CHEMICAL ENGINEERING TRANSACTIONS
VOL. 33, 2013
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at: www.aidic.it/cet
Guest Editors: Enrico Zio, Piero Baraldi

ISBN 978-88-95608-24-2; **ISSN** 1974-9791
DOI: 10.3303/CET1333151

Lifecycle Prognostic Algorithm Development and Application to Test Beds

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On-line monitoring of nuclear plant system degradation is quickly becoming a crucial consideration as the licenses of many nuclear power plants are being extended. Accurate measurement of the current degradation of system components and structures is important for correct estimates of their remaining useful life (RUL). The propagation of the uncertainty involved in both the measurements and model construction of these system components is vital for finding the uncertainty of the overall system RUL calculation.

Prognostic methods should seamlessly operate from beginning of component life (BOL) to end of component life (EOL). We term this "Lifecycle Prognostics." When a component is put into use, the only information available may be past failure times, and the predicted failure distribution can be estimated with reliability methods such as Weibull Analysis (Type I). As the component operates, it begins to consume its available life. This life consumption may be a function of system stresses, and the failure distribution should be updated (Type II). When degradation becomes apparent, this information can be used again to improve the failure distribution estimate (Type III). Current research typically focuses on developing methods for the three types of prognostics. This research focused on developing a framework using Bayesian methods to transition between prognostic model types and update failure distribution estimates as new information becomes available.

This paper will present methods developed that integrate models from the three prognostics categories into a single prognostic system to estimate RUL over the life of the component: Lifecycle Prognostics. The methods will also be validated on a range of test beds.

1. Introduction

The ultimate goal of prognostics is to obtain an accurate assessment for RUL predictions, shown in Figure 1, with as little uncertainty as possible. From a reliability and maintenance standpoint, there would be increased safety by avoiding all failures. Calculated risk would greatly decrease, saving money by avoiding unnecessary maintenance. However, many challenges must be overcome. One large bottleneck for data-driven prognostics is the availability of data. Without enough degradation data leading to failure, prognostic models can yield RUL distributions with large uncertainty, or mathematically unsound predictions. To address these issues a "Lifecycle Prognostics" method was developed to create RUL distributions from Beginning of Life (BOL) to End of Life (EOL). This employs established Type I, II, and III prognostic methods, and Bayesian transitioning between each Type.

1.1 Type I: Traditional Time-to-Failure

Historical time-to-failure (TTF) data, X, are collected and fit to a distribution. Using conditional probability, an RUL estimate can be made, given the current time. Methods to accomplish this are widely based on statistical distribution analysis. Three of the more common distributions include the Gaussian, exponential, and Weibull (Ebeling, 2010). Gaussian distributions are commonly used due to the tendency of the combination of a set failure distributions of unknown failure modes to tend towards this distribution as described by the central limit theory (Rice, 1995). Also for this reason, in the absence of a large number of observations, and without better information, the Gaussian or Normal distribution can give highly accurate

Please cite this article as: Nam A., Sharp M., Hines J. W., Upadhyaya B., 2013, Lifecycle prognostic algorithm development and application to test beds, Chemical Engineering Transactions, 33, 901-906 DOI: 10.3303/CET1333151

results in many cases. Due to factors explained later on, the Gaussian distribution will be used in this paper, when applying Type I.

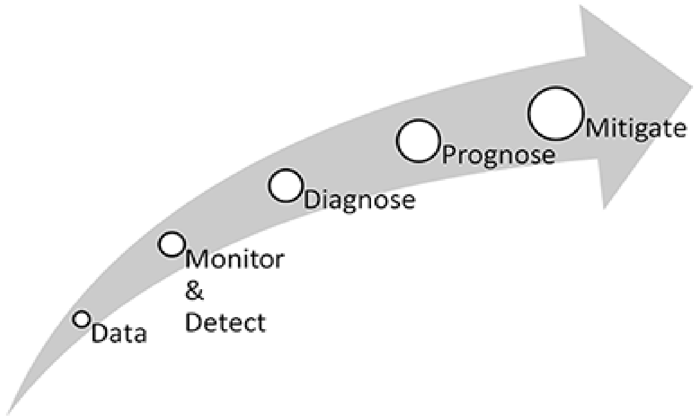

Figure 1: Prognostics Health Monitoring System

1.2 Type II: Condition-based

Type II, or condition information based prognostic methods, take into account the current and past stressor information. A stressor can be the environment in which the component or process operates, the listed workload, or any indication of the stress at work upon the system. For most cases, it generally is assumed that an object under greater stress degrades more quickly.

One method that can utilize stressor based information is the simulation of the most likely future stress levels, which can predict a failure time. Monte Carlo Markov Chain (MCMC) based techniques can be used in this fashion (Kharoufeh et al., 2005), using a Life Consumption Model (Ramakrishnan et al., 2003). Cox Proportional Hazards Model (Liao et al., 2006) is another model, which assumes proportionality between the distribution and some covariate information related to the stress indicator.

1.3 Type III: Degradation-based

In Type III methods, degradation is quantified, monitored, and trended, starting from when a fault occurs and ending in failure. If a model of the system under normal operation exists, then the residuals can be collected to form the degradation, or prognostic, parameter and can be considered a quantitative measure of how severe any detectable fault in the system has become. Zio et al. (2012) proposed a prediction model using infinite impulse response locally recurrent neural networks. Another widely used method to predict the future degradation of a system is through the General Path Model (GPM) approach. Lu et al. (1993) first developed the method. Upadhyaya et al. (1994) first applied it to prognostics. Garvey (2007) applied it resulting in a patent and commercial system. When using the GPM approach, a parametric trending function is fit to the degradation parameter, and extrapolated until it crosses some threshold, called the degradation 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 meets its design specifications.

One of the simplest implementations of the GPM is the linear regression model. Using ordinary least squares (OLS) regression, a linear model can be defined by the general form, equation 1 (Gelmin et al,. 2004), where Y is the response, X is the input matrix, β is the vector of parameters, and $\sigma^2 I$ represents independent observation errors with equal variance. The columns of X are the independent parameter measurements and X includes a column of ones to allow for a non-zero intercept.

$$Y|\beta, X, \sigma^2 \sim N(X\beta, \sigma^2 I) \qquad (1)$$

$$\hat{\beta} = (X^T X)^{-1} X^T Y \qquad (2)$$

2. Bayesian Statistics

Bayesian methods, as opposed to classical frequency statistics, show how an expected value, a priori, changes with new data to form a posterior distribution. They are best used when limited data is available.

The use of a prior also means that information is conserved when new data is available. The weightings of the a priori and sampling data are dependent on the variance of the prior, the variance (uncertainty) of the data, and the amount of the measured data (number of samples). If the variance of the prior is small compared to the uncertainty of the data, the prior b0 will be weighed more heavily. However, as more data is collected, the data will be weighted more heavily and will eventually swamp out the prior in calculating the posterior.

2.1 Bayes' Formula

Bayesian statistics is based primarily on Bayes' formula (Ghosh et al. 2006). In essence, the posterior distribution $\pi(\theta|x)$, of parameters θ, is updated from its prior distribution $\pi(\theta')$, in light of observed data x. In most practical applications, conjugate families can easily be referenced which solve Bayes' formula. One example is the Gaussian conjugate family, for which the posterior Most Likely Estimate (MLE) and variance are:

$$E(\mu|X) = \frac{\frac{\eta}{\tau^2} + \frac{\sum x_i}{\sigma^2}}{\frac{1}{\tau^2} + \frac{n}{\sigma^2}} = \frac{\frac{\eta}{\tau^2} + \frac{n}{\sigma^2}\bar{X}}{\frac{1}{\tau^2} + \frac{n}{\sigma^2}} \quad (3)$$

$$var(\mu|X) = \frac{1}{\frac{1}{\tau^2} + \frac{n}{\sigma^2}} \quad (4)$$

where n is the number of samples in x, σ^2 is the sampling variance, η is the prior mean, and τ^2 is the uncertainty associated with the prior distribution.

2.2 Linear Regression with Bayesian Priors

For the Bayesian OLS model, because the noise variance of Y, σ^2, is known, the conditional posterior distribution of β given σ^2 is Gaussian (Gelmin et al. 2004), for which the conjugate prior distribution also takes on a Gaussian form.

Before the Bayes prior information is incorporated, a data covariance matrix Σ is introduced. Instead of assuming equally distributed errors, $\sigma^2 I$, the covariance matrix is an n x n symmetric positive matrix, containing the variance at each point. The posterior MLE and variance are then

$$\hat{\beta} = (X^T\Sigma^{-1}X)^{-1}X^T\Sigma^{-1}Y \quad (5)$$

$$V\sigma^2 = (X^T\Sigma^{-1}X)^{-1} \quad (6)$$

To include Bayesian updating, the prior distribution ~N(b0,Σb) is treated as one additional data point to the OLS solution. To achieve this, each variable is appended with the prior distribution data, equation 7. The X is appended with an identity matrix, with ones representing the parameters for which prior distributions exist.

$$Y_* = \begin{bmatrix} Y \\ b_0 \end{bmatrix}, X_* = \begin{bmatrix} X \\ I_k \end{bmatrix}, \Sigma_* = \begin{bmatrix} \Sigma_Y & 0 \\ 0 & \Sigma_b \end{bmatrix} \quad (7)$$

3. Transitions Between Prognostic Types

When using Bayesian transitioning methods, there are a couple things to be aware of. Fundamentally Bayesian analysis updates a prior belief with new data to get a posterior belief. The general approach to applying Bayesian method consists of identifying the prior, which comes from the previous prognostics type. Then observational data is sampled from the newer prognostics type. They are then combined using the posterior expectations estimates, Eq. 3 and 4, or linear regression that includes prior information, Equations 5 to 7. For most prognostics types involving distributions, the former is used; for anything involving GPM, the latter.

3.1 Type I to Type II Transitions

As an initial test application, tire data was analyzed using Type I Gaussian, and Type II MCMC. The data consisted of 100 individual tires for which the operating conditions were tracked until failure. For three unfailed cases, Type I and Type II RUL distributions were found at each time step, Figures 2 and 3.

At each time step, the mean and standard deviation for both RUL distributions are easily obtained and applied to Eq. 3 and 4, with n set as the number of data points equal to the current time. In doing so, a posterior MLE was found at each time, Table 1. In this case study it is shown, using MCMC, the RUL at BOL matches the Type I distribution. The Bayesian transitioning methodology is meant to impact the BOL estimates. Since the Type II already matches Type I, such a transition is made unnecessary. In real applications, the more specific Type II data would be used, and the Type I discarded. However this method has shown a proof of concept of a mathematically sound way to transition from Type I to Type II, if such a transition is needed in other applications.

Table 1: RUL Estimation Through Lifetime of Unfailed Case #3

Time	Type I MLE	Type II MLE	Bayes MLE
1	364	365	364
2	363	365	364
3	362	362	362
4	361	360	360
...			
233	132	114	114
234	131	112	112
235	130	111	111
236(end)	129	110	111

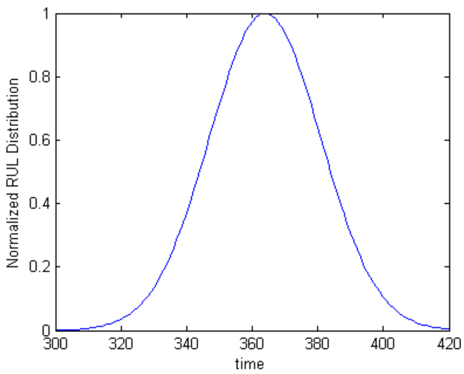

Figure 2: RUL Distributions at time=1 for Type I

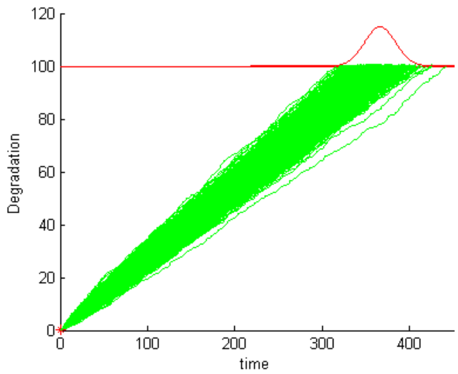

Figure 3: Type II RUL distribution

3.2 Type I/II to Type III GPM Transitions

To demonstrate the methodology for transitioning into a GPM approach, the 2008 Prognostics Health Management Challenge Data is presented as a case study. This data consisted of 260 training examples of 24 signals ending in failure, and 259 censored testing examples of the same 24 signals. The actual RUL of the testing examples were given for validation. Detailed information on applying the GPM to the PHM data can be found in Coble (2011). The data was specifically given with no underlying knowledge of the system.

Three GPM applications will be compared. (1) GPM - benchmark, (2) GPM with parameter priors, as explained in section 2.2, and (3) GPM with a RUL distribution prior. The last is a novel approach that addresses combining a prior RUL distribution with the prognostic parameter signal data. The problem with the GPM (2), using parameter distributions, is that it requires extensive degradation data of a population of systems. The GPM (3), using a prior RUL distribution, can incorporate available Type I or II analysis. Analogous to the previous method, the prior RUL estimate is treated as an additional data point. The X should be appended with one row of the prior MLE; the Y, threshold; the covariance matrix, the prior RUL uncertainty.

In many cases GPM by itself is a powerful tool for extrapolating degradation to the critical threshold, Figure 3. For test case 5, all 148 data points were fit to a quadratic functional fit using OLS. The RUL is found algebraically when the functional fit crosses the dashed threshold.

However, if the GPM is applied soon after the fault is detected, the noise of the data can throw off the OLS estimate, and a nonsense RUL estimate can result. Figure 4 shows the exact same algorithm applied to a censored set of the first 39 points, yielding poor results. Such undesirable RUL estimates can be avoided using Bayesian methods. The priors act as a guiding mechanism that forces the function to behave in the expected way. The more limited the data, the stronger the posterior estimates are forced towards the prior.

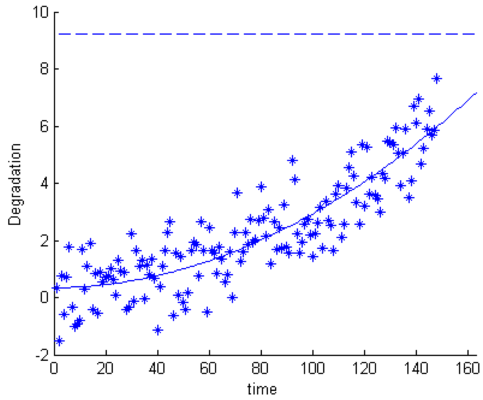

Figure 3: Applying GPM to Test Case #5

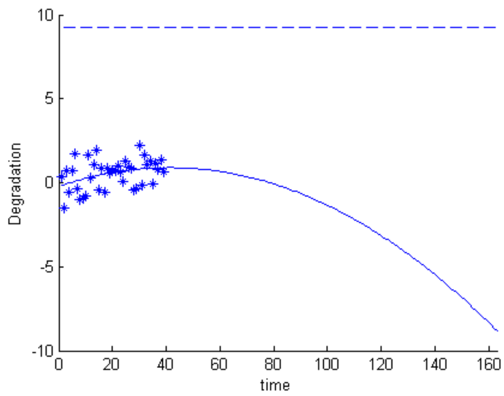

Figure 4: GPM on censored Test Case #5

Figure 5 shows GPM (2) applied to the same censored dataset as in Figure 5. Similar results were found in Coble (2011). Figure 6 shows the results of GPM (3). Both models show a vast improvement over simply applying GPM by itself.

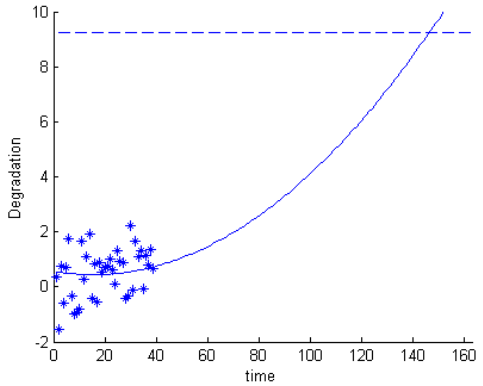

Figure 5: GPM (2) on censored Test Case #5

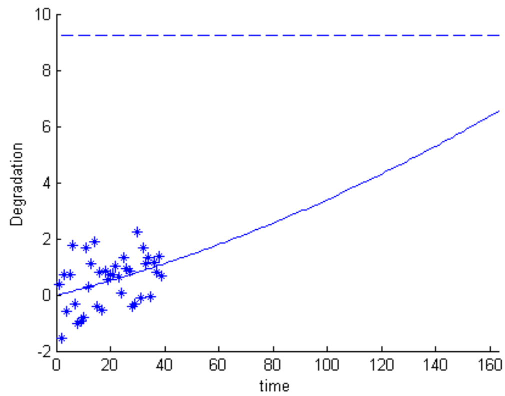

Figure 6: GPM (3) on censored Test Case #5

Additionally the RUL estimates for all 259 test cases, uncensored, were found using Type I, and GPM (1-3). They were compared using Mean Absolute Percent Error (MAPE), Table 2. The GPM models that included Bayesian performed more accurately than either the Type I or GPM by itself. And though the GPM (2) approach uses a lot more data, the GPM (3) achieved the lowest MAPE.

Table 2: MAPE for all PHM Test Cases

Type I	GPM (1)	GPM (2)	GPM(3)
105.4	68.7	60.9	59.5

4. Test Bed Validation

Five different test beds were developed, and are currently collecting data, in order to validate Lifecycle Prognostics and Bayesian transitioning methods. the first three are on-site at the University of Tennessee. A heat exchanger test bed was created to track degradation due to fouling. The exchanger, API Basco HT, is a shell and tube style exchanger with a brass shell, internal brass tube sheets, and 24 x ¼"copper tubes. As contaminated water passes through the hot tube side, it is expected to accumulate some fouling. The temperatures, flow rates, and pressure are monitored to accurately track the heat transfer as the exchanger degrades. For the motor test bed, U5P1G U.S. Electrical Motors/Emerson general-purpose, 3-phase, 3600 RPM motors are subjected to a cyclic thermal aging process designed to induce accelerated insulation breakdown and corrosion within the motors. Another setup consists of a six bladed neoprene impeller, which has been subjected to high levels of heat stress. The aged impeller is then placed in the pump in order to determine the time to failure. During testing the vibration, differential pressure and current of the pump is monitored to track thermal degradation of the impellers.

At Pacific Northwest National Laboratory (PNNL), a passive components test bed was constructed to monitor degradation. This data will be shared with the University of Tennessee. A fifth test bed for bearing failure by Analysis and Measurement Services (AMS) will provide additional information.

5. Conclusions

In this paper techniques for estimating RUL were presented as a holistic Lifecycle Prognostics method, in which Bayesian transitions were applied. These transitions were broken into two general cases based on whether the new information is a simple addition of failure distribution information or more case specific information. The first involved a simple Bayesian combination of different RUL distributions. This applies to very general cases in which RUL distributions can be combined to form estimates containing more data.

For the second general method, GPM, three different RUL prediction methods were compared on prognostic parameter data. Two were conventional regression methods, OLS regression, with and without parameter priors. The remaining novel method involved Bayesian analysis under restrictions of data availability, and utilizing prior RUL distributions, whether Type I or II. These methods will be developed further and validated using various test beds.

Acknowledgements

The authors would like to acknowledge the DOE Nuclear Engineering University Program (NEUP) under prime contract number DE-AC07-05ID14517 and Battelle Energy Alliance LLC Standard Contract No. 00118294, for continued funding. They also acknowledge PNNL and AMS for their work on test beds, and the Electric Power Research Institute (EPRI) for funding the motor test bed.

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