RENEWABLE NRG SYSTEMS

SEE THE POTENTIAL

Lubrication Oil Condition Monitoring and Remaining Useful Life Prediction with Particle Filtering

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Renewable NRG Systems

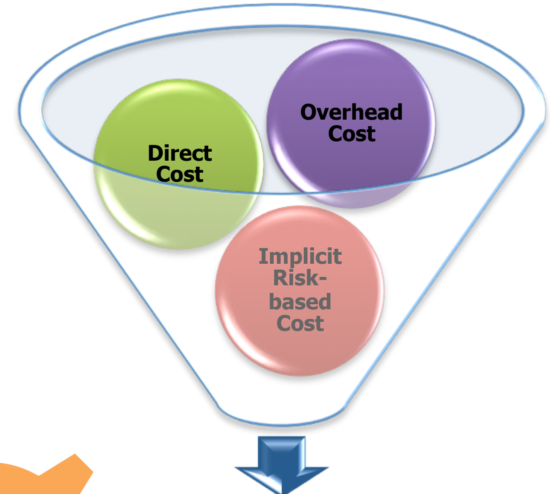
Outline

- Introduction
- Model Development
- Model Validation
- RUL Prediction Algorithm Development and Validation
- Conclusions

Introduction
Background & Motivation

Condition Based Maintenance (CBM) includes 3 Stages:

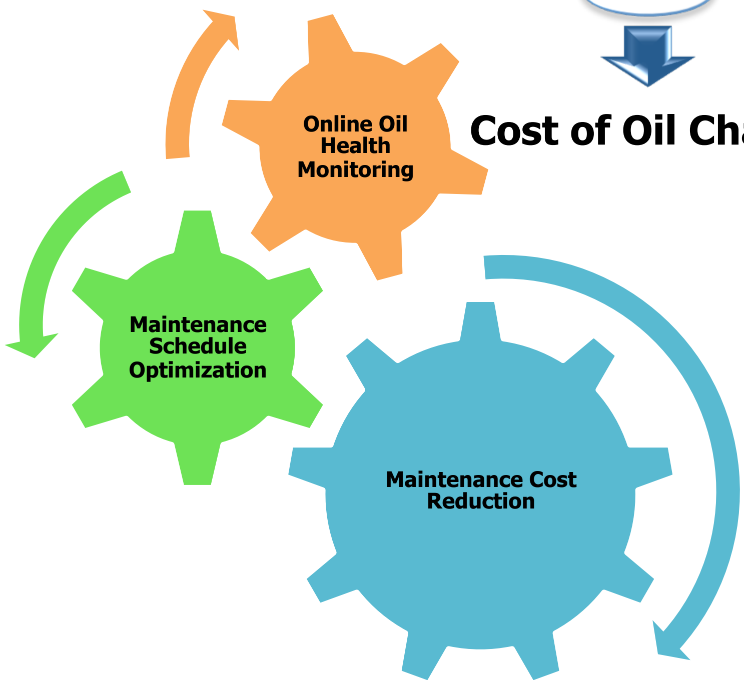
1) Diagnosis: Evaluate the current health condition of a component or subsystem.
2) Prognostics:
   a) Estimate the system health status at future time.
   b) Estimate the remaining useful life (RUL) of a component or subsystem.
3) Decision making.



Cost of Oil Change

The benefits of effective lubrication oil CBM includes:

- ✓ Improve drive train and gearbox reliability
- ✓ Earlier warning of possible failure compared to vibration analysis.
- ✓ Increase wind turbine availability
- ✓ Reduce maintenance costs
- ✓ Reduce labor cost
- ✓ Reduce environmental impact of mineral oil waste



Introduction
Background & Motivation

The purpose of this research is to develop an online lubrication oil condition monitoring and remaining useful life prediction technique based on a particle filtering algorithm and commercially available online sensors.

Research Contribution

- ✓ Summarized and evaluated current lubrication oil health condition monitoring techniques and solutions.
- ✓ Developed and validated physics based models for lubrication oil performance degradation based on selected performance parameters.
- ✓ The remaining useful life prediction of lubrication oil has been successfully performed with the help of adapted particle filtering technique.
- ✓ Validated the developed lubrication oil condition monitoring and RUL prediction technique using a simulation case study.

Introduction
Basic Degradation Features

The Principles of lubrication oil condition monitoring is by means of various sensing techniques to directly or indirectly monitor the basic lubricant degradation features.

✓Water contamination

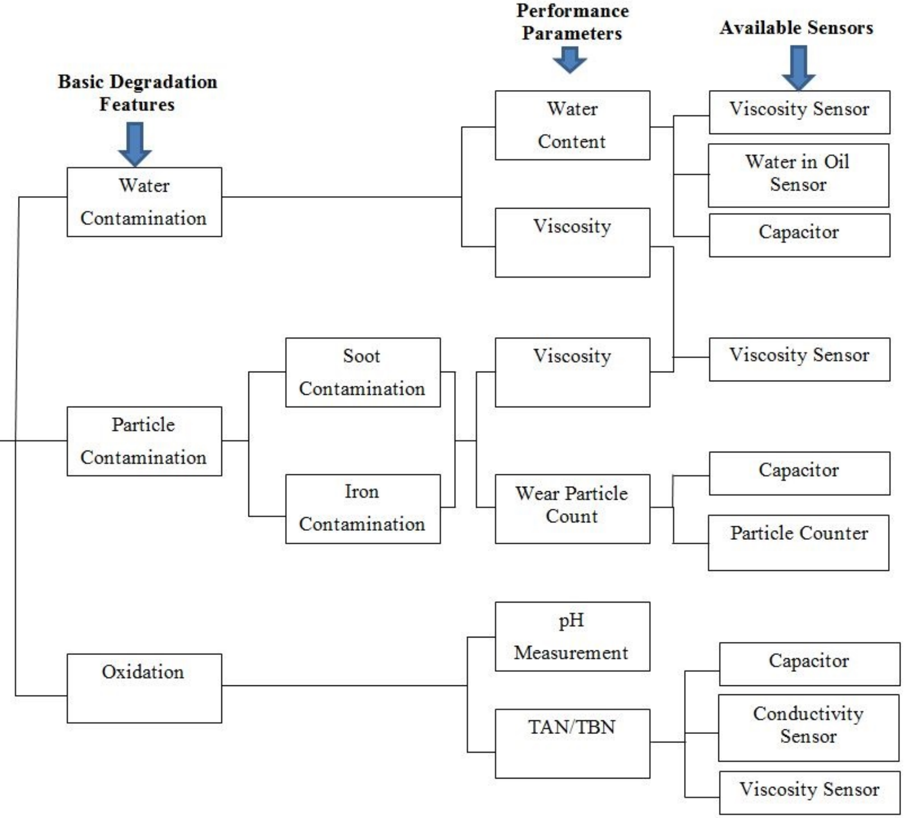
1) Cause: Leakage,, blow-by gas
2) Impact: Lubrication function reduction, increase corrosion, deposit formation

✓Oxidation

1) Cause: Chemical chain reaction from overheating and contamination.
2) Impact: Acid compound formation, insoluble products, varnish and sludge

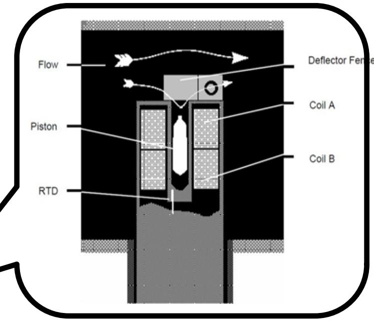
✓Particle contamination

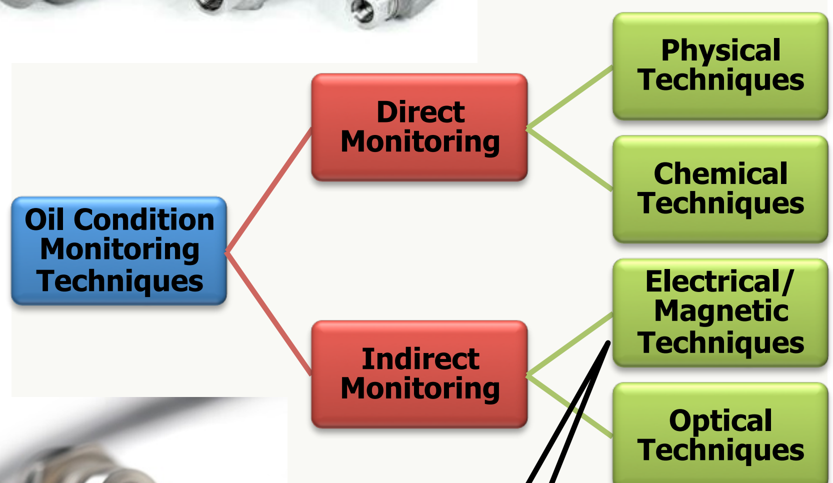
1) Cause: Oxidation by products, machine wear debris
2) Impact: Clog filters and valves, defective seal, sever components friction

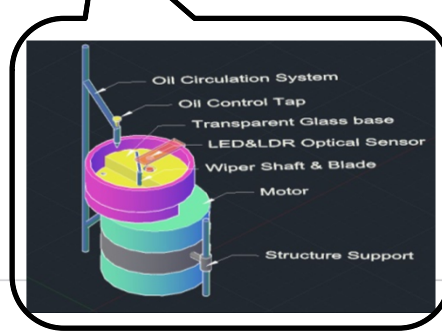


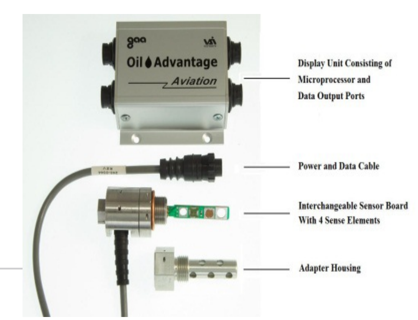
The relationship among the basic degradation features, performance parameters, and available oil condition sensors

Introduction
Current Oil Monitoring Techniques



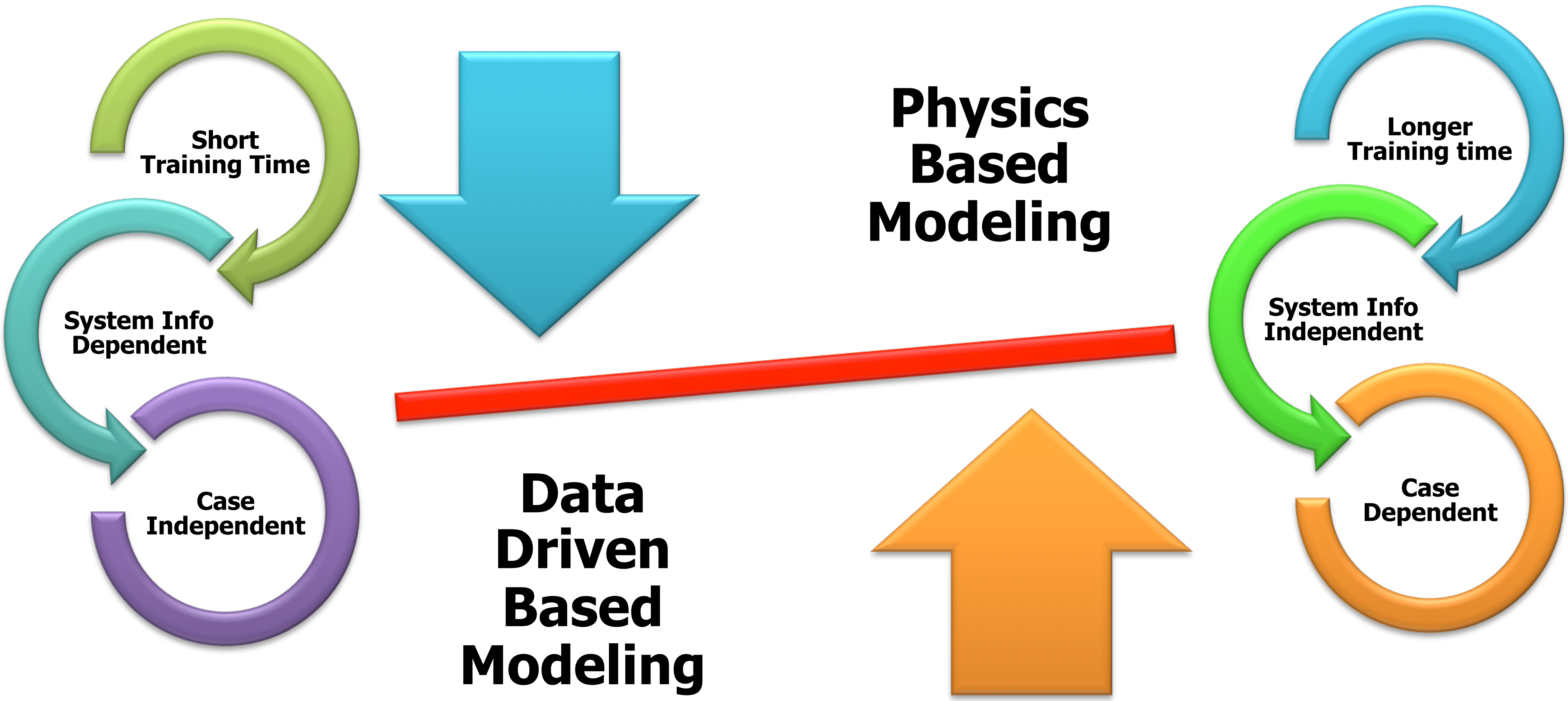






Model Development

Component Degradation Modeling

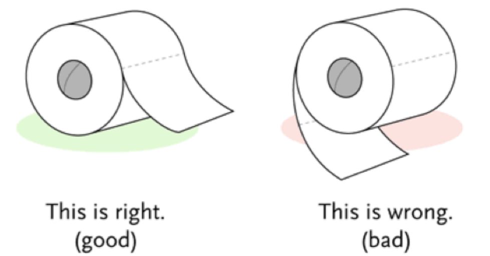


Model Development

Data Driven Based Modeling

System Encounter

Training Process



Diagnostic Capable

Physics Based Modeling

System Encounter

System Kinematic Information Acquisition

Diagnostic Capable

Model Development

Water Contamination Viscosity Model Development

$$V_{M,T} = (V_{oil,T} - V_{water,T}) \times (1 - P) + V_{water,T}$$

$$V_{water,T} = 2.414 \times 10^{-5} \times 10^{247.8/(T+273-104)} / \rho_{water,T} = -0.451 \times \ln T + 2.3591$$

(Water Physical Property)

$$V_{oil,T} = 57470.5189 \times T^{-1.935}$$

(Lubrication Oil Property from Initial Testing)

T = temperature, in Celsius

$V_{oil,T}$ = viscosity of the healthy oil at temperature T, in *Cst*

$V_{water,T}$ = viscosity of the water at temperature T, in *Cst*

P = water volume percentage

Model Development

Water Contamination Dielectric Constant Model Development

$$(\varepsilon_{eff}-\varepsilon_{m}/\varepsilon_{eff}+2\times\varepsilon_{m})=\delta_{i}\times(\varepsilon_{i}-\varepsilon_{m}/\varepsilon_{i}+2\times\varepsilon_{m})$$

(Maxwell Garnet Mixing Rule, Effective Medium Theory)

$$\varepsilon_{M,T}=\varepsilon_{oil,T}\times(1+3\times P\times\varepsilon_{water,T}-\varepsilon_{oil,T}/\varepsilon_{water,T}+2\times\varepsilon_{oil,T}-P\times(\varepsilon_{water,T}-\varepsilon_{oil,T}))$$

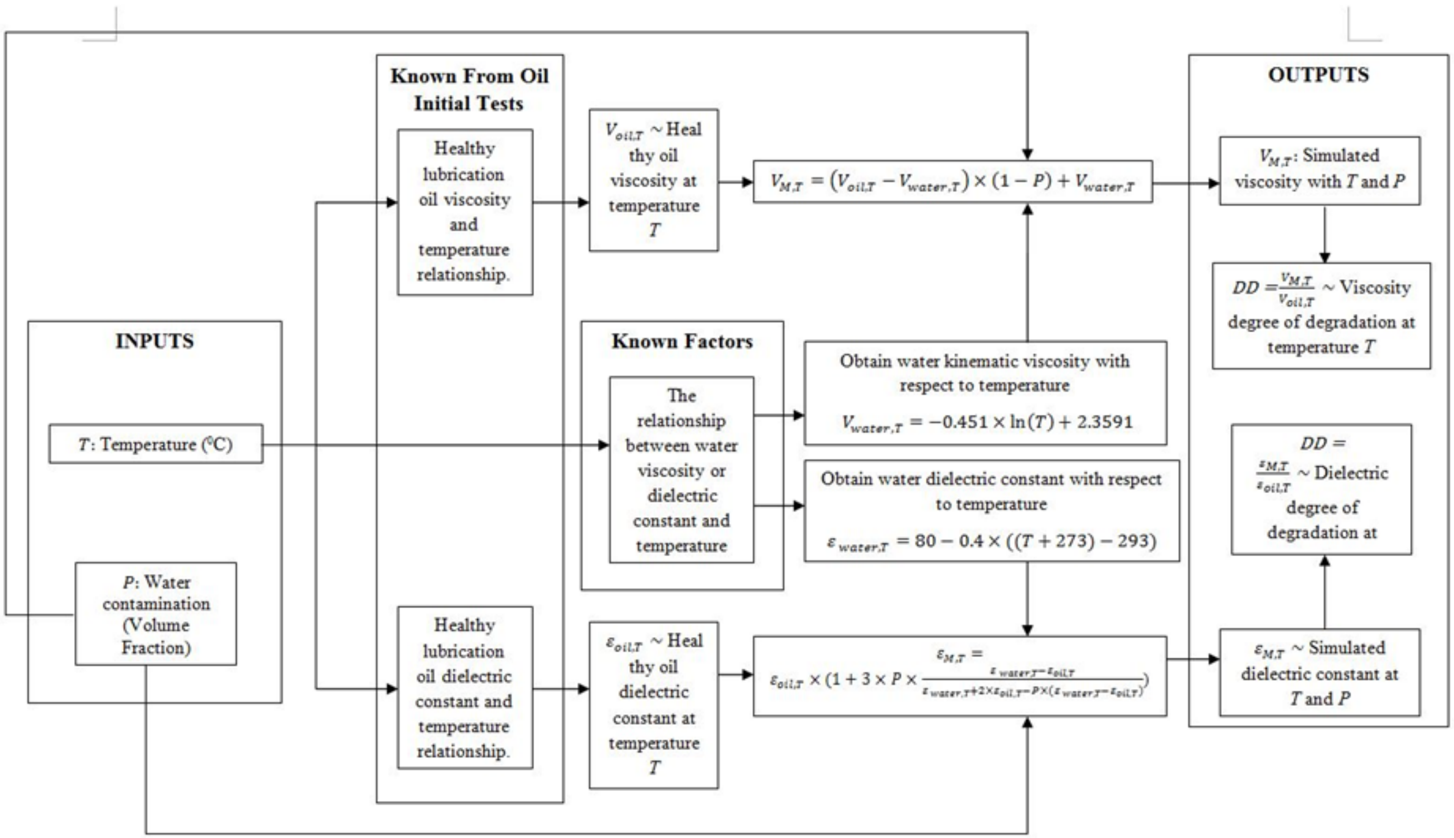
$\varepsilon_{water,T}=80-0.4\times((T+273)-293)$ (Water Physical Property)

$\varepsilon_{oil,T}=4.90028\times T^{-0.121}$ (Lubrication Oil Property from Initial Testing)

$\varepsilon_{oil,T}$ = dielectric constant of healthy oil at temperature *T*

$\varepsilon_{water,T}$ = dielectric constant of water at temperature *T*

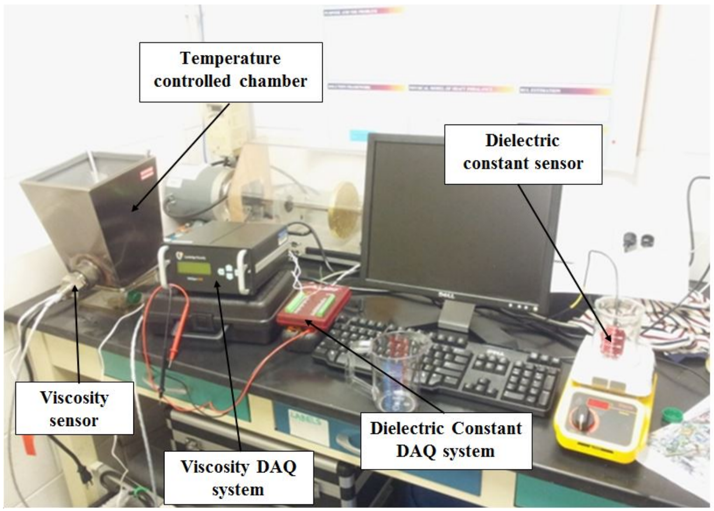
Model Development



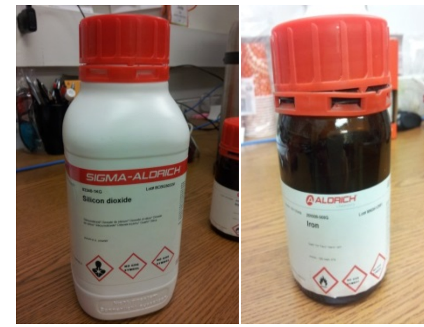
Lubrication oil water contamination simulation model for viscosity and dielectric constant

Model Validation

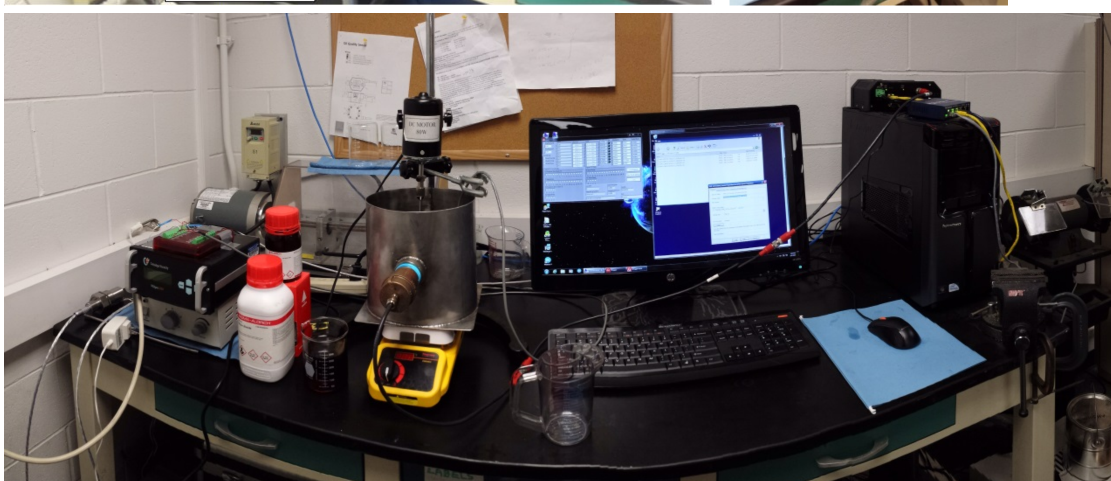
Experimental Setup



Dielectric constant sensor and the LabJack U12 data acquisition system



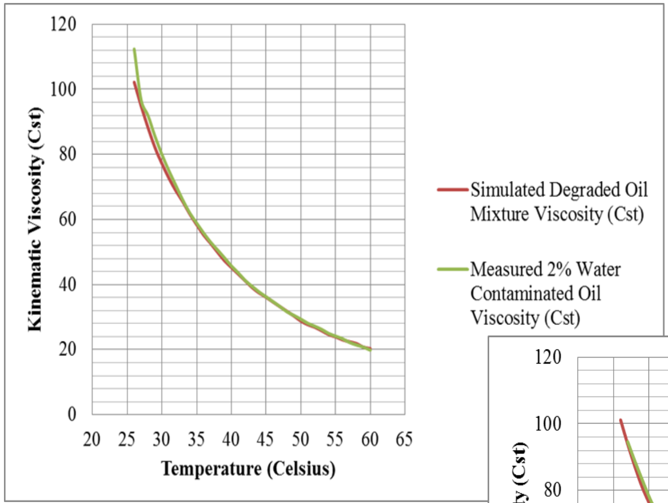
Iron and silicon dioxide powder from SIGMA-ALDRICH



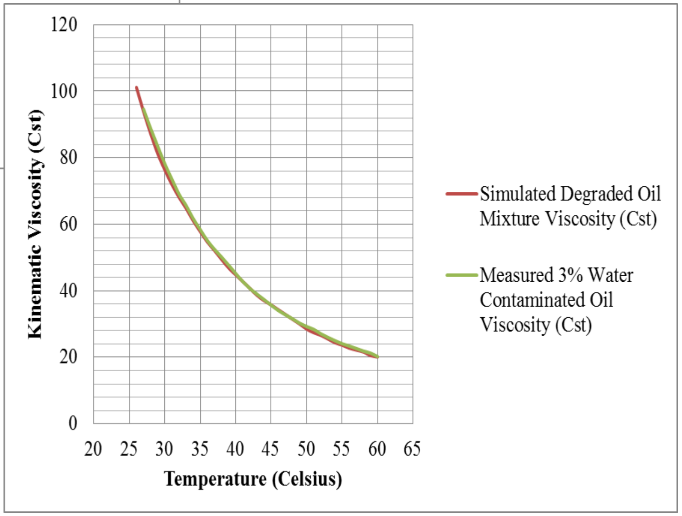
Viscometer and Its Data Acquisition System

Model Validation

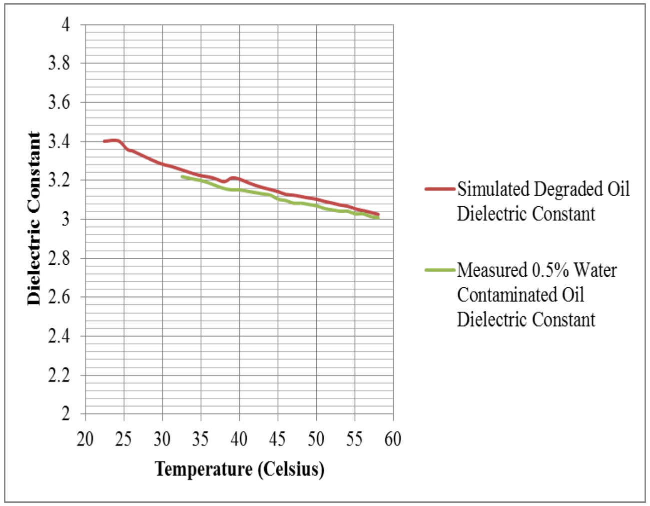
Water Contamination Model Validation



Kinematic viscosity comparison between simulated 2% water contaminated oil and measured 2% water contaminated oil



Kinematic viscosity comparison between simulated 3% water contaminated oil and measured 3% water contaminated oil



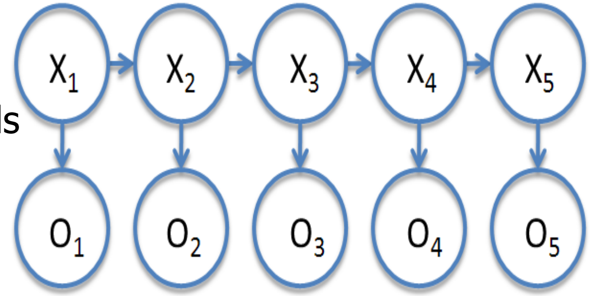
Dielectric constant comparison between simulated 0.5% water contaminated oil and measured 0.5% water contamination oil

RUL Prediction

Case Study: RUL Prediction for Water Contamination Model

Why Particle Filtering?

- ✓ In many applications, it is required to estimate a latent or 'hidden' process (the 'state' of the system) from noisy, convolved or non-linearly distorted observations.
- ✓ State estimation problems for non-linear non-Gaussian state-space models do not typically admit analytic solutions. Since their introduction in 1993, particle filtering methods have become a very popular class of algorithms to solve these estimation problems numerically in an online manner.
- ✓ Some Typical applications from the engineering perspective include:
  - ➢ Tracking for radar and sonar applications
  - ➢ Real-time enhancement of speech and audio signals
  - ➢ Sequence and channel estimation in digital communications channels
  - ➢ Medical monitoring of patient eeg/ecg signals
  - ➢ Image sequence tracking



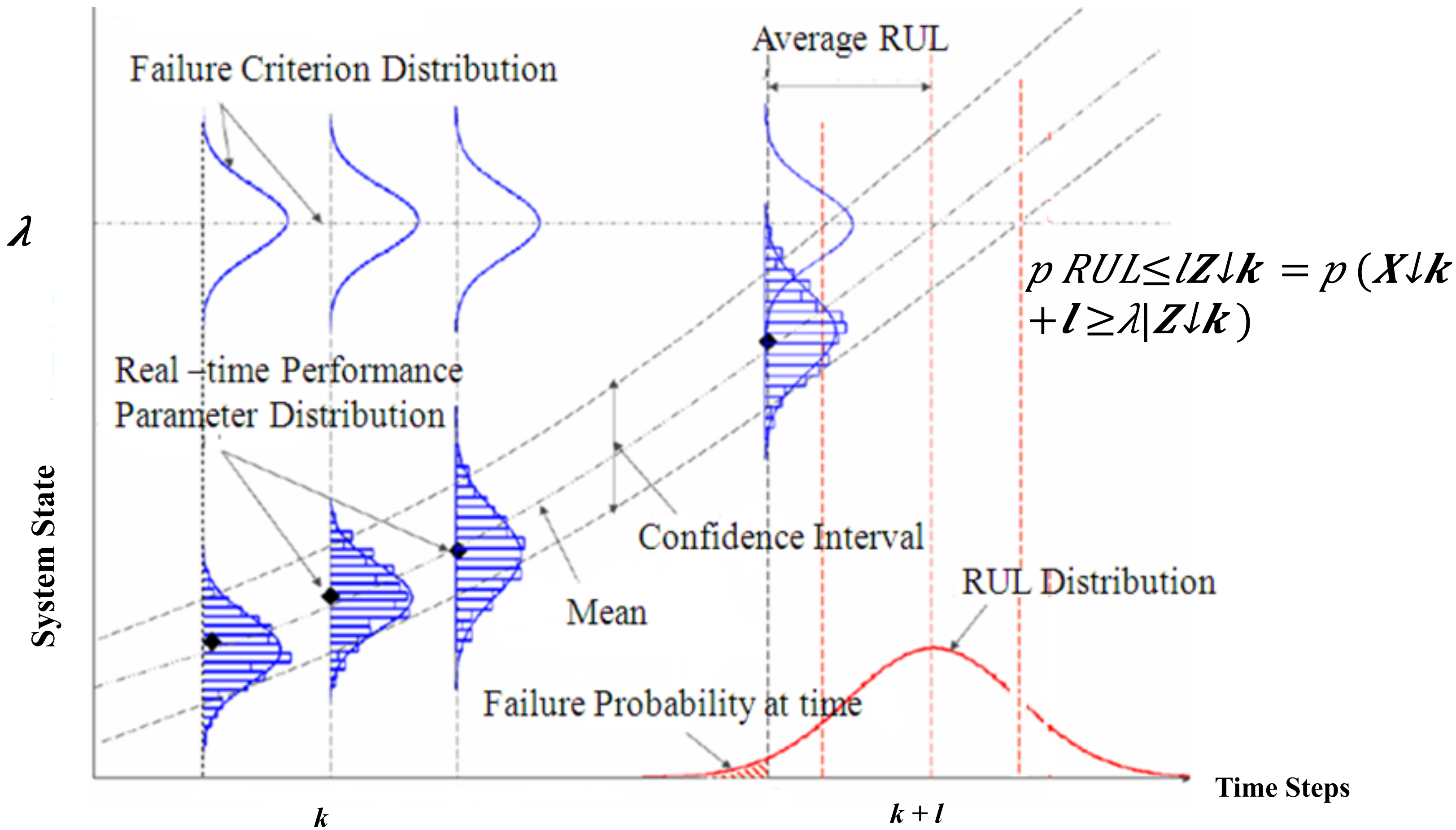
How about Kalman Filter?

- ✓ Linear system dynamic with Gaussian noise----Kalman Filter
- ✓ Non-Linear system with Gaussian noise----Unscented or Extended Kalman Filter
- ✓ Highly Non-linear system with either Gaussian or non-Gaussian noise----Particle Filtering

In practical applications, there are elements of non-Gaussianity and/or non linearity which make analytical computations impossible. Kalman Filter is linearization based technique, if the system nonlinearity grows, any of linearization (either local or statistical linearization) methods breaks down.

RUL Prediction

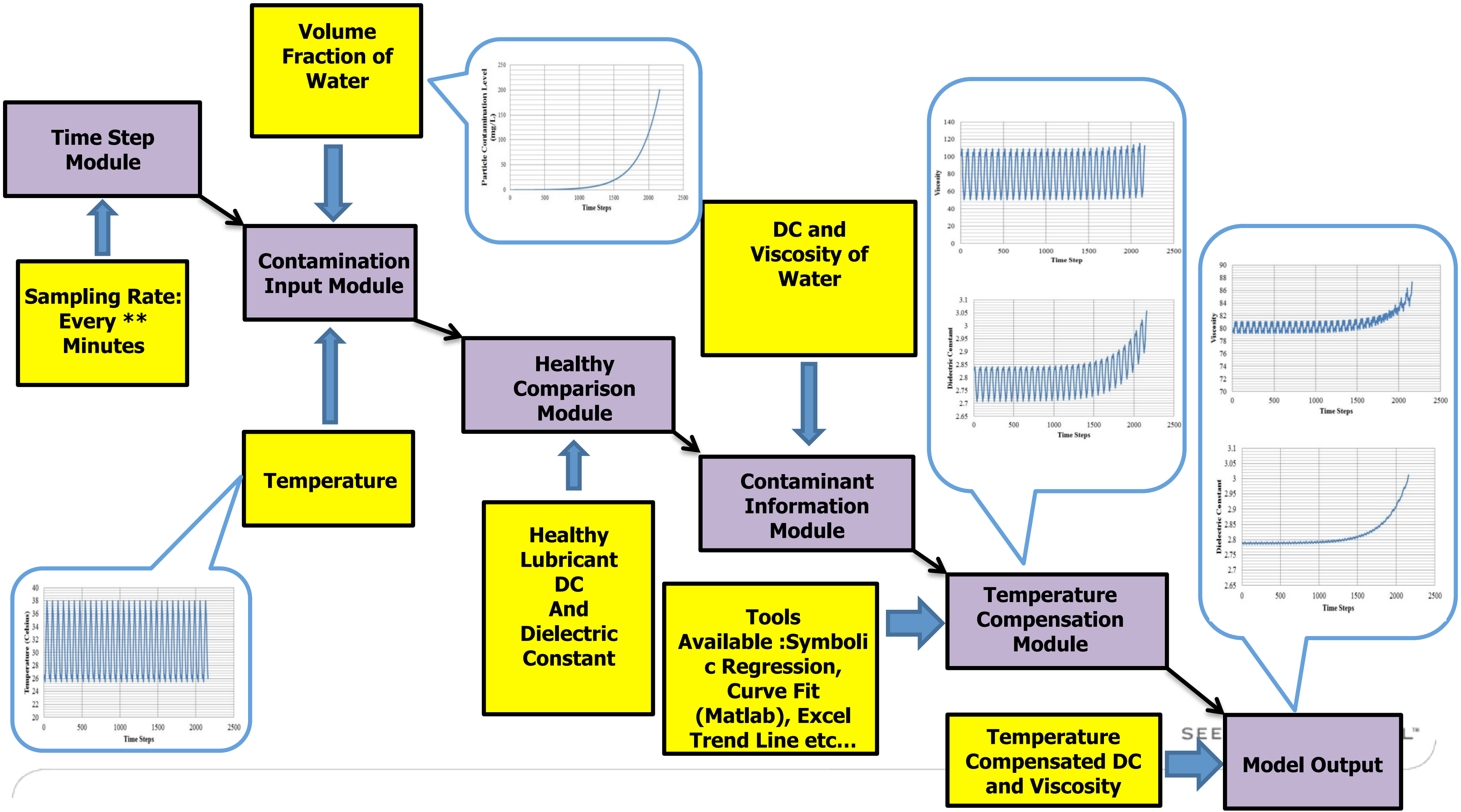
Case Study: RUL Prediction for Water Contamination Model



Particle Filtering and *l*-Step RUL Prediction Algorithm Demonstration

RUL Prediction Algorithm Development and Validation

Industrial Scenario Simulation Overview

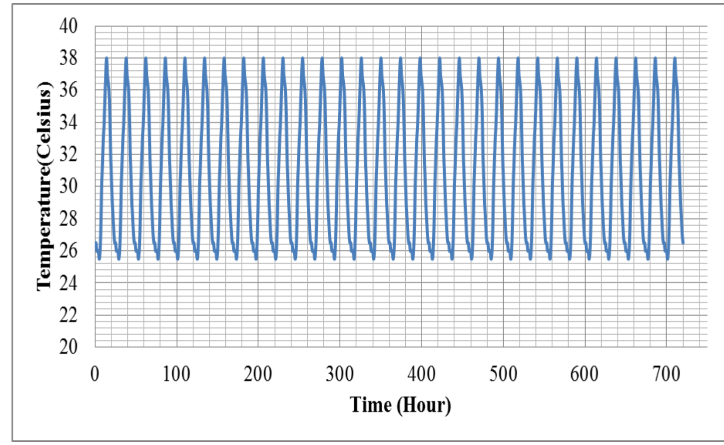


RUL Prediction

Case Study: RUL Prediction for Water Contamination Model

Simulation Condition

1) The deterioration state of the lubrication oil was defined as the water contamination level P.
2) The viscometer and dielectric constant sensor outputs were defined as observation data.
3) The lubrication oil deterioration process was simulated for 30 days (720 hours).
4) At the end of the simulation, the water contamination level P reached at 5%.
5) The sampling time interval was set to be every hour.
6) The failure threshold was set as 3% which was defined as the industry water contamination level limit.
7) At approximately the 525th hour, the water contamination level reached 3%.



Temperature Template

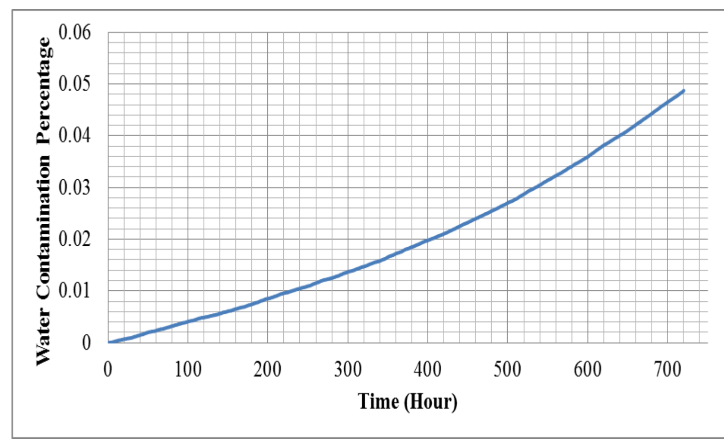
Particle Filtering Structure

State Transition Function

$$X_{k+1} = 1.0017 \times X_k + Random(0,1) \times 0.00007$$

Observation Function

$$Z_k = [\blacksquare(57470.5189 \times T_k^{-1.935 + 0.451 \times \ln T_k - 2.3591}) \times (1 - X_k) - 0.451 \times \ln T_k + 2.3591 @ 4.90028 \times T_k^{-0.121} \times (1 + 3 \times X_k \times$$



Water Contamination Propagation Template

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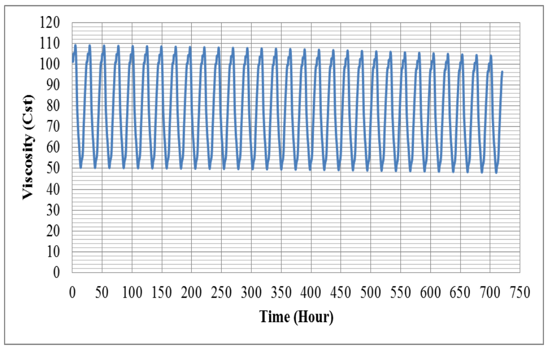
RUL Prediction

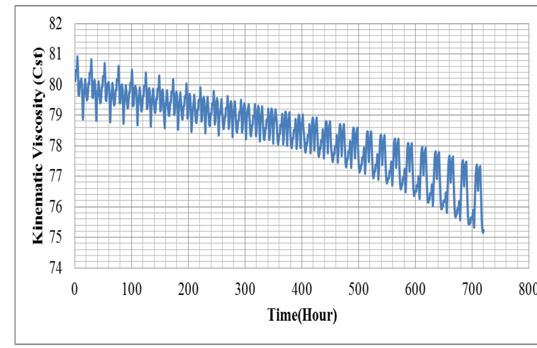
Case Study: RUL Prediction for Water Contamination Model

Water Contamination Model Validation



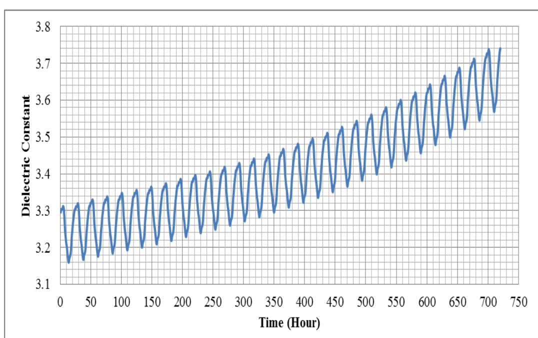
Observation data (kinematic viscosity) fluctuation before temperature compensation

In order to reduce observation data fluctuation and RUL prediction variation, a temperature compensation module was integrated into the physics models. With a reference to 30 degree Celsius, the observation data was adjusted according to viscosity or dielectric constant functions with respect to the temperature.



Observation data (kinematic viscosity) fluctuation after temperature compensation

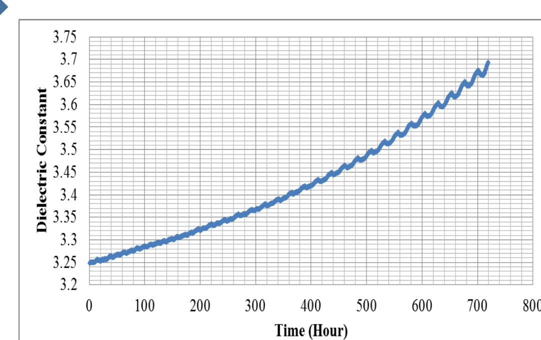
Temperature Compensation Module



Observation data (dielectric constant) fluctuation before temperature compensation

$$\varepsilon_{compensate,T} = \varepsilon_T + (\varepsilon_{30}' + \varepsilon_T') = \varepsilon_T + (\varepsilon_{30}' - (0.0001529 \times T^2 - 0.02241 \times T + 3.901));$$

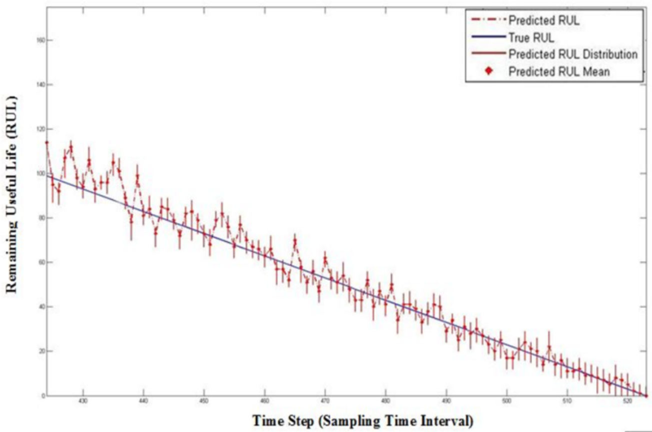
$$\varepsilon_T' = 0.0001529 \times T^2 - 0.02241 \times T + 3.901$$



Observation data (dielectric constant) fluctuation after temperature compensation

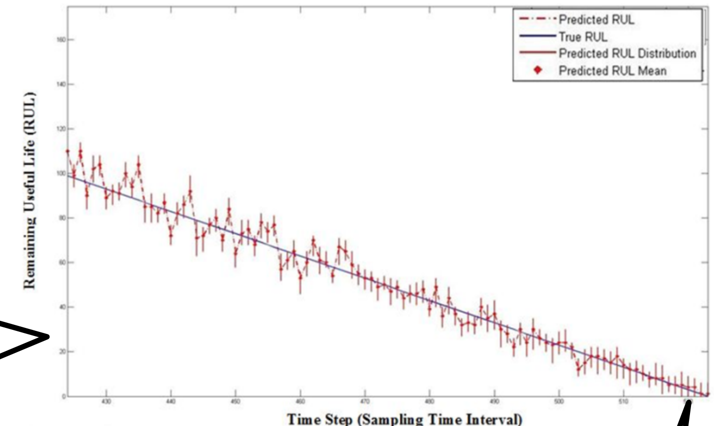
RUL Prediction

Case Study: RUL Prediction for Water Contamination Model



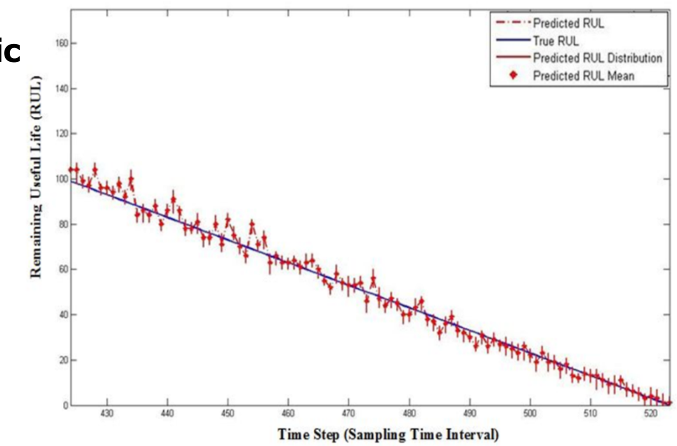
RUL prediction with only kinematic viscosity observation data (water contamination)

Y Axis: Time steps left until the end of life



RUL prediction with only dielectric constant observation data (water contamination)

X Axis: Time steps of the simulation model



RUL prediction with both kinematic viscosity and dielectric constant observation data (water contamination)

Conclusions

1. Comprehensive investigation and evaluation of current state of the art lubrication oil condition monitoring techniques and solutions have been conducted.
2. Based on the investigation and evaluation result, feasible performance parameters and commercially available sensors for online oil condition monitoring and RUL prediction have been selected. The chosen performance parameters in this case are kinematic viscosity and dielectric constant, respectively.
3. Lubrication oil degradation physics models based on the selected performance parameters for different basic degradation features have been developed and summarized.
4. The developed oil degradation physics models have been validated with commercially available sensors.
5. The developed physics models have been integrated into special designed particle filtering algorithm for lubrication oil remaining useful life prediction.
6. The effectiveness of the remaining useful life prediction algorithm with the developed physics model have been validated with simulation case study.

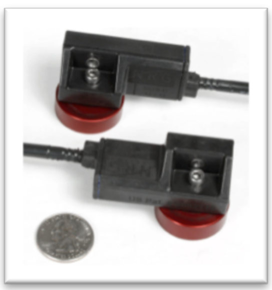
Conclusions

Implementation

TurbinePhD™

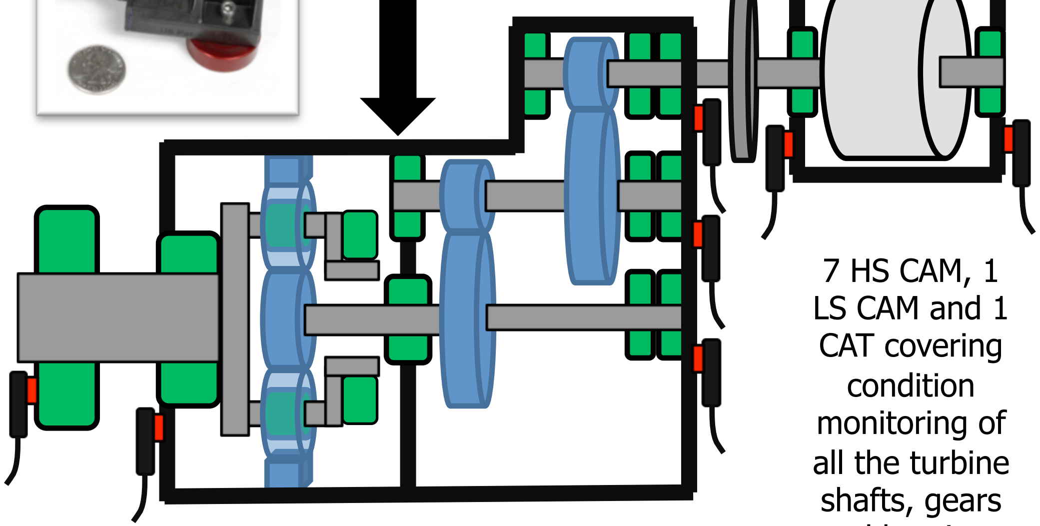
PREDICTIVE HEALTH MONITORING

Turbine Gearbox Oil Diagnostics and Prognostics Module



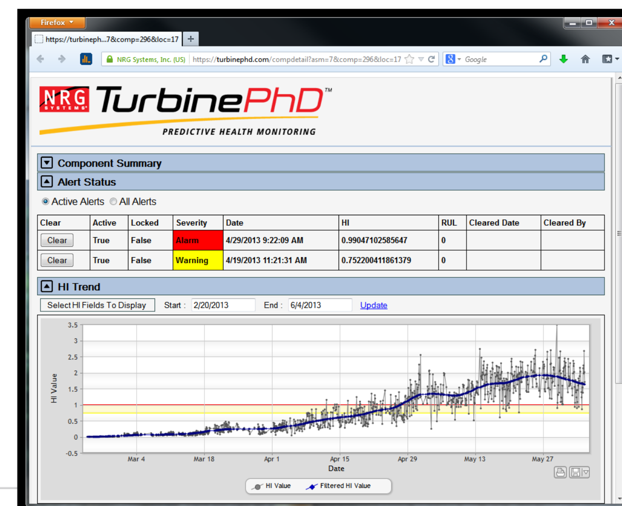
Seamless integration into current vibration based condition monitoring system

Single bus cable Local Data Concentrator (LDC)



7 HS CAM, 1 LS CAM and 1 CAT covering condition monitoring of all the turbine shafts, gears and bearings

Cloud Based Interface provides 24/7 continues monitoring and client access



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