could for example aim at improving the maintenance offer by taking into account information of how a truck has been utilized to dynamically adjust maintenance to align with the truck's actual need. These types of services for maintenance are often referred to as condition based maintenance (CBM) and more recently Integrated Vehicle Health Management (IVHM).

In this paper we explain how we at Scania developed an expert system for adapting the maintenance intervals dependent on operational data from trucks. The expert system is aimed at handling components which maintenance experts have knowledge about but do not find it worth the effort to create a correct physical wear-model for.

We developed a systematic way for maintenance experts to express how operational data should influence the maintenance intervals. The rules in the expert system therefore are limited in what they can express, and as such our presented system differs from other expert systems in general.

In a comparison between our expert system and another general expert system framework, the expert system we constructed outperforms the general expert framework using our limited type of rules.

1. INTRODUCTION

Expert systems have been around for a long time (Durking, 1990; Russel & Norvig, 2010). They have been successfully

used in a variety of applications ranging from diagnosing medical problems (Buchanan & Shortliffe, 1984) to facilitate space exploration (Marsh, 1988). Today the term expert system is not used to any large extent, especially not in industry, now days they are often referred to as rule engines. In this paper we will use the term expert system and not rule engine.

Scania Commercial Vehicles (Scania) is a manufacturer of heavy trucks, coaches and engines for industrial and marine usage. We at Scania have investigated how an expert system could be used for improving the maintenance of our products. The aim is to achieve perfect alignment with the maintenance program of a Scania product with the actual maintenance needs of the product. Using on-board sensors from our vehicles we collect data of how the vehicle is utilized. This operational data together with expert knowledge, captured in a type of expert system, is used to adapt the maintenance needs.

This paper is focused on describing the design considerations developing such adaptive system. We also relate our system to other general expert systems. The rest of the paper is organized as follows: In the next section we will look at rules and expert systems in greater detail. Then the current solution of vehicle maintenance at Scania is presented after that we present our proposed solution, its implementation and the findings from comparing it with a general expert system. The last section is dedicated to discussion and conclusions and finally we give pointers to future work.

2. EXPERT SYSTEMS AND RULES

An expert system has two major settings of operation, one when the knowledge base is updated and one when using the knowledge base.

In the former case an expert's knowledge of a domain is captured and inserted through the user interface. The information is then stored in the knowledge base in a

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suitable format for the inference mechanism. In the latter case a user (or computer) post a question using the user interface and the inference mechanism infer an answer which is presented for the user.

Expert systems are beneficial when developing advanced software systems because they fulfill the need of separating out the expert knowledge from the source code. This separation is typically beneficial for easy maintenance of the knowledge base over time. Re-use of proven inference mechanisms is also facilitated using this approach as the inference mechanism can be an external software module.

2.1. Rules

Rules come in different flavors, but there are two dominant types, production rules and logic programming rules. As noted in the paper by Kowalski and Sadri (Kowalski & Sadri, 2009), these two types of rules have traits which overlap but also have differences between them. In this paper we will make a simple distinction between them and use the term production rules for rules which use a forwardchaining inference mechanism and logic programming rules as rules which use a backward-chaining inference mechanism. For a clarifying paper about these inference mechanisms, see (Shapiro, 1987).

Basically the main difference between the two inference mechanisms is how search is conducted. In a search problem setting we have a certain goal and a current state, i.e. where we are now. If we choose to search from the current state until we find the goal, we are doing forwardchaining inference. If we start from the goal and search (backward) until we find a path to the current state, we are doing backward-chaining inference.

In a rule based system this type of search are conducted in a knowledge base together with a question or new fact. The type of inference mechanism is closely related to what type of reasoning we are interested in. For example are we interested in answer(s) to a certain question or do we want to see the implications of new facts that we just observed?

Typical heuristics for choosing one inference mechanism is to consider what event that trigger the problem solving. If the trigger is a new fact then the exploration of consequences given the new fact is naturally handled by forward-chaining mechanism. If on the other hand the trigger is a query to which an answer is required they are naturally handled by backward-chaining.

Other general rules for guidelines for choosing inference mechanism are to investigate the branching of the search space, i.e. depending upon the knowledge base. If the average state in the search space has more successors than predecessors backwards-chaining is desirable. If the average state has fewer successors than predecessor it is desirable to use forward-chaining. These two inference mechanisms can also be mixed.

3. HEAVY TRUCK MAINTENANCE – CURRENT SITUATION AT SCANIA

Today the maintenance plan for Scania vehicles is set when the vehicle is sold. This is typically done by sales personnel together with the buyer by selecting one of a set of predefined maintenance plans that best matches the vehicle specifications and the buyers intended usage.

The predefined maintenance plans are developed and maintained by skilled personnel having knowledge about both the products and customer's usage. Vehicle usage is divided into six typical applications types. For each application type and vehicle specification, a cyclic maintenance plan is given as the number of kilometers between maintenance occasions with fixed maintenance protocols.

Maintenance is always done in a cycle of S-M-S-L occasions, where S = Small, M = Medium, and L = Large are different maintenance modules for maintaining different sets of components.

There are a number of problems with the way maintenance plans are created today:

- 1. Much responsibility is put on the sales personnel to know the product as well as the customer's usage of the product.
- 2. Once created the plans are seldom updated even if the application of the vehicle changes. Thus, it is possible that the maintenance a vehicle receives does not correspond to its needs.
- 3. Although the fixed S, M, and L modules make it convenient to plan, they contain maintenance points that do not need to be grouped together with the effect that some components are maintained more than necessary.
- 4. The current maintenance plans are coarse in the sense that the precision in the type of application must be fitted into one of the six types of application. Therefore the experts dictating when maintenance ought to be done, use a safety margins given the uncertainty of the actual usage of a particular vehicle. This has two consequences, one is that plans are not individualized to the degree that they could be and the second consequence is that components are maintained more than necessary.

4. PROPOSED SOLUTION'S SCOPE, AIMS AND MOTIVATION

Many problems with the current situation can be improved with a system for Integrated Vehicle Health Monitoring (IVHM), see (Ian K. Jennions et al., 2011; Dunsdon & Harrington, 2008). Using modern IT technologies communication between Scania trucks and our system is feasible. This includes acquiring operational data from a specific trucks while in operation, this data can then be used to calculate the maintenance need of a vehicle.

This computation of the maintenance need can be done in a verity of ways with different complexities. Ranging from computer models that capture the maintenance point physical characteristics to simple preset deadlines, dependent on some operational data, which dictate when maintenance should be done.

The aim of our expert system was to capture the knowledge of our maintenance experts in a systematic and user friendly manner. The system was design so that the maintenance experts should be able to edit "rules" them self and also able to verify them.

The intension of the system was that it should be used when experts "know" how operational factors, measured via operational data, affect the maintenance need of a component, but we are not interested in creating a complex and fully verified maintenance model for the component. The reasons of why we want to use the expert system and don't want to create a "full" model can be motivated by the fact that the cost of creating such a model is regarded as to high compared to its benefits.

As a truck from Scania consist of around 80 to 160 unique maintenance points related to different components. Currently we have created four "full" maintenance models for components with vital importance and this figure will probably rise in the future. But for maintenance points that will not have "full" models an expert system seems like a logical way to address the need for individualized maintenance from a technical and business oriented view.

4.1. Expert system design

To create our expert system we firstly removed the maintenance points from their S, M and L modules and let the maintenance experts themselves define new maintenance points. Thus improving the precision as maintenance point no longer needs to be lumped together.

When experts express rules regarding maintenance points they need to convey information about "which specification is the maintenance point valid for?" and "when is the maintenance point valid?" The first question is specified by part-numbers used by Scania when assembling a truck. The second question is specified by intervals utilize three basic types of information; *mileage*, *operational hours* and *static time*.

Mileage is self-explanatory, operational hours is defined as time when the engine is running and static time denotes calendar time. For example can an interval be defined by **opHours_cond(0,+inf)**, which denotes that a rule is valid for a whole vehicles lifetime, as it is valid from 0 operating hours to infinity (inf) operating hours. Mileage is measured in km, operational time in hours and static time in days.

This interval validity condition was requested by the maintenance experts as they wanted to be able to express different rules for different ages of a component, i.e. check a chassis for cracks do not to happen frequently when a truck is new but when it's old it needs to be done more often. This type of rule also put a demands on the system to keep track of events which causes reset of the three type of conditions, for example even how unlikely it may be, if we replaced the chassis on a truck.

4.1.1. Operational data

Before we look in to how the experts can use operational data to influence the maintenance point we have to look at the characteristics of operational data at Scania trucks.

Operational data is captured in episodes, i.e. from time t_0 to time t_1 . These episodes can be of varying length, trucks with wireless telemetric can export episodes at a preset periodicity, while trucks not having wireless telemetric might have episodes that are equal to their operational time between workshop visits.

Three different data formats exist for operational data, scalar, vector and matrix format. Measurement for average fuel consumption is a scalar value, i.e. **fuel_consumption(53)** = 53 liter / 100 km, which is calculated for an episode. Vectors can for example be the **altitude(VeryLow, Low, Medium, High, VeryHigh)**, VeryLow = less than 110m, Low = 110m to 990m, Medium = 990m to 1950m, High = 1950m to 3000m, VeryHigh = 3000m or more over sea level.

The value for operational data variables are aggregated in bins and reflect the amount of time the truck is used under conditions for a particular bin. The same is true for matrix bins, but each bin has two conditions to adhere to. For example we could have a matrix measuring load in tons on the y-axis and speed of the truck on the x-axis.

4.1.2. Expressing how operational data influence maintenance

Using the three types of operational data collected from Scania products maintenance experts can via rules express boundaries for deadlines and how operational data should influence maintenance deadlines.

Rules have boundaries to make the maintenance point rules well defined, each rule has a minimum, maximum and a base value for at least one of three basic types and all three basic types can have these values. These values define the deadline span of the maintenance point and its central value, i.e. the base value. The application of the rule can never result in a lower value than the minimum value defined or higher than the maximum value defined.

For example can we use the basic type km and define the minimum value = $50\ 000$ km, base value = $100\ 000$ km and maximum value = $150\ 000$ km.

Using numbers in range [-9, 9], the users can express how one instance of operational data influence the basic types for a specific rule. For example if we have the expression **altitude(4, 2, 1, -3, -8)** with the base values as defined above and an operational data episode from a truck with the following values **altitude(0.1, 0.3, 0.6, 0, 0)**, where the aggregated values are normalized. This outcome for a rule is calculated in two steps, first the impact score in this case 4 * 0.1 + 2 * 0.3 + 1 * 0.6 + -3 * 0 + -8 * 0 = 1.6 then the we apply the impact score onto the basic types, in this case as the value is positive 150000 – 100000 / 9 = 5556, 5556 *1.6 + 100000 = 108889. Hence in this case the system would output 108889 km as deadline for this particular maintenance point.

More generally the impact is calculated as follows:

$$\frac{\sum_{i}^{op_factors} \sum_{j} op_factors_{ij} \times op_values_{j}}{|op_{factors}|}$$
(1)

Where the op_factors is the operational data influence specified by the maintenance expert, ranging from -9 to 9. The value can be set when answering the question "how much impact should we assign to observing this operational data in the relation to the base value and in what direction?"

Calculating the basic type outcome given impact:

$$imp_{v} \begin{cases} \geq 0, \frac{max_{v} - base_{v}}{9} \times imp_{v} + base_{v} \\ < 0, base_{v} - \frac{base_{v} - min_{v}}{9} \times imp_{v} \end{cases}$$
(2)

The maintenance expert is free to set the basic types base value anywhere between the minimum value and the maximum value. If it is set in the middle of these two values the "steps" will be equally long on each side of the base value, i.e. an impact value of 2 and -2 will amount in the same increase respectively decrease in the basic type. Setting the base value allows the expert to change how the impact will affect the outcome.

When the impact is zero the outcome is the base value and when it is 9 the outcome is the maximum value and -9 correspond to the minimum value. When experts define rules and use vector and matrix data which are distributions, it is unlikely that the impact will come close the endpoints of (+/-) 9.

However scalars do not have any predefined bins and it is up to the experts to create the bins and set the influence value of (-/+) 9 for each bin. For example **fuel_consumprion(from, to, influence_value)**, where *from* and *to* define the lower resp. higher bound for the bin. The scalars behave differently from vectors and matrix distributions in that one bin will get a 1 and the rest of the bins zero. Hence the influence value should be set with caution for scalars.

In conclusion a maintenance expert defines the following values for a rule: ValidSpecification, BasicRuleIntervalCondition, Min, Base, Max, ExpertMaintInfluenceList.

5. IMPLEMENTATION

We implemented the system in SICStus Prolog, see (Mats Carlsson et al., 2013). One of the motivations of choosing this language is that Prolog uses a backwards chaining proof (resolution) to prove questions posted to it together with goals and facts in its knowledge base (or program). This fits fine with our intention of creating a system that answers the maintenance needs given a trucks operational data and specification.

Using this programming language you get a complete and sound and tested theorem-prover "for free", which made it an ideal language for our purposes. Other expert system frameworks could have been chosen, which we will elaborate further upon at the end of the paper, but the primary reason is our limited and restrictive "rules", that did not need any fancier expert framework.

To ensure better modularity we used the Rule Interchange Format (RIF) (W3C, 2013) standard proposed by W3C. The standard is supported by a number of expert systems, for example IBM Websphere and ILOG JRules, OntoBroker, Oracle Business Rules (OBR) etc. To ensure backwards compatibility and development of new knowledgebase releases, we utilized Prologs blackboard functionality, using **version** and **status** as keys to a certain blackboard. Version is just a version number and status can be one of *development, testing* and *released*. Essentially a blackboard is a memory area where we post one knowledge base.

We created a webb-based GUI using AJAX technology for creating and simulating rules. The GUI also check rule validity, i.e. that the base value is higher than the minimum value and lower than the maximum value.

The expert system is a separate module and runs on a server exposing its services through the PrologBeans interface. Our solution make is possible to keep track of different user sessions and service many requests simultaneously. We have aimed for the modules to be self-contained with a clear interface. The expert system has two main services, loadRules and useRules. Loading a rule set check that it is syntactical correct, while semantics are pushed to the GUI, i.e. checks that intervals are defined correct etc. We also facilitate expert's creation of new rule sets and updates to existing rule sets by addRule and removeRule.

6. COMPARISON WITH OTHER SYSTEMS

The initial motivation for using a programming language as Prolog for implementing the expert system was to have the freedom to change the system depending on the need from the users and to explore different solutions to the problem.

There are a number of different expert systems available, both commercial and open-source. There does not exist, to the author's knowledge at least, a multitude of systematical comparisons of expert systems. But one comparison of rule engines has been done in the field of Semantic Web which recommended for the interested reader (Senlin Liang, et al., 2009).

One of the more successful open-source tools is Drools (Red Hat, 2013). Drools is part of the JBoss platform. It is an open-source software that aims at being "...a unified and integrated platform for Rules, Workflow and Event Processing". To investigating how our expert system performance is comparable to other established general expert systems, we choose Drools to compare with. The reason was mainly its availability as it is open source software and partly because it is well established.

The experimental setup was as follows:

We implemented the same type of reasoning in Drools as we do in our system. Then we created knowledge base's consisted of a base set of 1000 rules, each of these rules hade truck specification conditions (TSC) **not** matching an intended query. Into this knowledge base we injected rules at random that had TSC that matched the intended query. The TSC consisted of: **ValidSpecification** and **BasicRuleIntervalCondition** as mentioned before. Two **ValidSpecification** conditions were used for all rules. The number of the injected rules, where 60, 80 and 100. This procedure was repeated 10 times, so in total 30 rule bases was created, each with an random injection of rules, and equally many queries was made. For each query the CPU time was measured and the amount of memory used.

In Table 1 the amount of time (in milliseconds) for each system to answer a query is shown. The number of matches at each query is 60, 80 and 100 respectively. The minimum, average and maximum time is shown for the 10 queries.

Table 1. The minimum, average and Maximum CPU time in milliseconds used to answer the 10 queries with 60, 80 and 100 matches.

	60			80			100		
	MI	AV	MA	MI	AV	MA	MI	AV	MA
Drools	172	179	204	188	206	298	204	229	313
Prolog	109	129	187	109	125	156	109	139	187

The memory consumption is always the same when using Prolog, probably because its allocated memory in chunks and the different sizes of rule set does not render in need of more memory allocation. Drools on the other hand allocate different memory sizes on each run. See Table 2 for an overview, using the same structure as in Table 1 but measuring the memory needs in megabytes.

Table 2. The minimum, average and maximum memory used in megabytes used to answer the 10 queries with 60, 80 and 100 matches.

	60		80			100			
	MI	AV	MA	MI	AV	MA	MI	AV	MA
Drools	120	197	247	53	203	253	136	205	267
Prolog	3,9	3,9	3,9	3,9	3,9	3,9	3,9	3,9	3,9

One possible reason for the big memory needs for Drools compared with Prolog is that the rules cannot be written as compact as in Prolog. In Prolog a rule is one line, in Drools the same rule is written in around 40 lines. This extra size of the rule set is possibly an explanation of the extra time needed by Drools to answer the queries.

From the experiment it evident that our system outperforms Drools, both when it comes to response times and memory consumption.

7. CONCLUSION

We have presented a systematic way of capturing expert's knowledge in the field of heavy truck maintenance. The suggested way of making use of expert knowledge through an expert system is motivated for the bulk of components that we want to maintain, but do not want to create an advanced model for.

To achieve adaptive maintenance for vehicle's components we think our solution has a given place when considering a balance of cost and speed of creating rules in our system compared to more advanced models. Thus we believe this approach will be a starting point for adaptive maintenance for a majority of components.

The implementation we made also showed that our solution outperforms a leading off the shelf product. This is encouraging results and suggests that we are on the right track when developing our system.

What we need to investigate further is how verification of the rule base can be improved, i.e. checking the rule set for soundness and completeness. Completeness is probably easy to check, if each vehicle get a maintenance plan from the rule set, for each of its components that should be maintained, the rule set is complete. Soundness is a bit harder as it involves some measurement of quality. In this case we are considering automatic detection of outliers, to point users towards potential errors in the rule set.

Somewhat related to automatic verification of the rule set is the use of Machine Learning (ML) (Mitchell, 1997) techniques for learning rules and supporting the users creating rules. In such a setting components (maintenance points) could be coupled with operational data and presented for the maintenance experts, their task would then be to label each components maintenance point with the three basic types of intervals.

After sufficiently many components have been given intervals we could then use ML to generalize from the examples to generate new rules for the rule set. This rule set could be expressed in the same format we described earlier, making the rule set a white box from a maintenance expert's perspective.

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REFERENCES

Buchanan, B. G., & Shortliffe, E. H. (1984). *Rule Based Expert Systems: The Mycin Experiments of the Stanford Heuristic Programming Project.* Boston: Addison-Wesley.

- Dunsdon, J., & Harrington, M. (2008). The Application of Open System Architecture for Condition Based Maintenance to Complete IVHM. *Aerospace Conference*, (pp. 1-9).
- Durking, J. (1990). Application of Expert Systems in the Sciences. *Ohio Journal of Science*, *90*(5), 171-179.
- Ian K. Jennions et al. (2011). Integrated Vehicle Health Management: Perspectives on an Emerging Field. Warrendale: SAE.
- Kowalski, R. A., & Sadri, F. (2009). Integrating Logic Programming and Production Systems in Abductive Logic Programming Agents. In *Web Reasoning and Rule Systems* (pp. 1-23). Berlin: Springer.
- Marsh, C. A. (1988). The ISA expert system: a prototype system for failure diagnosis on the space station. *Proceedings of the 1st international conference on Industrial and engineering applications of artificial intelligence and expert systems. 1*, pp. 60-74. Tullahoma: ACM.
- Mats Carlsson et al. (2013). *SICStus Prolog Users's Manual.* Kista: Intelligent Systems Laboratory, Swedish Institute of Computer Science.
- Mitchell, T. (1997). *Machine Learning*. New York: McGraw-Hill.
- Red Hat. (2013, 09 25). *Drools*. (Red Hat) Retrieved 09 25, 2013, from http://labs.jboss.com/drools
- Russel, S. J., & Norvig, P. (2010). *Artificial Intelligence A Modern Approach (3rd edition)*. Upper Saddle River: Pearson Education.
- Senlin Liang, et al. (2009). OpenRuleBench: an analysis of the performance of rule engines. *Proceedings of the 18th international conference on World Wide Web.* Madrid.
- Shapiro, S. C. (1987). Processing, bottom-up and top-down. In *Encyclopedia of Artificial Intelligence* (pp. 779-785). New York: John Wiley & Sons.
- W3C. (2013, 02 05). *RIF RULE INTERCHANGE FORMAT CURRENT STATUS*. (W3C) Retrieved 08 21, 2013, from http://www.w3.org/standards/techs/rif#w3c_all

Some Diagnostic and Prognostic Methods for Components Supporting Electrical Energy Management in a Military Vehicle

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ABSTRACT

This work investigates the field of Integrated Vehicle Health Management (IVHM) and more specifically on the components which are producing or consuming electricity. Firstly, diagnostic and prognostic characteristics are defined. This allows later, from the mapped characteristics, to sort the most relevant methods for critical components. The mapping leads finally to define some scientific issues to be solved in order to improve the diagnostic and prognostic of such components.

1. INTRODUCTION

IVHM is defined by (Jennions, 2011) as "The unified capability of a system of systems to assess current or future state of member system health and integrate that picture of system health within a framework of available resources and operational demand". One of the purposes of the IVHM is to improve the availability of the vehicle to be able to achieve its mission (Benedettini et al., 2009). It offers online on board processes for components, and integrated processes with tactical and strategic level decision making to get on a dynamic decision of the maintenance based on an assessment of "real" hardware health. In that way, IVHM can provide the critical components, sub-system or system different diagnostic or prognostic processes, alone or combined (Balaban et al., 2010). This proactive consideration is the cornerstone of the Prognostics and Health Management (PHM) philosophy defined (Uckun et al., 2008) as "PHM connects failure mechanisms to system life-cycle management". To implement this proactive vision, it is necessary to investigate the methods of diagnostics and prognostics suitable to the field of Integrated Vehicle Health Management (IVHM) and more specifically to critical components which are those producing or consuming electricity (Wilkinson et al., 2004). This state of the art of diagnostic and prognostic methods addresses this problem. According to this context, firstly, the paper defines diagnostic and prognostic processes individually but also coupled to establish a mapping of their characteristics. After the identification of these different characteristics, it focuses on their applications on critical components corresponding to those producing or consuming electrical energy. This allows from the general mapping, to sort the most relevant methods for these critical components. The mapping leads finally to define some scientific issues to be solved in order to improve the diagnostic and prognostic of such components.

2. GLOBAL DIAGNOSTIC AND PROGNOSTIC DEFINITIONS

2.1. Diagnostic

The diagnostic process is generally defined as the actions for the detection, localization, and identification of the cause of failure/breakdown (EN 13306, 2001). (Isermann, 1984) also takes into account the estimation of failure/ breakdown following its identification, to allow the reuse of this estimation in a process of reconfiguration of the system (Zhang & Jiang, 2008).

The diagnostic process has two main characteristics: type of methods and steps of the process. The first characteristic is the type of methods. (Venkat & Raghunathan, 2003) classify fault diagnosis methods into three classes:

- Quantitative model-based methods
- Qualitative model-based methods
- Process history based methods

Another characteristic is the steps of diagnostic process. A decomposition of the process can be found in the ISO 13374-1 (ISO, 2003):

- Data Acquisition
- Data Manipulation
- State Detection

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Health Assessment

In summary the diagnostic process can be defined as the actions for the detection, localization, identification and estimation of the cause of failure/breakdown, characterized by three specific methods and four steps.

2.2. Prognostic

During the last decade, many definitions and methods were proposed in the field of prognostic. (Lebold & Thurston, 2001) define prognostic as "the ability to perform a reliable and sufficiently accurate prediction of the remaining useful life of equipment in service. The primary function of prognostic is to project the current health state of equipment into the future taking into account estimates of future usage profiles". (Byington et al., 2002) defines prognostic as "the ability to predict the future condition of a machine based on the current diagnostic state of the machinery and its available operating and failure history data."

The prognostic process has two main characteristics: type of methods and steps of the process. The first characteristic is the type of methods. Generally, prognostics have been classified into three types of methods (Byington et al., 2002) (Jardine et al., 2006) :

- Based on experience / statistic
- Data driven / based on artificial intelligence
- Model based

Another characteristic of prognostic is the steps of prognostic process. (Voisin et al., 2010) have proposed generic prognostic steps:

- To Initialize State and Performances
- To Project
- To Compute RUL (Remaining Useful Life)

In summary the prognostic process can be define as the ability to perform a reliable and sufficiently accurate prediction of the future condition of a system based on his current level of degradation (calculated or from a diagnostic process), projected into the future, characterized by three specific methods and three steps.

2.3. Diagnostic and Prognostic Combination

Diagnostic and Prognostic can be combined in several ways, by coupling methods or by coupling steps at the same hierarchical level of the system, or between two different levels. Further details will be provided later in the document for the combinations highlighted for critical components.

3. METHODS OF DIAGNOSTIC AND PROGNOSTIC IN CASE OF ELECTRICAL ENERGY MANAGEMENT SYSTEMS

To map the previously defined characteristics, the components are separated into several classes, in relation to their functions in an electrical energy management distributed architecture (NATO, 2004) (producer, consumer,

adapter, energy storage) and their technological heterogeneity (electronic, electromechanical, optronic). Each component will be mapped to the characteristic "method" (previously defined) applicable for the diagnostic and prognostic processes. Only methods that can provide fault estimation for the diagnostic process will be mentioned, all other methods can be connected to the survey of (Venkat & Raghunathan, 2003) and provides no added value.

3.1. Energy Producers Components : Rotary Machinery Systems

For diagnostic, quantitative model-based methods are available based primarily on Motor Current Signature Analysis (MCSA) (Haus et al., 2013), on Current Spectrum Analysis (Didier et al., 2007) or on the current amplitude demodulation (Amirat et al., 2010).

For prognostic, (Lee et al., 2014) data driven and model based methods has been applied on rotary machinery systems and he introduces several challenges and scientific issues relatives to this component.

3.2. Energy Adapter Components

For prognostic, (Goodman et al., 2007) defines a method based on the data of the current transformer, his reliability, and monitoring of various energy conversion parameters for power supply. (Impact Technologies, 2011) develops empirical methods based on the physics of components linking the transistor temperature to the Pulse-Width Modulation (PWM) duty cycle, which can be classified into degradation model based prognostic. Also (Balaban et al., 2010) introduces a model based on the physics of transistor, and data obtained from accelerated degradation.

3.3. Energy Storage Components

For diagnostic, a quantitative model based on multi-scale Extended Kalman Filter (EKF) (Hu et al, 2011) could be employed.

For prognostic, data driven methods can be used (Nuhic et al., 2013), or methods based on artificial intelligence using learning algorithms (Chen, 2011). (Pecht, 2011) proposes a physical model based method for Li-Ion batteries.

3.4. Energy Consumer Components : Electronic Controller - Avionic

For diagnostic, (Vichare, 2006) defines several quantitative model based methods for extracting the conditions of use of components from external monitoring (external sensors) or directly from the signals generated by the component.

For prognostic, The most widely used methods in the field of electronics are physics-of-failure (PoF) model based methods that use parameters on the conditions of uses, system life cycle, to identify potential failure and estimate the Remaining Useful Life (RUL). These methods are being developed on various components, from electronic controllers, to semiconductor microprocessors, via digital electronic components. For example (Impact Technologies, 2011) defines methods applicable to components using Global Positioning System (GPS) or Radio Frequency (RF). (Scanff et al., 2007) presents the results of methods on online replaceable avionic systems, comparing the use of prognosis for maintenance, through experience based methods (used independently of the component), with system life consumption methods (model based).

For combination, (Pecht & Jaai, 2010) defines in his roadmap applied on the development of electronics PHM methods, the possibility of developing hybrid methods (fusion prognostic approach) coupling the benefits of data based methods with model based methods.

3.5. Energy Consumer Components : Electromechanics - Optronics

For diagnostic, quantitative model-based methods of condition monitoring can be applied to the mechanical part (Hameed et al., 2009).

For prognostic (Impact Technologies, 2011) has developed a suite of model based methods for EMA Flight Control Actuators components. (Baysse et al., 2013) also provides model based methods for estimation of the state of an optronic system associated with a decision criterion to allow an adaptation of maintenance policies from the observed state of the system (settling time of the cooling machine).

In summary, for diagnostic, a number of quantitative modelbased methods for fault estimation can be used. Only energy adapter components and electronic controller or avionic have a lack of fault estimation methods due to their physical reality, faults are generally abrupt in electronic components. For prognostic, in most referenced work, methods incorporate few data for the step "To Project": only the current level of degradation is used and the system is covered by a single usage scenario for the projection. For combination few methods are available and the uncertainty is not quantified facing the use of hybrid methods. For all of these cases, component level methods are available, but they are not reused in an energy management system vision.

4. NEW CHALLENGE

The mapping leads finally to define some scientific issues to be solved in order to improve the diagnostic and prognostic of such components for implementing the proactive vision of IVHM:

• For diagnostic, combining diagnostics and prognostics to integrate the two sub-processes together could allow the use of fault estimation of diagnostic in prognostic process by merging "Health Assessment" step in diagnostic with "To Initialize State and Performances" step in prognostic.

- For prognostic, there is a need of contextualization of prognostics based on the operating environment of the vehicle: The methods need to be parameterized in accordance with the contextualization (e.g. mission, conditions, and environment) of the component.
- For combination hybrid approach to diagnostic and/or prognostic need to be explored for coupling the type of methods or step of the process. Uncertainties of these hybrid methods need to be quantified.
- For all of these cases, investigations need to be done to build an energy management system from all of the component methods. This need must necessarily lead us to investigate system level issues. More investigation need to be done for combining diagnostic and prognostic of component-level and provide a system approach focusing more particularly to service oriented vision that need to be rendered to the users by the system functions (to travel, to be protected etc.), as well as his associated targets (environmental impact, travel time etc.).

REFERENCES

- Amirat, Y., Choqueuse, V., & Benbouzid, M. E. H. (2010). Wind turbines condition monitoring and fault diagnosis using generator current amplitude demodulation. In *Energy Conference and Exhibition* (*EnergyCon*), 2010 IEEE International (pp. 310–315).
- Balaban, E., Narasimhan, S., Daigle, M., Celaya, J.,
 Roychoudhury, I., & Saha, B. (2010). A Mobile Robot Testbed for Prognostics-Enabled Autonomous Decision Making. In Annual conference of the prognostics and health management society (pp. 1– 16).
- Baysse, C., Bihannic, D., Gegout-petit, A., & Prenat, M. (2013). Maintenance Optimisation of Optronic Equipment. In *Prognostics and System Health Management Conference* (Vol. 33, pp. 709–714). doi:10.3303/CET1333119
- Benedettini, O., Baines, T. S., Lightfoot, H. W., & Greenough, R. M. (2009). State-of-the-art in integrated vehicle health management. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, 223(2), 157–170. doi:10.1243/09544100JAERO446
- Byington, C. S., Roemer, M. J., Kacprzynski, G. J., & Drive, T. P. (2002). Prognostic Enhancements to Diagnostic Systems for Improved Condition-Based Maintenance 1. In Aerospace Conference Proceedings.
- Chen, H. (2011). Predicting the Remaining Useful Life of Lithium- ion Batteries with Active Learning and Good- Turing Usage Profile Estimation. In *PHM workshop on battery*.
- Didier, G., Ternisien, E., Caspary, O., & Razik, H. (2007). A New Approach to Detect Broken Rotor Bars in

Induction Machines by Current Spectrum Analysis. *Mechanical Systems and Signal Processing*, 2007, 21(2), 1127–1142.

EN. (2001). 13306. Maintenance Terminology.

Goodman, D., Hofmeister, J., & Judkins, J. (2007). Electronic prognostics for switched mode power supplies. *Microelectronics Reliability*, 47(12), 1902– 1906. doi:10.1016/j.microrel.2007.02.021

Hameed, Z., Hong, Y. S., Cho, Y. M., Ahn, S. H., & Song, C. K. (2009). Condition monitoring and fault detection of wind turbines and related algorithms: A review. *Renewable and Sustainable Energy Reviews*, 13(1), 1–39. doi:10.1016/j.rser.2007.05.008

Haus, S., Mikat, H., Nowara, M., Kandukuri, S. T., Klingauf, U., & Buderath, M. (2013). Fault Detection based on MCSA for a 400Hz Asynchronous Motor for Airborne Applications, 1–19.

Hu, C., Youn, B. D., Chung, J., & Kim, T. J. (2011). Online Estimation of Lithium - Ion Battery SOC and Capacity with Multiscale Filtering Technique for EVs / HEVs. In *PHM workshop on battery*.

Impact Technologies. (2011). Avionics and e-PHM Applications Overview. Retrieved from http://www.impacttek.com/Resources/TechnicalPublicationPDFs/Aerosp ace/Impact_AAV_AvionicsAndE-PHMApplicationsOverview.pdf

Isermann, R. (1984). Process Fault Detection Based on Modeling and Estimation Methods A Survey. *Automatica*, 20.

ISO, I. S. O. (2003). Condition monitoring and diagnostics of machines ISO 13374-1. *Standard*.

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510. doi:10.1016/j.ymssp.2005.09.012

Jennions, I. K. (2011). Integrated Vehicle Health Management Perspectives on an Emerging Field. *Book*.

Lebold, M., & Thurston, M. (2001). Open standards for condition-based maintenance and prognostic systems. *Maintenance and Reliability Conference (MARCON)*.

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems* and Signal Processing, 42(1-2), 314–334. doi:10.1016/j.ymssp.2013.06.004

NATO. (2004). All Electric Combat Vehicles (AECV) for Future Applications. *Technical REPORT TR-AVT-*047, 323(July).

 Nuhic, A., Terzimehic, T., Soczka-Guth, T., Buchholz, M., & Dietmayer, K. (2013). Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. *Journal of Power* Sources, 239, 680–688.

doi:10.1016/j.jpowsour.2012.11.146

Pecht, M. (2011). Battery Health and Safety Management. In *PHM workshop on battery*.

Pecht, M., & Jaai, R. (2010). A prognostics and health management roadmap for information and electronicsrich systems. *Microelectronics Reliability*, 50(3), 317– 323. doi:10.1016/j.microrel.2010.01.006

Scanff, E., Feldman, K. L., Ghelam, S., Sandborn, P., Glade, M., & Foucher, B. (2007). Life cycle cost impact of using prognostic health management (PHM) for helicopter avionics. *Microelectronics Reliability*, 47(12), 1857–1864. doi:10.1016/j.microrel.2007.02.014

Uckun, S., Goebel, K., & Lucas, P. J. F. (2008). Standardizing research methods for prognostics. 2008 International Conference on Prognostics and Health Management, 1–10. doi:10.1109/PHM.2008.4711437

Venkat, V., & Raghunathan, R. (2003). A review of process fault detection and diagnosis Part I: Quantitative model-based methods. *Computers & Chemical Engineering*, 27, 293–311.

Vichare, N. (2006). Prognostics and health management of electronics by utilizing environmental and usage loads. *Thesis*.

Voisin, A., Levrat, E., Cocheteux, P., & Iung, B. (2010). Generic prognosis model for proactive maintenance decision support: application to pre-industrial emaintenance test bed. *Journal of Intelligent*.

Wilkinson, C., Humphrey, D., Vermeire, B., & Houston, J. (2004). Prognostic and Health Management for Avionics. In Aerospace Conference, Proceedings IEEE.

Zhang, Y., & Jiang, J. (2008). Bibliographical review on reconfigurable fault-tolerant control systems. Annual Reviews in Control, 32(2), 229–252. doi:10.1016/j.arcontrol.2008.03.008

BIOGRAPHIES

Guillaume Bastard received the degree of Ingénieur from the Conservatoire National des Arts et Métiers in 2013. He is currently in part time training with the University of Lorraine to receive a M.S in system engineering, diagnostic and prognostic. He works as a Research Scientist at Cassidian Test & Services. His research focus lies in developing and evaluating diagnostic and prognostic methods for engineering systems.

Identification and evaluation of the potentials of Prognostics and Health Management in future civil aircraft

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ABSTRACT

After the stepwise implementation of health management systems in form of diagnostic on-board maintenance systems in the latest generation of aircraft (e.g. AiRTHM (Airbus Real-Time Health Monitoring) - Airbus, AIMS (Airplane Information Management System) - Boeing, AHEAD (Aircraft Health Analysis and Diagnosis) - Embraer) and other technical equipment such as jet engines (Engine Condition Monitoring - MTU, Performance Based Logistics -GE) or trains (Remote Condition Monitoring - Future Railway), the pressure is high for an evolution of this technology. Integrated Vehicle Health Management (IVHM) represents a set of capabilities that enable sustainable and safe operation of components and subsystems within aerospace platforms. [Rajamani, 2013]. The next step in IVHM is the ability to give prognoses on the Remaining Useful Life (RUL) of a system or component and the structure of the aircraft. This approach is covered in the term "Prognostics and Health Management" (PHM). PHM in this context consists of Integrated Systems Health Management (ISHM) and Structural Health Monitoring (SHM). To put that step into practice in an industrial environment, it is inevitable to weigh up costs vs. benefits in a Cost-Benefit Analysis (CBA). This trade-off is subject of the following investigation. A methodology is presented with which it is possible to evaluate PHM on aircraft level and examples are given to show its applicability. The study shows that, under the assumptions made, a PHM system can benefit the design and operation of future civil aircraft. The dimensioning of structures can be modified, maintenance processes adjusted, system reliability, aircraft availability and safety increased. With the help of the results presented herein and further indepth studies of the aircraft structures/systems of interest, a sufficiently well-founded evaluation of the possible costs and benefits of the implementation of this advanced approach on the PHM technology can be performed.

1. INTRODUCTION

Integrated Vehicle Health Management is a highly promising game changer for the design and operation of civil aircraft. Over the last 50 years, this technology has gone through major development steps. An overview of the evolution of IVHM in commercial aviation is given by [Hölzel, 2013]:



Figure 1: Evolution of HM/IVHM in Commercial Aviation [Hölzel, 2013]

Prognostics as the next level of IVHM integration is defined by [Goebel, 2010] as a prediction of "damage progression of a fault based on current and future operational and environmental conditions to estimate the time at which a component no longer fulfils its intended function within the desired bounds". Prognostics can be based on the results of accurate diagnostic systems and data-driven and/or physicsbased models. Depending on the level of integration, different implementation approaches for PHM systems are distinguished by [Hölzel, 2013] in Figure 2. This paper deals with the 3rd level, the integration in the conceptual design phase:

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	Legacy Aircraft	New Aircraft	
Level of Integration:	1. Retrofitting or Integration on System Level	2. Integration in A/C and System Design Phase	3. Integration in Conceptual Design Phase
Potential benefits:	 Advanced warnings of failures Reduction of unscheduled events and NFFs Improved trouble-shooting Reduction of operation interruptions and DMCs 	In addition to 1: • Condition-based maintenance • Reduced waste of life • Increased operability and a/c utilization • Reduction of maintenance downtimes and DMCs	In addition to 2: • Reduction of redundancies and safety factors • Lower material consumption, production cost, weight, SFC, etc.
Expected effort & challenges:	 PHM design and integration Limited sensors, low integration 	 Certification of CBM for safety- critical items 	Certification: PHM/IVHM would be safety-critical item

Figure 2: Implementation approach based on the level of integration [Hölzel, 2013]

The main requirements for a complex system such as a civil airplane have to be decided on before the actual development starts in order to control the committed costs. In later development stages, the implementation of new technologies leads to higher investments. In an early design phase, major changes to the architecture of a plane are still possible and the greatest benefit is expected. With this approach, the amount of unscheduled maintenance and the number of No-Fault-Found (NFF) events can be reduced, while the components' use is safer and based on their actual condition. With the help of PHM, the overall platform safety and operational availability can be increased, whereas system redundancies and structural safety factors can be reduced. As a consequence, a decrease in the weight of the airplane is achieved. This allows for further savings by snowball effects such as the decrease of required thrust level or wing area due to lower weight and generates revenues in form of additional passenger or freight capacity and lower fuel consumption.

Benefits of PHM as found in various literature (e.g. [Wheeler, 2010] or [Banks, 2005]) include:

- Reduction of maintenance and operational costs, especially through reduction of unscheduled events and attributed costs for delays, cancellations and material (Condition-Based Maintenance)
- Faster and more accurate troubleshooting during maintenance events
- Ability to trend and predict the Remaining Useful Life (RUL) of a component prior to failure and resulting optimized component use
- Increase in operational/dispatch reliability and aircraft/fleet availability
- Inventory management optimization (spare parts) and intelligent aircraft route allocation (maintenance centers)

Examples of PHM systems for the analysis can consist of a PZT^1 sensor network connected with fiber optic cables generating & capturing guided Lamb waves, acousto ultrasonic patches, Eddy Current, thermography etc. with the respective data processing e.g. in the ACMS (Aircraft Condition

Monitoring System). A variety of sensors specialized on certain functionalities for Systems Health Management, such as sensors for current, vibration, flow, pressure are used for the evaluation. Especially on systems level, a lot of data can be retrieved from already installed Built-In Test Equipment (BITE) as shown e.g. by Taleris' "Intelligent Operations", a service by GE and Accenture focused on improving efficiency by leveraging aircraft performance data, prognostics and recovery [http://www.taleris.com/].

Most of the current literature is focusing on the technical feasibility of PHM solutions on component level or Systems Engineering approaches for requirements and implementation but only few authors show its quantitative benefit. To fill this gap, the following thread is chosen for this project:



Figure 3: Project thread [Speckmann, 2008] states:

"Due to current maturity level of the SHM technologies, the economic benefits are not yet available for customer and cannot be realistically reached before 2008." Six years later, the PHM technologies are more mature and the awareness for this technological evolution in aircraft design and operation is growing. Now is the time to make the stakeholders aware of its economic benefits and potential gains in order to foster innovation.

2. APPROACH

The methodology implemented in this project makes it possible to evaluate the effects of PHM on different levels. The aircraft systems as well as the structure are examined separately according to ATA-chapters. In order to achieve representative results, the qualitative influences of PHM are translated into a "Transfer Function" to show the economic benefit by means of Cost-Benefit Analysis (CBA). This analysis can be used as an argument for the quantitative evaluation of the implementation of the new PHM technology. The improvements of a PHM system for aircraft structure, systems, maintenance and availability are estimated with the help of the DLR-internal CBA-tool, the "Multi-Technology Aircraft Demonstrator" (MTAD) (Figure 4):

¹ Lead zirconium titanate



Figure 4: Multi Technology Aircraft Demonstrator [Weiss, 2007]

With this tool, it is possible to evaluate new technologies in terms of costs, emissions and socio/eco efficiency. The new technology in form of innovative materials, systems or structural layout is translated into a Transfer Function to compare its effect on aerodynamic, weight and propulsion efficiency with a reference aircraft. With the integrated lifecycle calculation, it is possible to compute economic values such as the Net Present Value (NPV) or Internal Rates of Return (IRR) for the aircraft operator and ecological emissions in form of CO and NO_x. The base of comparison for the studies is a single aisle short-range aircraft such as the A320. The scenario is the application of PHM on future aircraft, e.g. an A320 successor.

3. RESULTS

After a thorough literature research on the mentioned topics and performance of respective CBA calculations, results of the project include:

- Qualitative evaluation of Prognostics and Health Management on structural and system level → Benefits in terms of weight savings, Operational Interruption (OI) reduction – availability increase, maintenance task escalation, effective use of RUL, Direct Maintenance Cost (DMC) savings, Non-Recurring Costs (NRC) & Recurring Costs (RC)
- Long-term benefit: Reduction of redundancies on system level and changed structural design principles (damage tolerance, allowables, safety factors) based on better knowledge of structural state and prognostic capability; verification and specification of 10 % acquisition cost reduction potential ([MacConnell, 2007])
- Quantification of benefits concerning aircraft design and operation on ATA-level based on Transfer Function and advanced CBA; verification and comparison with 30 % life-cycle cost reduction potential ([MacConnell, 2007])

3.1. Structural Health Management

The possibility of Structural Health Monitoring on aircraftlevel is evaluated parametrically from an operational (sensors, cables, power and data transmission) and economic point of view (added mass, higher fuel consumption vs. reduced structural reserves, higher availability, reliability) and response surfaces are created.

One example for the alternative structural design with PHM is the dimensioning of stringers in the fuselage. According to current design principles, stringers have to be assumed broken if the skin is torn. With a PHM system, e.g. in form of a network of PZT sensors and Lamb waves, the stringer can be monitored intact above a skin crack and therefore this design constraint is no longer valid. According to [Assler, 2004], the allowable stress level can be increased by 15 % which leads to 15 % weight savings (assumed linear correlation between weight and stress level [Speckmann, 2006]). The saving sums up to around 190 kg. The weight of sensors and cables for this SHM is approximated to be 15 kg which reduces the savings to 0.04 % of the aircraft Operating Empty Weight (OEW). Through snowball effects, the wing weight can be reduced by 0.01 % and the fuel consumption drops accordingly. A trade-off study shows that this corresponds to a delta of app. 1.5 \$/kg OEW. This reduction of 1.5 \$/kg for an OEW of 41,680 kg results in 62,520 \$ per aircraft. Multiplying this by the number of expected sales gives an idea about the margin for NRC and RC for the implementation of the PHM system. Assuming a market of 1,000 aircraft results in a budget of 62,520 k\$, or 43,764 k\$ with a profit margin of 30 % for the OEM (Original Equipment Manufacturer). An approximation of NRC & RC via percentage values from [Curran, 2004] and [Lammering, 2012] shows that a completely new design of the stringers can be possible with this saving but a partial redesign due to changed constraints is more cost-effective. False alarm events have to be taken into consideration, reducing the overall benefit. On the other side, an increase of the flight safety is a clear benefit which cannot be expressed in monetary value.

Another benefit of PHM is the escalation of maintenance intervals. The inspection interval (II) is derived from "lives" n_i (number of flights) and a 'life factor' j_L as explained in [Teske/Schmidt, 1999]: $II \leq \frac{n_2 - n_1}{i_L}$

As an example, the life factor for bearings in service doors can be reduced from three to one due to the new SHM inspection method that guarantees continuous monitoring, e.g. in form of oil debris and vibration analysis (see [Goebel, 2005]). Thereby, the check interval can be increased from 13,500 to 40,500 FH which leads to the escalation or even deletion of the maintenance task.

Assuming similar factors for other inspections, the escalation of the entire structural inspection check from e.g. 12 to 13 years leads to an NPV increase of about 4 % within 16 years. This however requires a thorough assessment of all carried out tasks. The ultimate goal regarding scheduled maintenance is a complete performance monitoring with a warning from the PHM system when the performance drops



Figure 5: Escalation of scheduled maintenance tasks This way, scheduled checks can be reduced to a minimum and unscheduled events become predictable.

3.2. Systems Health Management

On ATA-level, systems that are particularly suited for PHM and have a great effect on reliability/availability, installation, maintenance effort, operational costs (e.g. avionics, hydraulics, air conditioning) are analyzed parametrically. In this "top-down" approach, parameters such as the weight, functionality and numbers of parts of a system are used to generate a function for the necessary sensors and the possible impact on NRC, RC and weight on the cost-side opposed to benefits such as reduced maintenance effort and Operational Interruptions. This parameterized approach will have to be validated and improved by a detailed analysis of the respective aircraft systems.

A paradigm shift in system redundancy can be triggered by PHM systems. If failures of systems can be predicted with a sufficiently high reliability (depending on the Failure Effect Category), redundancies can be reduced in order to save weight, complexity and potential failure causes. Examples are air conditioning packs (~82 kg), one of the three hydraulic systems (~290 kg each) or parts of the oxygen systems. An explicit consideration of the respective failure categories per component/function is hereby inevitable. For the systems, a major benefit of a PHM system is expected through a reduction of OI rates. These interruptions lead to delays and cancellations which can be reduced with the help of PHM. Another benefit is the DMC reduction through less scheduled & unscheduled maintenance tasks, troubleshooting times and spare part logistics.

The possible benefits of PHM for ATA21 – Air Conditioning are discussed in the following example: With an assumed amount of parts with different part numbers of 67, seven basic functionalities (compression, distribution, pressurization control, heating, cooling, temperature control, moisturize/air contamination control) that need to be covered. Temperature, flow, pressure and hygrometer sensors are necessary to guarantee the functionality and the amount of sensors adds up to 13 (without already installed BITE) (no. of parts * 0.2; Pareto approach: 80 % of failures caused by 20 % of components/functions) with a corresponding weight of 0.938 kg. As most of the systems are already supplied with power and data transfer, no additional effort will be assumed. A typical OI-rate (per 100 revenue flights) for ATA21 as mentioned by [Feng, 2013] is around 0.044. On the basis of the Pareto distribution (80 % of failures covered by 20 % prognostic capability), a new OI rate of 0.044 * 0.2 = 0.0088 is approximated. The corresponding mean saving per 100 flights (mean delay of 63 min with costs of 8,000 \$/hour) is estimated to be around 296 \$. Considering flights over 16 years with 4.5 flights/day, app. $296 \/100 \ * \ 26280 = 77,789 \$, which corresponds to an NPV of 38,037 \$ after 16 years with a constant discount rate of 0.1, are expected. Multiplying this with the number of expected sales of 1,000 aircraft results in a budget of 38,037 k\$, around 26,625,900 \$ with a profit margin of 30 % for the OEM. This expected gain justifies the costs for development and RC for the PHM system. Approximated via the weight and number of parts of the system, NRC (development & installation) are estimated in relation to the approximate costs of 1 B\$ for a new aircraft development and account to app. 10 M\$ for ATA21. The remaining delta can be used for the inevitable recurring maintenance costs which are approximated via percentage values taken from [Lammering, 2012]. Reduction of redundant features such as the second air conditioning pack allows for further weight savings of 82 kg with respective snowball effects, around one extra passenger. The corresponding reliability for the functionality of the pack has to be guaranteed by the system.

3.3. Response surface

As the examples shown here are assuming a perfect PHM system and no technical system can guarantee 100 % reliability, a trade-off for uncertainties and failure possibilities has to be carried out. For this project, the approach is to show this interdependency by means of response surfaces for different degrees of reliability and coverage of the PHM system (see Figure 6). The run of the curve is approximated with a logistics function as used for many statistical problems (Figure 7). It is based on the assumption that very low coverage as well as low reliability lead to low savings due to high risk and lack of credibility. Respectively, very high coverage and reliability are required for according savings as dramatic improvement opportunities are exhausted.



Figure 6: Response surface for weight savings plotted against coverage and accuracy



Figure 7: Logistics function for response surfaces Other relations, such as combinations of logarithmic, linear and exponential functions are possible.

4. CONCLUSIONS

A methodology for the assessment of costs and benefits of PHM systems for future civil aircraft is presented and its applicability is shown on the basis of case studies. Exemplary business cases on structural parts such as stringers and systems like air conditioning prove that the potential benefits in terms of weight reduction, increased availability and reduced maintenance efforts can outweigh additional weights, costs for the development and maintenance of the diagnostic/prognostic system. By using a parametric approach, the analysis can be further refined. The uncertainty of prognostics and failures of the PHM system is represented by the use of response surfaces for the potential benefit.

5. OUTLOOK

In order to state the costs and benefits for respective structures and systems more thoroughly, a dedicated assessment on component level is suggested with the FMECA process and decision metrics as justification method, also for future certification. The potentials of already installed BIT/BITE and the architectures for new sensors, data transfer and processing will have to be evaluated. A detailed economic assessment with different scenarios for the various systems/structures and complete analysis of task escalation/ deletion for respective components can take place in order to implement PHM for the most cost-effective systems.

REFERENCES

- Assler, H., Telgkamp, J. (2004), *Design of aircraft structures under consideration of NDT*, WCNDT-World Conference of Non-Destructive Testing, Montreal, Canada, October 2004
- Banks, J., Reichard, E., Crow, E., Nickell, E. (2005), How Engineers Can Conduct Cost-Benefit Analysis for PHM Systems, IEEE Aerospace Conference, paper #1363, 2005, 0-7803-8870-4/05
- Curran, R., Raghunathan, S., Price, M. (2004), Review of aerospace engineering cost modelling: The genetic causal approach, Progress in Aerospace Sciences 40 82004) 487-534, doi: 10.1016/j.paerosci.2004.10.001
- Goebel, K., Bonanni, P., Eklund, N. (2005), Towards an Integrated Reasoner for Bearings Prognostics, Proceedings of 2005 IEEE Aerospace Conference, paper #1309, 2005, 0-7803-8870-4/05/
- Goebel, K. (2010), *Prognostics*, Presentation of the NASA Prognostics Center of Excellence, NASA Ames Research Center, Moffett Field CA94035, April 2010
- Guo, F. (2013), Fleet Performance Management CAAC A320 Fleet Performance Seminar, Airbus China, Shenyang, July 2013
- Hölzel, N., Pape, O., Schilling, T. (2013), Internal presentation on IVHM, DLR/Hamburg, September 2013
- Lammering, T., Franz, K., Risse, K. et al. (2012), Aircraft Cost Model for Preliminary Design Synthesis, 50th AI-AA Aerospace Sciences Meeting, January 2012, Nashville, Tennessee
- MacConnell, J.H. (2007), ISHM & Design: A review of the benefits of the ideal ISHM system, IEEEAC Paper #1596, 2007, 1-4244-0525-4/07
- Rajamani, R., Saxena, A., Kramer, F., Augustin, M. et al. (2013), *Developing IVHM Requirements for Aerospace Systems*, SAE Technical Paper 2013-01-2333, 2013
- Speckmann, H., Roesner, H. (2006), Structural Health Monitoring: A contribution to the Intelligent Aircraft Structure, ECNDT-European Conference of Non-Destructive Testing, September 2006, Berlin, Germany
- Speckmann, H., Henrich, R. (2008), Structural Health Monitoring (SHM) - Overview on technologies under development, Airbus, Bremen, Germany
- Teske/Schmidt (1999), *Guidelines for the damage tolerant design of aircraft structures*, Handbuch Struktur Berechnung, 62200-01, Issue B
- Weiss, M. (2007), Ein Vorschlag zur Berücksichtigung der Schallemission bei der Betriebskostenbewertung im Vorentwurf von Verkehrsflugzeugen und dessen Anwendung an einer neuartigen lärmarmen Konfiguration, Forschungsberichte aus den Ingenieurwissenschaften, Verlag: Mensch & Buch; 1. Auflage, ISBN-13: 978-3866642911
- Wheeler, K. R., Kurtoglu, T., Poll, S. D. (2010), A survey of Health Management user objectives in aerospace systems related to Diagnostic and Prognostic metrics, International Journal of Prognostics and Health Management, ISSN 2153-2648.

Health Management System for the Hydraulic Servoactuators of Flyby-wire Primary Flight Control Systems

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ABSTRACT

Aircraft maintenance is one of the most important cost items faced by the operators of air fleets and is a major contributor to the aircraft life cycle cost. An aircraft fly-by-wire flight control system has a total of primary flight control actuators ranging from 10 to 20 depending on the aircraft type, with a failure rate of 1/1000 flight-hours; therefore, a health monitoring system for primary flight control actuators, able to recognize an actuator degradation in its early stage could greatly contribute to optimize the maintenance operations, reduce the airplane downtime and prevent missions interruptions.

This note presents the initial part of an ongoing research project aimed at developing a prognostic and health management system for fly-by-wire primary flight control actuators. A key feature of the project is to develop a PHM system for these actuators suitable for the flight control actuators of legacy airplanes, which are poised to operate for still a long time, and not only for those of new aircraft. The primary flight control actuators of fly-by-wire flight control systems of existing aircraft are electrohydraulic servoactuators with a typical configuration and complement of transducers, and there is no practical possibility of introducing additional sensors. For this reason, the research activity was directed towards the study of algorithms able to identify faults only by using the already available information of the servoactuators state variables.

The implemented algorithms are a combination of mathematical and neural network based ones, and the identification of degradations was performed by the analysis of the response of the servoactuators to a sequence of selected stimuli provided in preflight or postflight. The servovalve current and the feedback position are processed by dedicated algorithms in order to obtain significant indicators of the servocatuator health condition. The values of the indicators obtained during the sequence of stimuli are analyzed in combination with those obtained in the past.

Andrea Mornacchi et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. This is performed by the neural network part of the algorithm which allows a reliable identification of presence and of type of a degradation.

The results obtained from the initial part of the research activity are interesting and encouraging. Individual degradations of the servoactuator parameters have so far been addressed and the algorithms for identifying them have been developed. All that makes up the foundations of the future research activity which will be focused on analyzing the effects of simultaneous multiple degradations and to the estimation of the remaining useful life.

1. INTRODUCTION

The development of a PHM system suitable for flight control actuators of legacy airplanes presents numerous problems related mainly to the impossibility to increase the number of sensors, and consequently of information, useful to recognize the appearance of a degradation. Comes the need to best combine the information already acquired not only for control of the servosystems but also the normal control operation, as the hydraulic oil temperature. In addition, the inability to detect the external loads acting on the wing surface makes it necessary to think of prognostic systems capable of working when the aircraft is pre/postflight condition. Injection of selected stimuli during ground test offers the possibility to recognize all possible degradations of servovalve; however the detection of actuator degradations is not possible by the reason of absence of external load. (Borello, Dalla Vedova, Jacazio and Sorli 2009).

The research conducted to date has focused on the analysis of major degradation of the servovalve: toque motor degradation, spool friction increase, growth of radial clearance between spool and sleeve, feedback spring degradation and progressive clogging of a nozzle.

2. MATHEMATICAL MODEL

Studies of the effect of different degradations on the behavior of the servo actuator were carried out using a high-

fidelity mathematical model especially implemented in Matlab-Simulink. In the realization of the mathematical model all the typical nonlinearity that characterizes the behavior of electrohydraulic servoactuators have been taken into consideration.

The servovalve torque motor model is implemented with equations presented by E. Urata (2007) which express the magnetic flux as a function of the armature position and dielectric constant of air-gap and also give the possibility to set an unequal air-gap thickness. In the dynamic equations of servovalve flapper and spool the influence of feedback spring force, coulomb and viscous friction and structural stiffness and damping, have been considered, furthermore each parameter can be modified in order to simulate a degradation of the components. The servovalve control flows resulting, for each port, from the difference of the contributions coming from supply and direct to return. Each contribution is a function of: spool position, pressure drop, radial clearance and discharge coefficient; the last term, in turn, depends on the port opening, Reynold number and on the ratio between corner radius and port opening.

The hydraulic actuator is describe by a 3-DOF model: the first two are the rod and the surface position, the last concerns the deformation of the attachment point of the actuator with the fixed structure. Special attention has been committed to modelling the actuator coulomb friction, which is function of dynamic condition of the rod and as well as of geometrical and physical data of the seal and of pressures in the actuator chambers.

The model also includes the electronic part of the servosystem, the LVDT demodulator, the analog-to-digital converters, the data refresh rate and the computation time of the fly-control-computer are implemented. In the purpose of increasing the fidelity of mathematical model electrical noise in A/D converter and the noise that corrupts the servovalve current command are taking in to account.

2.1. Environmental condition

The dynamic response of a servoactuator is also a function of the external loads and environmental conditions, such influence, in particular severe conditions, can become particularly significant and to vary heavily indices of health considered in the PHM system.

Being the prognostic test carried out in pre/post-fight the aerodynamic force is due exclusively from atmospheric wind, this has been modeled as the sum of three distinct components:

- Velocity of atmospheric wind, obtained by a normally distributed random number.
- Wind gust, whose amplitude and duration are determined by a random number generator. Gusts occur in a random pattern.

• Turbulence, whose characteristics are calculated using the Dryden model.

The airstream velocity thus obtained is used with atmospheric density and drag coefficient to obtain the aerodynamic force.

The environmental conditions, in particular the temperature, influence also the oil properties, hence the mathematical model includes a set of equations that updates the values of density, viscosity and bulk modulus.

2.2. Mathematical model validation

The mathematical model has been validating using a set of experimental data consisting of frequency responses for different command amplitude and step response. As shown in Figure 1 the behavior of the model and the experimental data are particularly close.



The absence of experimental data concerning degrade servosystems did not allow to validate the mathematical model in fail to failure condition, however the physicalbased nature of the model affords to hypothesize a good fidelity of the model even in case of those parameters that allow to introduce degradations.

3. INDICATORS OF HEALTH CONDITION

The PHM system developed is based on the observation, both punctual and the trend, of significant indicators of the servocatuator health condition. The indices are obtained by the processing of servovalve current and feedback position get as response of servoactuators to a sequence of selected stimuli provided in preflight or postflight.

The command set is designed to maximize the number of health index obtainable, it is 1.8 s long and it is the combination of four different input kinds (Figure 2):

- Sinusoidal command: amplitude equal to 5% of half stroke at 5 Hz frequency.
- Step command: amplitude equal to 10% of half stroke.

- Constant command: amplitude equal to 10% of half stroke.
- Ramp command: ratio equal to 22 mm/s.



The analysis of the servosystem response, both in terms of feedback position and servovalve current, to the different stimuli allows to obtain eleven different indices, five from the position and six from the current. The indexes are presented in Table 1 divided by type of command.

Command	Position Index	Current index
	Gain	Min current
Sinusoidal	Dhasa	Max current
	Phase	Mean current
Step	Rise time	Decries time
Constant	Limit cycle	Limit cycle
Ramp command	Rate error	Rate current

 Table 1: Indicators of health condition

The tests were carried out to identify the influence of each degradation on the health index had put in evidence that is possible correlate univocally the trends of the indices to deterioration, since any deterioration involves a unique set of variation of the indices. In addition, tests have revealed a greater sensitivity of the indices of the current with the degradations, but at the same time also a greater sensitivity to noise and environmental conditions. Therefore it was decided to combine the two types of indices: those of the current for an early identification of the degradation and the position indices to have a reliable estimate of the condition of the servosystem.

3.1. Nominal variation range

The indicators of health condition, exactly as the response of the servo system in its entirety, are strongly influenced by environmental conditions, by the aerodynamic loads and noise. The value of the index is also dependent on the geometric tolerances provided for in the design phase, thus making impossible to define a nominal values of the index valid for a family of servoactuators. Several tests carried out in order to define a range of variation of the indexes in the absence of degradation. The simulations have been conduct combining different environmental conditions and changing flow and pressure gain of the servovalve, in accordance with technical specification. The limits so defined have been multiplied by a safety factor in order to avoid false alarms. This procedure has allowed to identify a range, function of the oil temperature, in which the variation of the health index taken into consideration does not involve the presence of a degradation.

4. PHM ALGORITHM

The developed PHM algorithm is composed of three different subroutines, which work jointly to detect and identify degradations. The first subroutine is dedicated to the processing of the current and position recorded during the pre/post-flight test and it is also designated to detecting the appearance of the degradations. The algorithm, after obtaining the value of the health indices, compares these with the range of nominal variation relative to the oil temperature. If an index comes out from these limits for three consecutive times, the algorithm indicates the presence of a degradation and activate the second subroutine that identifies the type of degradation. In case the first degradation has already been identified, the first subroutine will begin to analyze the historical trend of indices in order to identify the occurrence of further failure. The appearance of a new degradation induces a variation of the rate of the trend indices, which entails a peak in the second derivative curves of all of the indexes in the same instant. Due to of the derivatives performed, and the identification of the necessary filtering of the indices takes place with about twenty acquisitions delay. The detection of a second failure involves the start of the third subroutine.

The second subroutine includes in its interior a double layer neural network, which receives in input the values of the eleven indices normalized and limit between -1 and 1; 1 corresponds to the upper limit of nominal band exceeded by the index, -1 the lower limit exceeded. The output of the neural network is the indication of the type of degradation. The neural network has been subjected to a learning process in order to optimize its operation, the training function adopted working in according with Levenberg-Marquardt optimization (Levenberg 1944 and Marquardt 1963). During the process of learning 1366 set of indices taken at random from the simulation results has been provided to the neural network.

The third subroutine is composed of a double layer neural network with eighteen inputs and seven outputs. The first seven inputs are the indication of the previous degradation, 1 indicates that the degradation was detected previously otherwise the corresponding value is zero; the other eleven inputs correspond to the signs of the peaks of second derivative of the indexes trend detected from the first subroutine. Using the supplied input the neural network provides to classify the new degradation. The neural network has been trained using the same learning function used for the second subroutine; in this case ten different multiple degradations were provided in input.

5. RESULTS

The algorithms have been tested using data generated by a large number of simulations, in which the environmental and operative conditions were changed in order to test all the possible operative scenarios.

In the following sections the results of validation algorithms tests are present divided in single degradation and multiple degradations case. In both cases the algorithms were proved robust and the nominal variation ranges were reveled very useful for the purpose of avoid false alarms due to fluctuations of the indices caused by changes of environmental conditions.

5.1. Single degradation detection

The classification of a single degradation carried out by the second subroutine provides very interesting results. The neural network has been verified with a large numbers of set indices, 13631, the classification was successful except that in 42 cases, corresponding to an error less than 0.31%. The classification errors appear mainly in the presence of high degradations level, where all the degradations affect in a similar way all the indices. The test results are shown in the Figure 3. In Table 2 are shows the average values for each failure in which occurs the recognition and classification.



Figure 3: Single degradation classification

Table 2:	Value of	recognition
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Degradation	Value
FMM degradation	6.2 %
Feedback spring yield	10.3 %
Feedback spring backlash	13.4 µm
Clogging nozzle	2.5 %
Spool radial gap	8.8 µm
Spool friction	5.0 N

5.2. Multiple degradation detection

The recognition of multiple degradations present greater difficulties than in the single case, since the recognition of the peaks of the second derivative is particularly complex because of the fluctuations in the indices due to disturbances and noise.

The verification of the algorithms has been made by providing twenty different combinations of degradations as input to the neural network. In seventeen cases the classification of the second degradation was successful, in two cases there were errors of classification, while in one case the second degradation was not recognized.

Failure to recognize the degradation has occurred in the case of a reduction of the magnetic force and friction, the main cause of the error is the small amplitude of the peeks as a consequence of the low influence of friction on the health indices.

6. CONCLUSION

The research carried out has proved particularly interesting and can provide an excellent starting point for a prognostic algorithm able to estimate the RUL. The algorithms developed are particularly robust and do not require a priori knowledge of the fail to failure mechanisms, since all strategies identified to recognize and classify the degradations are based on the analysis of certain data acquired during normal operation of the actuator.

An improvement in the quality of research will be to validate the algorithms by using experimental data, in addition the reliability of algorithms could increase exploiting the data from an entire fleet of aircraft, thus optimizing both the neural networks and nominal range of indices variation.

REFERENCE

- Borello L., Dalla Vedova M., Jacazio G. & Sorli M. (2009). "A Prognostic Model for Electrohydraulic Servovalves". *Annu. Conf. Progn. Heal. Manag. Soc.*, Sept. 27 - Oct. 1, San Diego
- Levenberg K. (1994). "A method for the solution of certain problems in least squares". *Quart. Appl. Math.*, Vol. 2.
- Marquardt D. (1963), "An algorithm for least squares estimation of non-linear parameters", *J. Ind. Appl. Math*, Vol. 11, No. 2.
- E. Urata (2007), "Influence of unequal air-gap thickness in servo valve torque motors," *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.*, Vol. 221, No. 11.

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