An Automated Approach for Fusing Data Sources to Identify Optimal Prognostic Parameters

Jamie Coble

The University of Tennessee, Department of Nuclear Engineering, Knoxville, TN, 37909

jcoble1@utk.edu

1. PROBLEM STATEMENT

Individual-based prognostic methods use a measure of degradation to make estimates of remaining useful life (RUL). Degradation measures may be derived from sensed measurements, such as temperature or vibration level, or inferred measurements, such as model residuals or physics-based model predictions using other sensed measurements. Often, it is beneficial to combine several measures of degradation to develop a single parameter. Selection of an appropriate degradation parameter is key for making useful RUL estimates. Degradation parameter features such as trendability, monotonicity, and prognosability can be used to compare candidate prognostic parameters. Several methods for identifying possible prognostic parameters are available, including expert opinion using engineering judgment, visual inspection of sensed data and model residuals, Principal Component Analysis, and optimization methods. With a formalized set of metrics to characterize the goodness of each candidate parameter, traditional optimization methods can be used to automate the identification of prognostic parameters, such as gradient descent methods, genetic algorithms, and machine learning techniques.

Traditional reliability analysis uses failure time data to estimate a failure time distribution. As equipment components become more reliable, few failure times may be available, even with accelerated testing. Although failure time data becomes more sparse as equipment reliability rises, often other measures are available which may contain some information about equipment degradation. Lu and Meeker [1] developed the General Path Model (GPM) to assess equipment reliability using these degradation measures, or appropriate functions thereof. The GPM assumes that there is some underlying parametric model to describe component degradation. Although it was originally conceived as a method for estimating population reliability characteristics, such as a time to failure distribution, GPM has since been extended to individual prognostic applications [2]. Most commonly, the fitted model is extrapolated to some known failure threshold to estimate the RUL of a particular component. Because the prognostic estimate depends solely on the prognostic parameter, selection of an appropriate parameter is key for making useful RUL estimates. This work introduces a set of metrics for characterizing the suitability of a given prognostic parameter. Parameter features such as trendability, monotonicity, and prognosability can be used to compare candidate prognostic parameters to determine which is most useful for individual-based prognosis. Trendability indicates the degree to which the parameters of a population of systems have the same underlying shape. Monotonicity characterizes the underlying positive or negative trend of the parameter. Finally, prognosability gives a measure of the variance in the critical failure value of a population of systems. By formalizing the suitability of each candidate prognostic parameter, identification of an optimal parameter may be automated via any traditional optimization routine, such as gradient descent, genetic algorithms, particle swarm, etc.

2. ORIGINAL CONTRIBUTIONS

1. Development of a set of metrics to characterize the suitability of a population of parameters for application to GPM prognostic method.
2. Application of these metrics to traditional optimization methods to allow for an automatic identification of prognostic parameters from numerous data sources.
3. Input selection method based on candidate parameter constituents to alleviate the computational burden of the optimization routine.
4. Development of the MATLAB-based Process and Equipment Prognostics (PEP) toolbox to facilitate prognostic model development.

3. PRELIMINARY RESULTS

A set of eleven residuals from a monitoring system are considered candidate inputs to a prognostic parameter. For this example, the parameter is limited to a linear combination of the eleven inputs. Applying a genetic algorithm optimization with fitness function according to

$$fitness = monotonicity + prognosability + trendability$$

optimizes the coefficient for each of the eleven residuals. In general, the GA fitness function may not equally weight each of the three suitability metrics, depending on the needs of the specific system. In addition, it may consider other features of the parameter, including noise, complexity, concavity, etc. The GA optimization identified appropriate coefficients for the linear combination of the eleven variables; while a parameter identified via visual inspection involved several weeks of expert analysis, the GA optimization involved only a fraction of an actual manhour and approximately and hour of unsupervised computer runtime. While the time needed for the GA optimization to run will scale with the number of possible inputs and complexity of possible functions (i.e. non-linear combinations), it involves mainly computer runtime and is only a fraction of the time needed for parameter identification through expert opinion. Figure 1 gives a comparison of the weights for the parameter identified by visual inspection and the one selected by the GA, and Table 1 gives the resulting parameter suitability metrics. The optimal weights found through the GA are roughly equivalent to those determined though expert analysis. As such, the fitness of the GA-optimized parameter is equivalent to that of the parameter identified via visual inspection. This may be further improved by standard GA improvement techniques, such as coupling the result with a gradient descent optimization or running the GA several times to find the best result.

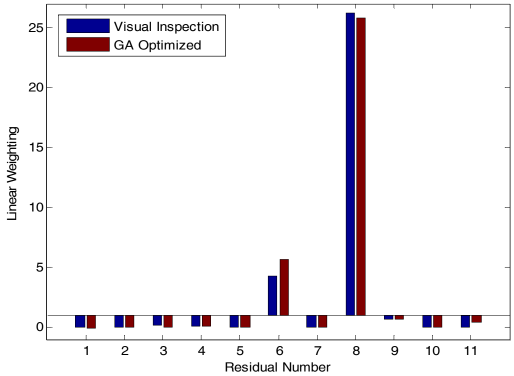

Figure 1: Comparison of Weights for VI and GA Parameters

Table 1: Parameter Suitability Metrics

	Monotonicity	Prognosability	Trendability	Fitness
VI Param	0.918	0.894	0.807	2.623
GA Param	0.933	0.894	0.814	2.652

4. ONGOING WORK

Several tasks remain in this research. Preliminary functional forms of the parameter suitability metrics have been identifed; however, these formulations are highly susceptible to noise in the prognostic parameters, which may not reduce the efficacy of the parameter. A sensitivity analysis of the metrics will be completed and methods to mitigate the effects of noise will be developed. Denoising the prognostic parameter before analysis and model fitting may improve model estimations and give more accurate parameter suitability characterization.

Systems with many candidate parameter inputs, which may include residuals, measured variables, fault alarm results, etc., may prove to be too computationally intensive to allow for optimization of prognostic parameters. To alleviate this burden, an input selection technique will be developed to pre-select inputs which are expected to be useful and remove inputs which will have no prognostic value. This will reduce computation time and also improve optimization performance.

Preliminary work has investigated the use of genetic algorithm optimization with the parameter suitability metrics. However, many other optimization techniques are available, including gradient descent, bellman optimization, particle swarm, etc. Additional optimization methods will be investigated and compared for ease of use, speed, and performance.

Work continues on the PEP toolbox, which will incorporate parameter suitability metrics and parameter optimization techniques to facilitate and, to some extent, automate prognostic model development.

5. REFERENCES

[1] Lu, C.J. and W.Q. Meeker, "Using Degradation Measures to Estimate a Time-to-Failure Distribution," *Technometrics*, Vol 35, No 2, May 1993, pp. 161-174.

[2] Upadhyaya, B.R., M. Naghedolfeizi, and B. Raychaudhuri, "Residual Life Estimation of Plant Components," *P/PM Technology*, June 1994, pp. 22-29.