

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 the steps necessary to develop a lifecycle prognostics model for a heat exchanger system with a short explanation of each

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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 (Jonsson 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.

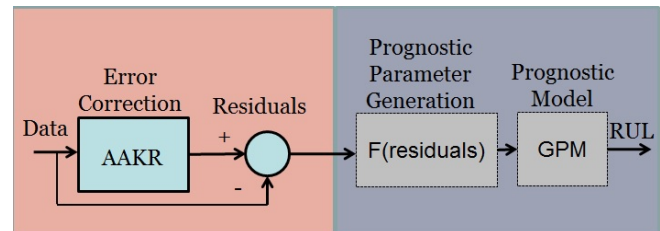


Figure 1 – Basic arrangement of an AAKR based prognostic system.

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.

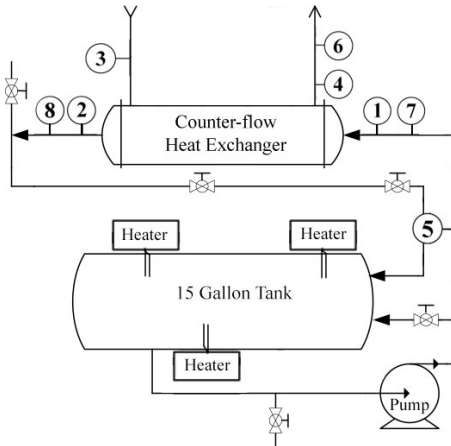


Figure 2 – Schematic of heat exchanger physical setup

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.

Table 1 – Major systems components, brand, and location

	Component	Brand	Location
Sensors	Thermocouple	Omega	Hot Leg Inlet Hot Leg Outlet Cold Leg Inlet Cold Leg Outlet
	Turbine Flow Meter	Blancett	Hot Leg Inlet Cold Leg Outlet
	Pressure Transducer	Dwyer	Hot Leg Inlet Hot Leg Outlet
	Data Acquisition System	Texas Instruments	N/A
Components	Heat Exchanger	Basco	N/A
	250 Watt Heater	Tempco	Two on top of tank One on bottom of tank
	15 Gallon Reservoir Tank	McMaster-Carr	Hot Leg - Below Heat Exchanger
	0.5 HP Pump	Berkeley	Below Tank

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.

$$\dot{Q}_{h/c} = \dot{m}C_p(T_1 - T_2) \tag{1}$$

$$LMTD = \frac{(T_{h1}-T_{c2})-(T_{h2}-T_{c1})}{\log\left(\frac{T_{h1}-T_{c2}}{T_{h2}-T_{c1}}\right)} \tag{2a}$$

$$U_{h/c} = \frac{\dot{Q}_{h/c}}{LMTD \cdot A} \tag{2b}$$

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 (LMTD and heat transfer coefficients). There are moderate correlations between signals 1 to 6 (5 and 6 are the flow rates) and 13 to 15.

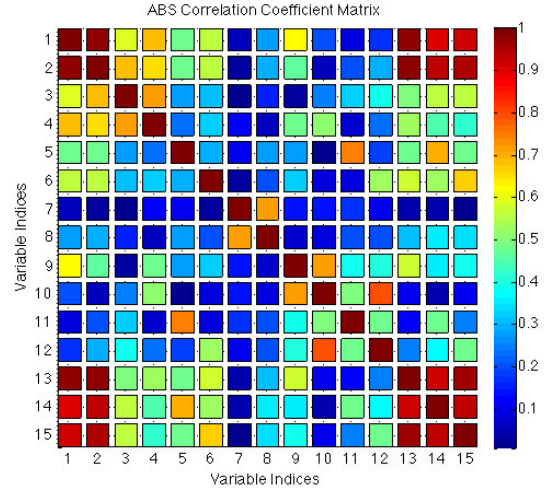


Figure 3 – Correlation coefficients of signals and features

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.

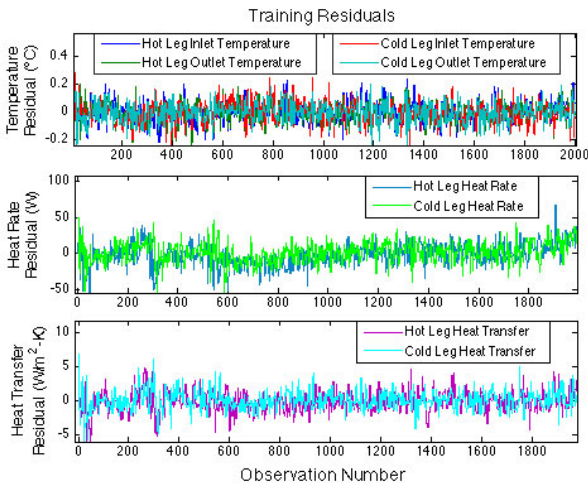


Figure 4 – Training residuals for signal set 2.

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 $10\text{ W}/\text{m}^2\text{K}$. 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.

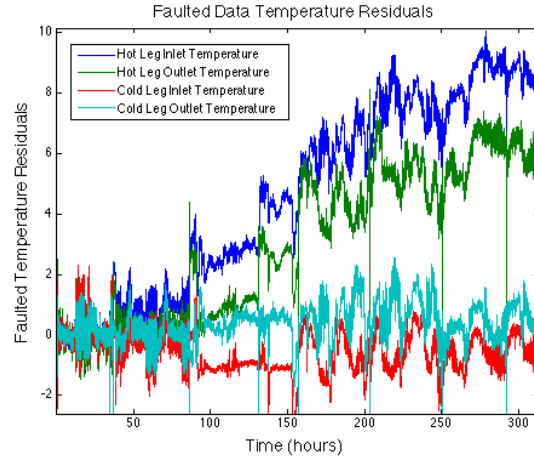


Figure 5 – Faulted residuals of temperature signals (indices 1-4) using the signal set 2 model

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 $\mathbf{n} \times \mathbf{s}$ matrix, \mathbf{X} , where \mathbf{n} is total data points in all test cases, and \mathbf{s} is the number of signal residuals output from the model. This \mathbf{X} matrix is regressed against the $\mathbf{n} \times 1$ vector \mathbf{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

$$\hat{\beta} = (X^T X)^{-1} X^T y \quad (3)$$

where $\hat{\beta}$ is an $\mathbf{s} \times 1$ 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:

$$y|\beta, X, [\sigma] \sim N(X\beta, \sigma^2 I) \quad (4)$$

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.

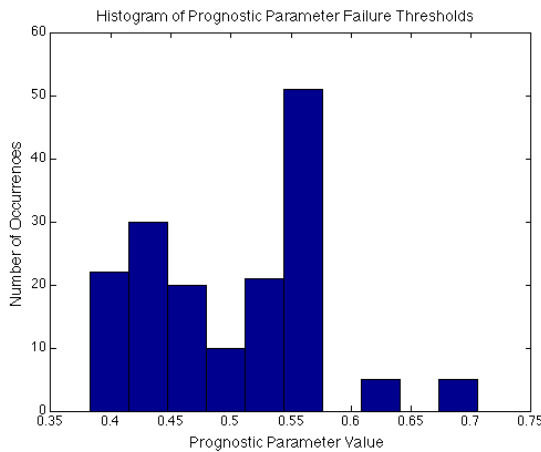


Figure 6 – Histogram of failure thresholds

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 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:

$$Y = \begin{bmatrix} y \\ thresh \end{bmatrix}, X = \begin{bmatrix} X \\ MTTF \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma_y & 0 \\ 0 & \Sigma_{RUL} \end{bmatrix} \quad (5)$$

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):

$$\hat{\beta} = (X^T \Sigma^{-1} X)^{-1} X^T \Sigma^{-1} y \quad (6)$$

$$V \sigma^2 = (X^T \Sigma^{-1} X)^{-1} \quad (7)$$

$$\sigma^2 = \frac{1}{n-k} (y - X\hat{\beta})^T \Sigma^{-1} (y - X\hat{\beta}) \quad (8)$$

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.

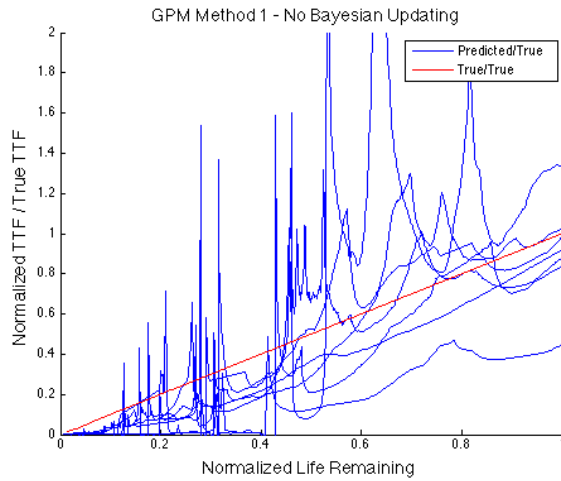


Figure 7 – Plot of the GPM method 1 TTF predictions across cycles without Bayesian updating

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.

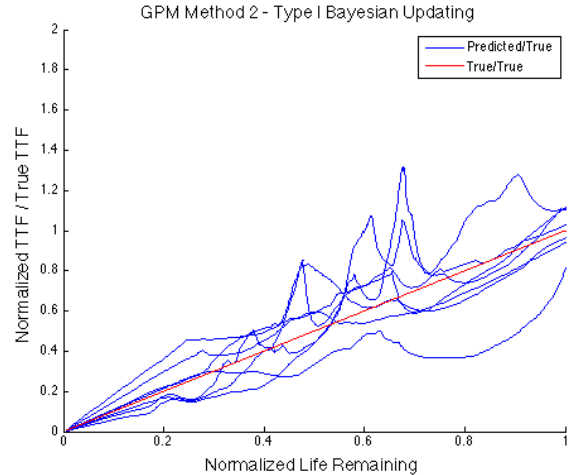


Figure 8 - Plot of the GPM method 2 TTF predictions across cycles with Type I Bayesian updating

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.

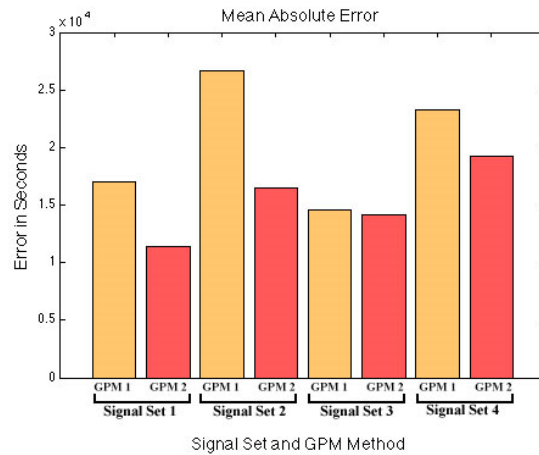


Figure 9 – Absolute error mean for four signal set models and two GPM methods

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.

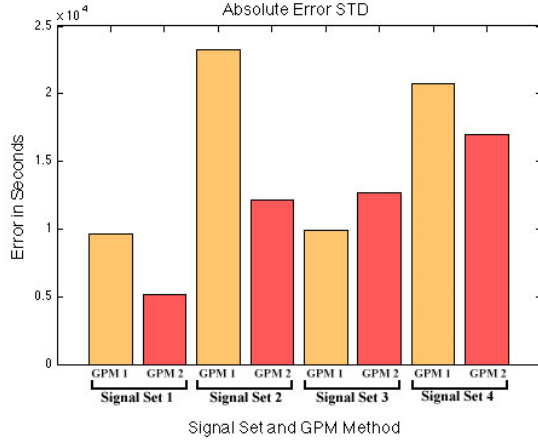


Figure 10 – Absolute error standard deviation for four signal set models and two GPM methods.

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.

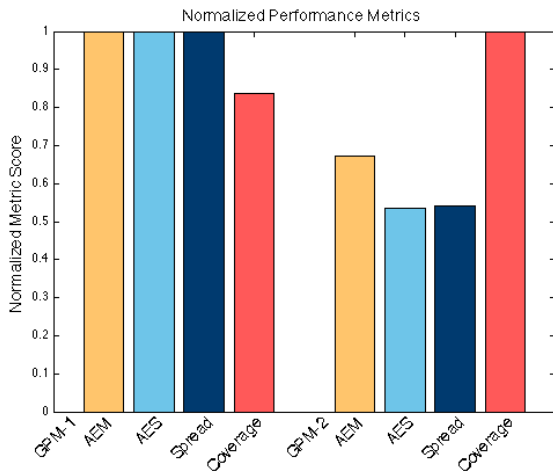


Figure 11 – Plot of normalized performance metrics for two GPM methods and signal set 1

These metrics indicate that the Bayesian updating method (GPM Method 2) is more accurate for predicting RUL for this data set.

Table 3 – Performance Metrics Scores

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

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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APPENDIX

Table A1 – Measured signals and calculated features and their indices

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