Identifying Optimal Prognostic Parameters from Data: A Genetic Algorithms Approach

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ABSTRACT

The ultimate goal of most prognostic systems is accurate prediction of the remaining useful life of individual systems or components based on their use and performance. This class of prognostic algorithms is termed Effects-Based or Type III Prognostics. Traditional individual-based prognostics involve identifying an appropriate degradation measure to characterize the system's progression to failure. These degradation measures may be 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, called a prognostic parameter. A parametric model is fit to this parameter and then extrapolated to some predefined critical failure threshold to estimate the system's remaining useful life. Commonly, identification of a prognostic parameter is accomplished through visual inspection of the available information and engineering judgment. However, a set of metrics to characterize the suitability of prognostic parameters has been proposed. These metrics include monotonicity, prognosability, and trendability. Monotonicity characterizes a parameter's general increasing or decreasing nature. Prognosability measures the spread of the parameter's failure value for a population of systems. Finally, trendability indicates whether the parameters for a population of systems have the same underlying trend, and hence can be described by the same parametric function. This research formalizes these metrics in a way that is robust to the noise found in real world systems. The metrics are used in conjunction with a Genetic Algorithms optimization routine to identify an optimal prognostic parameter for the Prognostics and Health Management (PHM) Challenge data from the 2008 PHM conference. *

1. INTRODUCTION

Prognostics is one component of a full health monitoring system for a system or component of interest. Health monitoring systems commonly use several modules which monitor a system's performance, detect changes, identify the root cause of the change, and then predict the remaining useful life (RUL) or probability of failure (POF). Prognostics completes the final step of this system; estimation of the RUL of a system and associated uncertainty bounds. Accurate RUL estimation can play an important role in increasing safety, reducing downtime, ensuring misson completion, and improving the corporate bottom line.

For most safety-critical components, the ultimate prognostic goals is accurate RUL estimation based on the current and projected future condition of the specific component. (Lu and Meeker, 1993) developed the General Path Model (GPM) to assess equipment reliability using degradation measures of the specific component or system, or appropriate functions thereof. The GPM assumes that there is some underlying parametric model to describe component degradation. The model may be derived from physical models or from available historical degradation data. Typically, this model accounts for both population (fixed) effects and individual (random) effects.

Although GPM was originally conceived as a method for estimating population reliability characteristics, such as a time to failure distribution, it has since been extended to individual prognostic applications (Upadhyaya et al, 1994). In prognostic applications, the fitted model is extrapolated to some known failure threshold to estimate the RUL of a particular component or system. The data used to fit this model is called a prognostic parameter. Prognostic parameters may be 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 parameter is key for making useful RUL estimates. 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 visual inspection of sensed data and model residuals, Principal Component Analysis, and optimization methods. With a formalized set of metrics to characterize the suitability of each candidate parameter, traditional optimization methods, such as gradient descent methods, genetic algorithms, and machine learning techniques, can be used to automate the identification of prognostic parameters.

This paper presents the results of research in automating prognostic parameter identification. The following section presents the methodologies used, including the GPM prognostic model and Genetic Algorithms method of optimization. Then, the proposed methodology is applied to the Prognostics and Health Management (PHM) Challenge problem posed at the 2008 PHM Conference. Finally, some conclusions are made about the proposed parameter identification system and areas of future work are outlined.

2. METHODOLOGY

Prognostics is one component in a larger health monitoring system which also includes system monitoring, fault detection, and diagnostic modules. Figure 1 gives a diagram of a typical health monitoring system. Data collected from a system of interest is monitored for deviations from normal behavior. Monitoring can be accomplished through a variety of methods, including first principle models, empirical models, and statistical analysis (Hines et al, 2006). The monitoring module can be considered an error correction routine; the model gives its best estimate of the value of the system variables assuming that the system is operating in a nominal way. These estimates are compared to the data collected from the system to generate a series of residuals. Residuals characterize system deviations from normal behavior, and can be used to determine if the system is operating in an abnormal state. A common test for anomalous behavior is the Sequential Probability Ratio Test (SPRT) (Wald, 1945). This statistical test considers a sequence of residuals and determines if they are more likely from the distribution that represents normal behavior or a faulted distribution, which may have a shifted mean value or altered standard deviation from the nominal distribution. If a fault is detected, it is often important to identify the type of fault; systems will likely degrade in different ways depending on the type of fault and so different prognostic models should be used for each fault mode. Expert systems, such as fuzzy rule-based systems, are common fault diagnosers. Finally, a prognostic model is employed to estimate the RUL of the system. This model may include information from the original data, the monitoring system residuals, and the results of the fault detection and isolation routines. Estimation of the RUL is the focus of the current work.

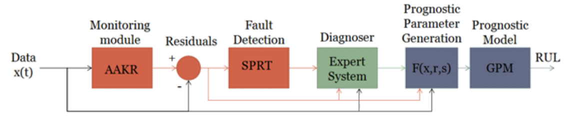


Figure 1: Modules in a Full Health Management System

The problem of accurately and precisely predicting remaining useful life is very complicated; as such many methodologies and algorithms have been proposed to address this problem. These methods can be classified based on the type of information used to make predictions (Hines et al, 2007). This scheme leads to three classes: traditional reliability-based, stressor-based, and condition-based. Type I, or reliability-based, prognostics is traditional time to failure analysis. Examples include Weibull analysis, exponential and normal distribution analysis. This group of methods does not consider operating conditions or environment when making RUL estimates. Typically, systems operating in harsher conditions will fail more quickly while those in milder environments, more slowly. Type II, or stressor-based, prognostics incorporate operational and environmental condition data in RUL estimation. Type II methods can be used if operating conditions, such as load, input current and voltage, ambient temperature, vibration, etc., are measurable and correlated to system degradation. Algorithms in this class include specific formulations of the Markov Chain model and shock model. Although more specific than Type I models, Type II models are deficient because they neglect unit-to-unit variance. The final class of algorithms, Type III or condition-based prognostics, characterizes the lifetime of a specific unit or system operating in its specific environment. Extrapolation of a general path model (GPM) to some pre-defined failure threshold is the most common Type III method. The GPM is employed in the current research and is described in detail in the following section.

2.1 The General Path Model

The General Path Model (GPM), also called degradation modeling, was first proposed by (Lu and Meeker, 1993) to move reliability analysis methods from failure-time analysis to failure-process analysis. Traditional methods of reliability estimation use failure times recorded during normal use or accelerated testing to estimate a time of failure (TOF) distribution for a population of identical components. In contrast, GPM uses degradation measures to estimate the TOF distribution. The use of historical degradation measures allows for the direct inclusion of censored data, which gives additional information on unit-wise variations in a population.

GPM analysis begins with some assumption of an underlying functional form of the degradation path for a specific fault mode. The degradation of the i^{th} unit at time t_j is given by:

$$y_{ij} = \eta(t_j, \phi, \theta_i) + \varepsilon_{ij} \qquad (1)$$

where φ is a vector of fixed (population) effects, θ_i is a vector of random (individual) effects for the i^{th} component, and $\varepsilon_{ij} \sim N(0,\sigma^2_\varepsilon)$ is the standard measurement error term. Application of the GPM methodology involves several assumptions. First, the degradation data must be describable by a function, η; this function may be derived from physics-of-failure models or from the degradation data itself. In order to fit this model, the second assumption is that historical degradation data from a population of identical components or systems is available. This data should be collected under similar use (or accelerated test) conditions and should reasonably span the range of individual variations between components. Because GPM uses degradation measures instead of failure times, it is not necessary that all historical units are run to failure; censored data contains information useful to GPM forecasting. The final assumption of the GPM model is that there exists some defined critical level of degradation, D, beyond which a component no longer meets its design specifications, i.e. the component has failed. Therefore, some components should be run to failure in order to quantify this degradation level. Alternatively, engineering judgment may be used to identify this threshold if the nature of the degradation parameter is explicitly known.

The GPM reliability methodology has a natural extension to estimation of remaining useful life of an individual component or system; the degradation path model, y_i, can be extrapolated to the failure threshold, D, to estimate the component's time of failure. This type of degradation extrapolation was first proposed by (Upadhyaya, et al, 1994). In that work, the authors used both neural networks and nonlinear regression models to predict the RUL of a small induction motor. The prognostic methodology used for the current research is described below.

First, exemplar degradation paths are used to fit the assumed model. These stage-1 parameter estimates are used to evaluate the random-effects distributions, to determine the mean population random effects, the mean time to failure (MTTF) and their associated standard deviations, and to estimate the noise variance in the degradation paths. The MTTF distribution can be used to estimate the time of failure for any component which has not yet been degraded. As data is collected during use, the degradation model can be fit for the individual component. This component-specific model can be used to project a time of failure for the component.

The methodology described considers only the data collected on the current unit to fit the degradation model. However, prior information is available from the historic degradation paths used for initial model fitting, including the mean degradation path and associated distributions. This data can provide valuable knowledge for fitting the degradation model of an individual component, particularly when only a few data points have been collected or the collected data suffers from excessive noise. A basic methodology to include prior knowledge in linear regression models via dynamic Bayesian updating has been investigated and is briefly described below. The interested reader is referred to (Gelman et al, 2004; Lindley and Smith, 1972; Robinson and Crowder, 2000) for a more thorough discussion.

A linear regression model is given by:

$$Y = bX \tag{2}$$

The model parameters are estimated as:

$$b = \left(X^T \Sigma_y^{-1} X\right)^{-1} X^T \Sigma_y^{-1} Y \tag{3}$$

where Σ_y is the variance-covariance noise matrix for the response observations. It is important to note that the linear regression model is not necessarily a linear model. The data matrix X can be populated with any function of degradation measures, including higher order terms, interaction terms, and functions such as $sin(x)$ or e^x. If prior information is available for a specific model parameter, i.e. $\beta_j \sim N(\beta_{jo}, \sigma^2_\beta)$, then the matrix X should be appended with an additional row with value one at the j^{th} position and zero elsewhere, and the Y matrix should be appended with the a priori value of the j^{th} parameter.

$$\begin{aligned} X^* &= \left[X; \quad 0 \quad \ldots \quad 0 \quad 1 \quad 0 \quad \ldots \quad 0\right] \\ Y^* &= \left[Y; \quad \beta_j\right] \end{aligned} \tag{4}$$

Finally, the variance-covariance matrix is augmented with a final row and column of zeros, with the variance of the a priori information in the diagonal element.

$$\Sigma_y^* = \begin{bmatrix} \sigma_y^2 & 0 & \ldots & 0 \\ 0 & \ddots & 0 & 0 \\ 0 & \ldots & \sigma_y^2 & 0 \\ 0 & 0 & 0 & \sigma_{\beta_j}^2 \end{bmatrix} \tag{5}$$

If knowledge is available about multiple regression parameters, the matrices should be appended multiple times with one additional row for each parameter.

It is convenient to assume that the noise in the degradation measurements is constant and uncorrelated. Some a priori knowledge of the noise variance is available from the exemplar degradation paths. If this assumption is not valid for a particular problem, then other methods of estimating the noise variance must be used. The assumption of uncorrelated noise allows the variance-covariance matrix to be a diagonal matrix consisting of noise variance estimates and a priori knowledge variance estimates. If this assumption is not valid, including covariance terms is trivial; again these terms can be estimated from historical degradation paths.

After a priori knowledge is used to obtain a posterior estimate of degradation parameters, this estimate becomes the new prior distribution for the next estimation of degradation parameters. The variance of this new knowledge is estimated as:

$$\frac{1}{\sigma^2_{post,\beta_i}} = \frac{n}{\sigma_y^2} + \frac{1}{\sigma^2_{prior,\beta_i}} \tag{6}$$

where n is the number of observations used to fit the current model.

Several limitations and areas of future work of the GPM have been identified by (Meekeret al, 1998). Some of these areas have been addressed in work by other authors. First, Meeker, et. al. cite the need for more accurate physics of failure models. While such models are helpful for understanding degradation models, they may not be necessary for RUL estimation. In fact, if exemplar data sets cover the range of likely degradation paths, it is adequate to fit a function which does not explain failure modes but accurately models the underlying relationships. With this idea, neural networks have been applied to GPM reliability analysis (Chinnam, 1999; Girish et al, 2003).

In addition, the GPM was originally developed for reliability analysis of only one fault mode. In practical applications, the system of interest may consist of several components each with different fault modes, or of one component with several possible, even simultaneous fault modes. These multiple degradation paths may be uncorrelated, in which case extension of the GPM is trivial: reliability of a component for all degradation modes is simply the product of the individual reliabilities, and RUL can be considered some function of the RULs for each fault mode, such as the minimum. If, however, the degradation measures are correlated, extension of the GPM is more complicated. For example, in the case of tire monitoring, several degradation measures may contain information about tire reliability, including wall thickness, tire pressure, and tire temperature. However, it is easy to see that these measures may be correlated; a higher temperature would cause a higher pressure, etc. The case of multiple, competing degradation modes is beyond the scope of the current work, but is a key topic in prognostic methods of this kind. A discussion of the problem can be found in (Wang and Coit, 2004).

2.2 Choosing a Prognostic Parameter

Identification of an appropriate prognostic parameter is key for applying a GPM prognostic model to a system. An ideal prognostic parameter has three key qualities: monotonicity, prognosability, and trendability (Coble and Hines, 2009). Monotonicity characterizes the underlying positive or negative trend of the parameter. This is an important feature of a prognostic parameter because it is generally assumed that systems do not undergo self healing, which would be indicated by a non-monotonic parameter. It should be noted that this assumption is not valid for some components such as batteries, which may experience some degree of self repair during short periods of nonuse. However, for mechanical components or systems with a combination of electronic and mechanical components, this assumption holds. The importance of the monotonicity measure should be determined by the operator for a specific system. Prognosability gives a measure of the variance in the critical failure value of a population of systems. A wide spread in critical failure values can make it difficult to accurately extrapolate a prognostic parameter to failure. Finally, trendability indicates the degree to which the parameters of a population of systems have the same underlying shape and can be described by the same functional form. These three intuitive metrics can be formalized to give a quantitative measure of prognostic parameter suitableness. Ideally, these metrics would each range from zero to one, one indicating a very high score on that metric and zero indicating that the parameter is not suitable according to the particular metric.

Monotonicity is a straightforward measure given by:

$$Monotonicity = \left| \frac{no.of\ {}^{d}\!/\!_{dx} > 0}{n-1} - \frac{no.of\ {}^{d}\!/\!_{dx} < 0}{n-1} \right| \quad (7)$$

where n is the number of observations in a particular history. The monotonicity of a population of parameters is given by the average absolute difference of the fraction of positive and negative derivatives for each path. When using data collected or inferred from actual systems, it is important to adequately smooth the data to give more accurate estimates of the derivatives.

Prognosability is also easily calculated as the variance of the final failure values for each path divided by the mean range of the path. This is exponentially weighted to give the desired zero to one scale:

$$Prognosability = \exp\left(-std(p_{fail}) / mean\left|p_{start} - p_{fail}\right|\right) \quad (8)$$

where p is the value of the prognostic parameter.

Characterizing the trendability of a population of parameters is slightly more complicated than the other two. A candidate parameter is trendable if each parameter in the population can be modeled by the same underlying functional form. This can be measured to some degree by comparing the fraction of positive first and second derivatives in each parameter. Again, when using real-world data, these parameters should be smoothed to give a more accurate estimate of the derivatives. The current working formalization of trendability is given by:

$$t_i = \frac{no.of\ {}^{d}\!/\!_{dx} > 0}{n-1} + \frac{no.of\ {}^{d^2}\!/\!_{dx^2} > 0}{n-2}$$

$$Trendability = 1 - std(t_i) \quad (9)$$

where n is the number of observations in the i^{th} parameter. This metric is particularly sensitive to noise. Improvements to the measure are the subject of ongoing research.

A population of good parameters is shown in Figure 2. This group of parameters monotonically increases, has closely clustered failure values, and appears to have the same basic shape. Figure 3 shows the same population of parameters with measurement noise artificially added to the curves. Again, this is a very useful parameter, but the addition of noise will make it more difficult to fit parametrically. This is reflected in the parameter metrics. Finally, Figure 4 gives an example of a poor prognostic parameter. The parameters for the population do not share the same basic shape, nor does failure occur at the same value. The monotonicity, prognosability, and trendability metrics for the three sets of parameters are given in Table 1.

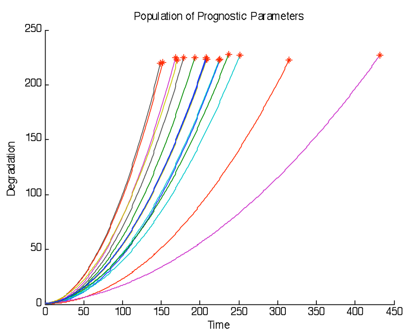


Figure 2: An Example of a Good Prognostic Parameter

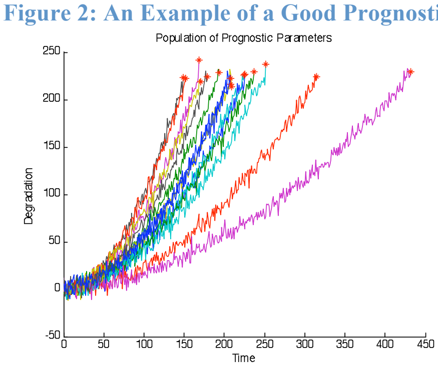


Figure 3: An Example of a Noisy Prognostic Parameter

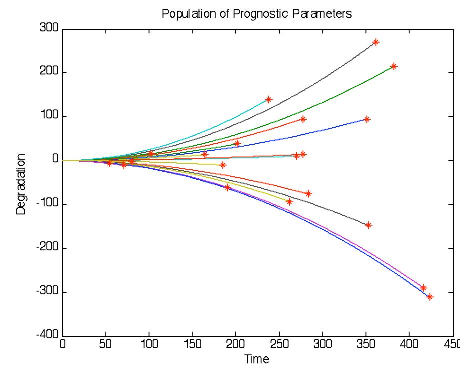


Figure 4: An Example of a Poor Prognostic Parameter

Table 1: Prognostic Parameter Suitability Metrics

	Monotonicity	Prognosability	Trendability
Good Parameter (Fig 1)	1.00	0.976	1.00
Noisy Parameter (Fig 2)	1.00	0.789	0.935
Poor Parameter (Fig 3)	0.500	0.264	0.026

Several methods are available for identifying candidate prognostic parameters, including visual inspection of sensed data and model residuals, Principal Component Analysis, and traditional optimization methods. Traditionally, parameter identification is done through visual inspection and engineering judgment. While visual inspection can lead to the identification of useful prognostic parameters, it can be tedious and time consuming when parameters are needed for several components or fault modes, and the optimal parameter may be overlooked in favor of a suitable one. Automated methods for identifying prognostic parameters are possible with a formalized set of metrics to characterize their suitability. By defining a fitness function as a weighted sum of the three metrics:

$$fitness = a * monotonicity + b * prognosability + c * trendability \qquad (10)$$

a set of prognostic parameters can be compared to determine the most suitable one. Here, the constants *a, b,* and *c* control how important each metric is in the optimization. In addition to optimizing simply for the parameter metrics, the prognostic parameter can also be optimized for other features perhaps not directly related to parameter performance. For instance, in order to reduce the uncertainty in the RUL prediction, it is beneficial for the first and second derivatives to have the same sign, i.e. increasing functions are convex and decreasing functions are concave. This can be included in the fitness function by simply adding a large penalty for mismatch of first and second derivatives. Other such features may also be included as they apply to the desired parameter optimization. These constants can each be identically one to give equal weight to each parameter feature, or they may give unequal weight to more important features depending on the specific application. This fitness function is used with optimization techniques such as gradient descent, genetic algorithms, and genetic programming to identify useful prognostic parameters.

2.3 Genetic Algorithms

Classical optimization attempts to minimize the cost function by starting at an initial set of parameter values and utilizing function and derivative information to hone in on a minimum value. This type of optimization can quickly breakdown if the initial values are close to a local minimum; classical optimization will assume the first minimum it finds is the global minimum which is not necessarily true. Genetic algorithm (GA) optimization works differently by testing a random population of initial parameter values and mimicking the processes of evolution to optimize these values, as outlined in Figure 5. Because of the pseudo-random nature of the parameter populations evaluated, GA optimization is sometimes able to ignore local minima in search of a global minimum. The specifics of GA optimization are not vital to this paper; a full discussion of continuous genetic algorithms is available in (Haupt and Haupt, 2004)

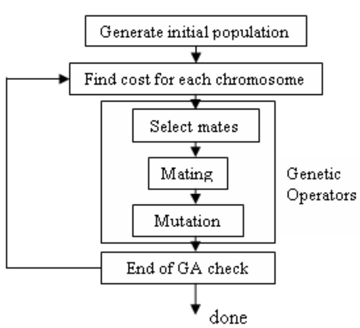


Figure 5: Flowchart of Genetic Algorithm Optimization

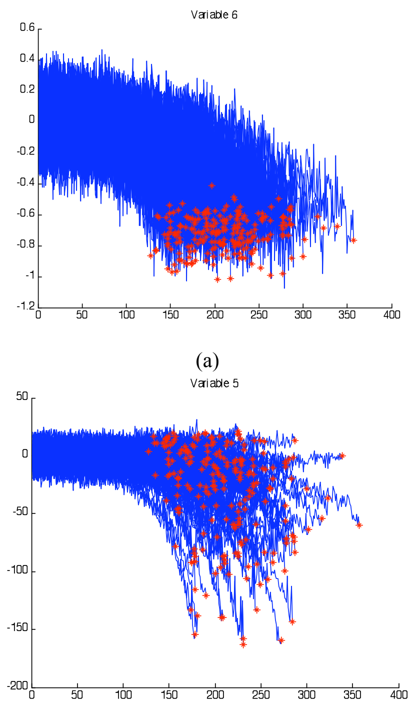
3. APPLICATION TO DATA

This section presents the results of applying the described prognostic parameter identification methodology to the data set given in the 2008 PHM Challenge Problem.

3.1 PHM Challenge Data Description

The PHM Challenge data set consists of 218 cases of multivariate data that track from nominal operation through fault onset to system failure. Because the nature of the PHM challenge was to develop a prognostic model without any specific knowledge of the system of interest, the exact nature of the data simulation is not described here. The interested reader is referred to (Saxena et al, 2008). The data has three operational variables and 21 sensor measurements. Initial data analysis resulted in the identification of six distinct operational settings and 10 sensed variables that seemed to change with cycle time; therefore, the set used in this section has been reduced to 11 variables: 5 (the operating condition indicator), 7, 8, 9, 14, 16, 19, 20, 22, 25, and 26. For this example application, the eleven variables are monitored with an auto associative kernel regression (AAKR) model. The residuals between the measured values and the AAKR "corrected" values are candidates for inclusion in the prognostic parameter. Two of these residuals are shown below in Figure 6. The residual shown at the top is expected to be useful for prognostic predictions, while the residual shown at the bottom is not expected to be useful because the population of residuals do not all have similar shapes or equal failure values. These type of residuals can grouped into several groups of similar residuals; this may be indicative of different failure modes, but this idea was not pursued for this work. For this simple application, only linear combinations of the residuals are considered for possible prognostic parameters. However, it is a straightforward extension of the method to include other features, such as the measured data or fault detection results, or to allow for higher order terms such as nonlinear combinations of several inputs, exponential terms, etc.

Competing prognostic parameters are identified from the monitoring system residuals, one identified through visual inspection and one identified using genetic algorithms. Both of these parameters are used to develop a basic prognostic model and make RUL estimations for an example case. The following sections present the results of prognostic parameter identification and RUL estimation.



(b)

Figure 6: Residuals which are expected to be (a) useful and (b) un-useful for prognostics

3.2 Results

Two competing prognostic parameters are identified. The first parameter is based on visual inspection and expert analysis. Another parameter is identified using the suitability metrics described coupled with a GA routine. The resulting prognostic parameters and results of RUL estimation using them are given below. A GPM model with dynamic Bayesian updating is developed using each candidate parameter. The models are tested on a set of validation data and the mean absolute percent error is given as a measure of performance.

Visual Inspection Visual inspection of the residuals suggests that an appropriate parameter might be a weighted average of residuals 2, 3, 4, 6, 8, and 9. For this work, the six residuals are simply summed to give one prognostic parameter. The resulting parameter is shown in Figure 7. Using a linear combination of different useful features in this way is sometimes referred to as parameter bagging and is a common variance reduction technique. Table 2 gives the parameter suitability metrics for each of the residuals and the final prognostic parameter. As the table shows, each of the chosen model residuals have total suitability greater than 2.0. In addition, the final parameter that is used for prognostics has higher suitability than any one of the constituent residuals. Identification of this parameter involved several weeks of expert analysis of the available data.

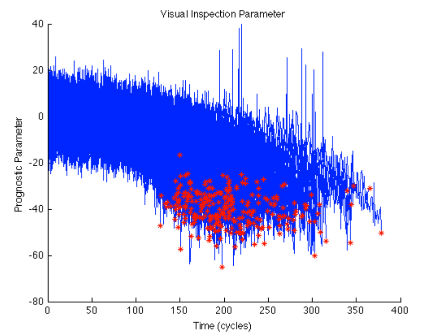


Figure 7: Prognostic Parameter Identified by Visual Inspection

Table 2: Prognostic Parameter Suitability Metrics

Residual #	Monotonicity	Prognosability	Trendability	Total
1	0.43	0.38	0.74	1.55
2	0.63	0.66	0.77	2.06
3	0.61	0.70	0.75	2.07
4	0.76	0.78	0.77	2.31
5	0.70	0.33	0.69	1.72
6	0.84	0.84	0.78	2.46
7	0.71	0.30	0.61	1.61
8	0.74	0.63	0.75	2.13
9	0.70	0.73	0.77	2.20
10	0.59	0.28	0.75	1.62
11	0.57	0.29	0.76	1.61
Final Parameter	0.86	0.89	0.82	2.57

This prognostic parameter was used to develop a GPM prognostic model with dynamic Bayesian updating, as described previously. The results of this model are given in Figure 8. As the figure shows, most of the estimations are close to the actual values, but several large outliers are present which reduce the performance of the model significantly. When considering all 259 test cases used, the mean absolute percent error is nearly 100% because of these outliers; however, most estimates are correct to within a few percent.

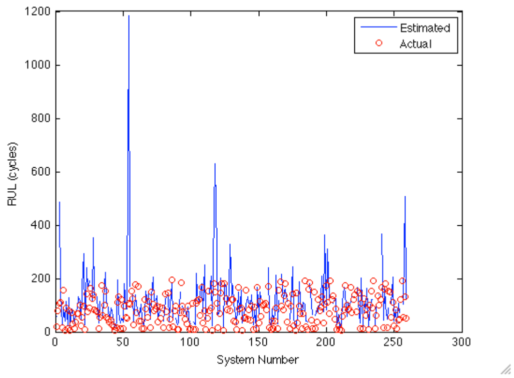


Figure 8: RUL Estimation with the Visual Inspection Parameter

GA Optimized Parameter Another parameter was identified through genetic algorithm optimization. The GA was used to optimize the coefficients in a weighted sum of the eleven parameters. A genetic algorithm optimization was applied to the following fitness function, which gives equal weight to each of the three parameter suitability measures:

$$fitness = monotonicity + prognosability + trendability \quad (11)$$

The GA optimization identified appropriate coefficients for the linear combination of the eleven variables. While the visual inspection parameter involved several weeks of expert analysis, the GA optimizations involved only a fraction of an actual manhour and approximately an hour of unsupervised computer runtime. While the time needed for the GA optimization to run will scale with the number of possible inputs, it involves mainly computer runtime and is only a fraction of the time needed for parameter identification through expert opinion. The parameter identified by the GA optimization is given in Figure 9.

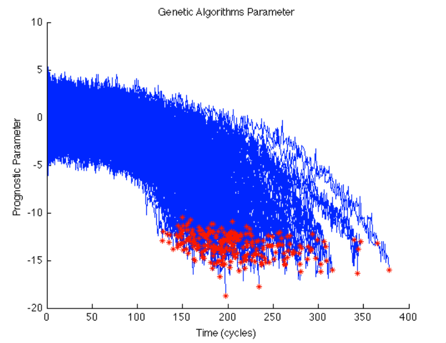


Figure 9: GA-optimized Prognostic Parameter

The parameter suitability metrics for each parameter are given in Table 3. The fitness of the GA-optimized parameter is slightly better than 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.

Table 3: Parameter Suitability Metrics

	Monotonicity	Prognosability	Trendability
VI Param	0.859	0.894	0.817
GA Param	0.933	0.909	0.805

The GA-optimized prognostic parameter was also used to develop GPM prognostic models. Figure 10 gives the results for the prognostic model developed with the GA-optimized parameter. The RUL estimates resulting from the model built with the GA parameter are better than those from the first model. Further research is needed to improve the fitness function for the parameter identification method and application to RUL estimation; this is left to future work.

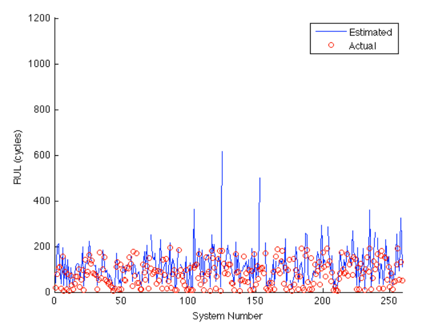


Figure 10: RUL Estimates for First GA-optimized Parameter

The sample application presented here benefited from the extensive expert analysis needed to identify a parameter through visual inspection, in that a subset of possible parameter inputs had already been identified. In applications with a larger domain of inputs, which could include the actual signals, the monitoring system predictions, information on usage, environment, and load, and fault alarm and diagnostic results, as well as higher order terms of any of these inputs, an input selection technique may be applied to identify possibly useful parameter inputs prior to the GA optimization. This will greatly reduce GA runtime and help ensure that a near optimal parameter is identified.

4. CONCLUSIONS

This research presented a set of suitability metrics and a methodology for identifying prognostic parameters from data. Prognostic parameters are used in individual-based prognostic models to characterize the lifetime of a specific component in its specific environment. Identification of appropriate parameters is vital to accurate and precise remaining useful life (RUL) estimation. Three parameter suitability metrics were proposed: monotonicity, prognosability, and trendability. Monotonicity characterizes a parameter's general increasing or decreasing nature. Prognosability measures the spread of the parameter's failure value for a population of systems. Finally, trendability indicates whether the parameters for a population of systems have the same underlying trend, and hence can be described by the same parametric function. An example application was given to illustrate the identification of prognostic parameters from monitoring system residuals. First, a parameter was identified through visual inspection and expert analysis. An additional parameter was identified using genetic algorithm optimization. The GA optimized parameter had slightly higher parameter suitability metrics and resulted in more accurate RUL estimates. For this example, the major benefit of using the optimization routine was in the reduced time needed to identify an appropriate parameter. More complicated systems, i.e. systems with more monitored variables and candidate parameter constituents, may also benefit from increased prognostic model performance as visual inspection will likely result in a significantly less optimal parameter.

5. FUTURE WORK

Several areas of greater study remain to complete this work. Most importantly, the robustness of the suitability metrics to noisy data needs to be studied. There is a particular concern about the robustness of the trendability metric; formulation of a metric which is immune to the effects of noise but still captures the dynamics of the data is ongoing. Addition of other features in the fitness function might help identify simpler parameters. Other desirable features of the prognostic parameter can be included to encourage those features in the final parameter selection, such as correlations between the starting degradation and the failure time, estimates of the noise in the parameters, and desirable concavity features. In addition, the multi-objective fitness function equally weighted each of the suitability metrics; however, it may be more useful to weight the metrics differently. A study of the resulting prognostic model performance will reveal the importance of this weighting. Finally, development of an input selection technique to couple with the GA optimization will greatly improve optimization runtime by reducing the number of possible combinations which may be considered and will help extend the applicability of the method to systems with many sensed variables.

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