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Invited Article

Maintenance-based prognostics of nuclear plant equipment for long-term operation

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A R T I C L E I N F O

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A B S T R A C T

While industry understands the importance of keeping equipment operational and well maintained, the importance of tracking maintenance information in reliability models is often overlooked. Prognostic models can be used to predict the failure times of critical equipment, but more often than not, these models assume that all maintenance actions are the same or do not consider maintenance at all. This study investigates the influence of integrating maintenance information on prognostic model prediction accuracy. By incorporating maintenance information to develop maintenance-dependent prognostic models, prediction accuracy was improved by more than 40% compared with traditional maintenance-independent models. This study acts as a proof of concept, showing the importance of utilizing maintenance information in modern prognostics for industrial equipment.

1. Introduction

As the industry evolves, there is an increasing reliance on data and information that can be extracted from data, to improve operation and equipment performance. Data science and analytics are becoming a key area of focus for many industries and companies. The emergence of online monitoring and predictive analytics has indicated the importance of accurately quantifying system behavior, as well as using information about the health of the system, in order to improve the way equipment is operated, maintained, and optimized. Two of the most common data sources for full-scale industry are process data (signals, features, and operating constraints) and maintenance data. The availability of these data repositories allows for condition monitoring, diagnostics, prognostics, etc., by developing characteristic models for plant equipment, identification, and prediction of failure. These prognostic models can be used to estimate system degradation and predict when equipment will no longer operate as designed.

When developing models for prognostics, the condition of the equipment is traditionally assumed to be restored to as good as new condition at the end of each cycle. This assumption means that the equipment is essentially replaced with a brand new part at the time of maintenance. By making this assumption, any information about residual degradation in the system is lost. Unfortunately, assuming that all traces of degradation are removed regardless of maintenance action is not regularly applicable to repairable systems. For example, consider a generic repairable filter that accrues dust, particulates, and other potential degradation. Industrial filters can often be repaired in many unique ways. Large filters may consist of multiple stages such as an outer layer filter and an inner layer filter. Either stage of the filter can be replaced, or methods to clean the filter so that it may be reused are potential maintenance action options. Imagine that after 1,000 h of operations, a filter has accrued significant degradation and is scheduled for maintenance. In this scenario, the maintenance worker replaced the outer filter, and the system continues to run within the acceptable operating efficiency range. However, because only the outer filter is replaced, degradation in the composite filtering system is present at the beginning of the following operating cycle due to the residual degradation within the inner filter. If a model was developed for the filter system and each cycle was assumed to begin at an as good as new condition, the predictions of subsequent failures after the outer filter was replaced would likely be significantly inaccurate. In order to prevent unnecessary error in failure prediction, information about the type of maintenance conducted after each failure would need to be known and in some way incorporated into model development so that the initial conditions at the beginning of each operating cycle could be correctly captured.

The focus of this study is to determine the influence of maintenance information on prognostic model development. In systems where the maintenance action is captured in maintenance work

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order information, are the prognostic model prediction accuracy and uncertainty improved by utilizing maintenance information to increase model specificity? By developing maintenance-independent and maintenance-specific models, the relative performance of each can be compared for a system that is significantly influenced by the type of maintenance conducted. This study is important because it identifies the need to collect and utilize maintenance information for accurate prognostic model development and failure prediction.

2. Background

Interest in utilizing prognostics for failure prediction in industrial equipment is quickly growing. By collecting information on equipment failure, prognostics allows degradation to be tracked through the life of components and can be used to accurately estimate the remaining useful life (RUL) of specific equipment under the influence of degradation related to specific fault modes.

2.1. Prognostic model classification

Many different types of prognostic models are available. These models can be classified depending on the amount of information used to predict RUL. One way of grouping prognostic models is presented by Coble and Hines [1], and Sharp et al. [2]. This method groups prognostic models into three "types." Type I prognostics is similar to traditional reliability analysis and uses historical time-to-failure (TTF) data to develop failure distributions for a given system. In Type I prognostic models, predictions of TTF and RUL are developed for average components under average conditions. A more specific prognostic model that considers the operating conditions of the equipment is classified as a Type II prognostic model. These models, such as Markov chain and proportional hazards, are used to predict the RUL of average components under specific conditions. If data are collected for a component through the life of the equipment, sensor data specific to an individual component can be used to predict RUL. Models that utilize sensor data related to equipment degradation are classified as Type III prognostic models. These models are used to predict RUL of specific components under specific conditions. As condition and signal data are collected, prognostic models can be transitioned from Type I to Type III, as shown in Fig. 1.

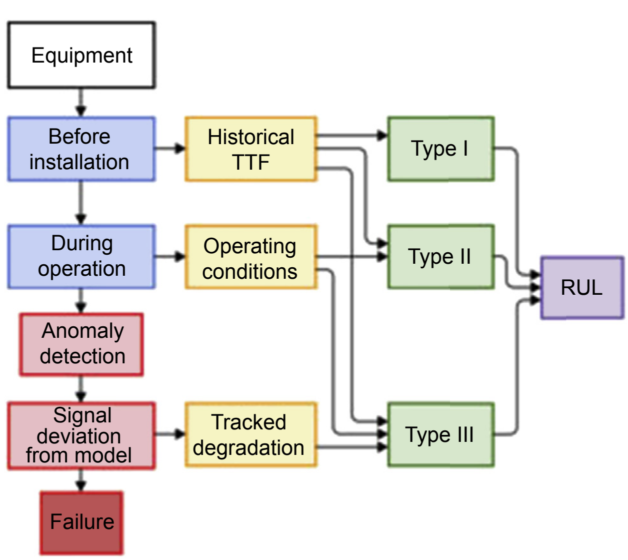

Fig. 1. Transition between prognostic model types dependent on availability of information [3]. RUL, remaining useful life; TTF, time to failure.

One common observation from experience developing these prognostic models is that the accuracy of RUL predictions improves as prognostic modeling is transitioned to more specific types: availability of additional information allows for improved understanding of the influence that degradation has on equipment life. This relationship between model specificity and model performance is one of the key influences of this research. If information leading to improved system understanding results in improved model performance, it is expected that utilizing maintenance information to further individualize model development may result in additional improvement to RUL prediction accuracy.

2.2. Classical maintenance

For prognostic model development, it is generally assumed that each operating cycle begins with virtually no degradation; however, it is also understood that systems typically undergo different types of maintenance upon failure. Jardine and Tsang [4] divide maintenance actions into the three major categories shown in Fig. 2.

The assumption that all operating cycles are returned to as good as new follows the idea of perfect repair, where cycle degradation is completely removed upon maintenance. An older filter with significant particulate buildup that has a major blockage within the inlet line, which is removed upon maintenance, represents the idea of minimal repair, where a system is returned to working condition,

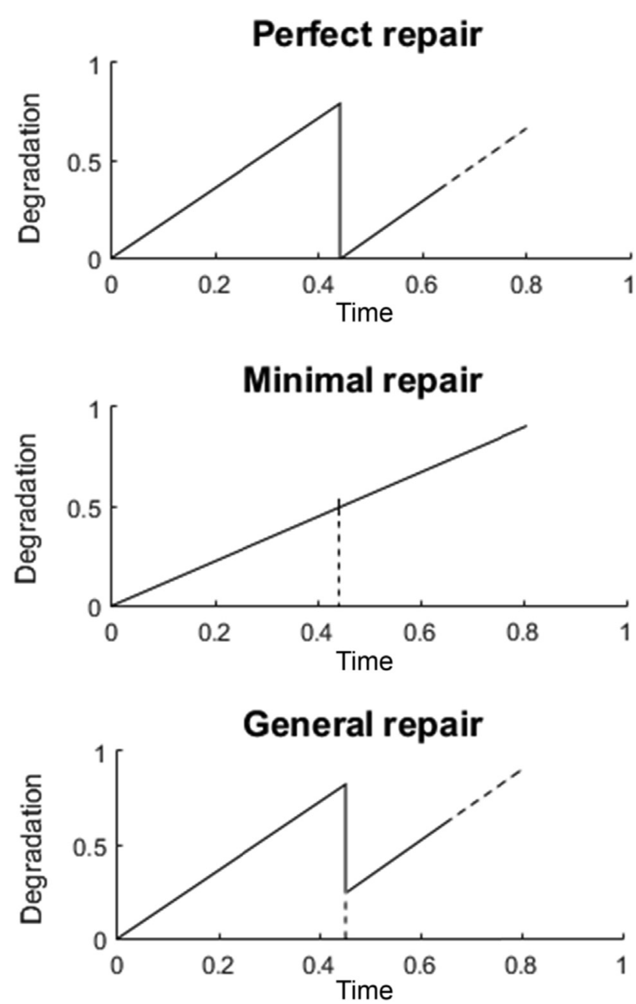

Fig. 2. Categories of maintenance action based on repair quality [4].

but almost no degradation is removed from the system upon maintenance. A broader type of maintenance is general repair, which is used to describe a maintenance action that both returns equipment to working condition and removes a significant amount of degradation from the system, similar to the filter example provided in Section 1. For simplicity, these categories of repair can be reduced to two maintenance actions: replacement, which represents a system that is returned to as good as a new condition, and repair, which represents a system that is returned to working condition but removes less degradation than replacement (as good as used). These terms are used to represent differences between two ambiguous categories of maintenance and do not explicitly represent systems that are given replacement parts versus parts that are repaired. While maintenance action information is useful, the influence of maintenance actions on cycle degradation is equally important. Maintenance-based equipment degradation typically influences operating cycles in three ways: initial degradation levels (postmaintenance), rate of equipment degradation, and time until onset of degradation. The result of this influence affects degradation paths and resulting failure times of subsequent operating cycles.

2.3. *Reliability-centered maintenance versus maintenance-centered reliability*

One method of merging maintenance and reliability methods is reliability-centered maintenance. In reliability-centered maintenance, maintenance actions are chosen to satisfy a desired system reliability or availability [5]. This is consistent with the traditional method in which maintenance information is used within industry; existing maintenance data may be used to evaluate the effectiveness of certain maintenance actions so that reliability models can be developed to meet availability needs. In this research, the attention is shifted from reliability-centered maintenance to a more maintenance-focused study. The only similar research, by Martorell et al. [6], that has been found is related to age-dependent reliability models. In their study, the idea of equipment age versus chronological time is discussed to highlight the effects of imperfect maintenance across cycles. The information is used to assess the reliability of nuclear plants during operational life and for life extension applications. In their study, every maintenance action is treated as imperfect, and results in age reduction or age setback. The result is an accelerated aging model for equipment under imperfect repair conditions. The methods discussed within this paper differ slightly due to the utilization of perfect and imperfect maintenance action possibilities. Unlike the work presented by Martorell et al. [6], this research utilizes maintenance-dependent models to capture the effects of imperfect maintenance and predict failure times for both perfect and imperfect maintenance cycles.

3. Materials and methods

The system used for this research is a small-scale accelerated aging test bed for a cross-flow heat exchanger shown in Fig. 3. A list of signal names for Fig. 3 is provided in Table 1.

This system is used to generate data for a heat exchanger that undergoes degradation through fouling. In order to accelerate the rate of fouling, clay powder was introduced to the closed hot leg loop. This clay accumulates along the walls of the hot leg within the heat exchanger and reduces the heat transfer coefficient over time. The results of early attempts to develop accurate prognostic models for the heat-exchanger test bed are published [7]. This early work did not attempt to develop maintenance-dependent models, and therefore the system contains only one maintenance action, which was to drain the heat exchanger, replace the clay water mixture with clean water, and pressure wash the walls of the heat exchanger. As a

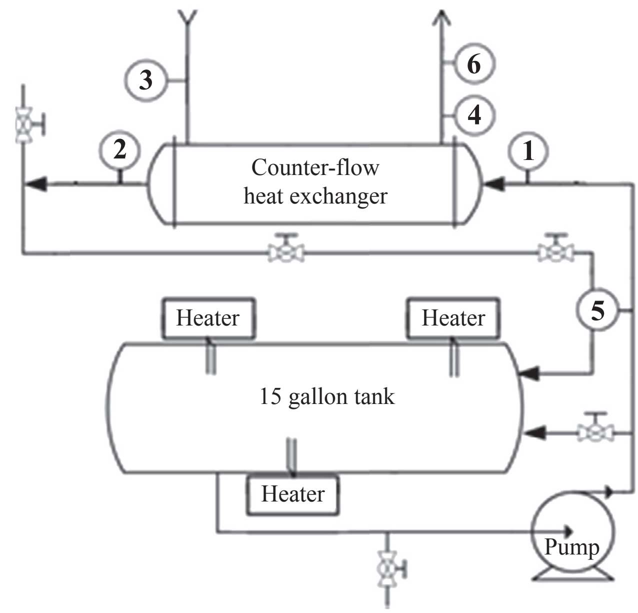

Fig. 3. Simplified diagram of the small-scale accelerated aging heat exchanger [7].

Table 1
List of heat exchanger signals.

Signal index	Signal/feature	Abbreviation
1	Hot leg inlet temperature	Thin
2	Hot leg outlet temperature	Thout
3	Cold leg inlet temperature	Tcin
4	Cold leg outlet temperature	Tcout
5	Hot leg flow rate	Mh
6	Cold leg flow rate	Mc

result, few degradation runs that satisfy the needs of this research were collected; additional data for the heat exchanger system that undergoes two distinctive maintenance actions are, therefore, generated from a simulation to expand upon earlier work. To relate these maintenance actions to real work done to restore a heat exchanger during maintenance, two possible choices are explained: flush and clean. A flush is a simple maintenance action where high-pressure water is forced through the heat exchanger to quickly remove excess fouling. By contrast, a full clean uses both high-pressure water to flush the system, and disassembly of the heat exchanger and mechanical cleaning of the equipment's inner walls. Flush and clean can be thought of as repair and replace, respectively.

Rather than building a simulation from scratch, previously collected data from the heat exchanger are used to improve similarities between the simulation and real data. The first step in generating maintenance-dependent cycles is to process the real data for each signal into distributions for the initial signal values, degradation rate of the signal path, signal noise, TTF, and signal value. This allows cycle parameters to be sampled from distributions representing the real data. The second step is to calculate the heat transfer coefficient for the real data. Fouling influences heat transfer efficiency; therefore, calculation of the heat transfer coefficient should allow the degradation in heat exchanger performance to be quantified. Equations for calculating the heat exchanger heat transfer are as follows [8]:

$$\mathrm{LMTD} = \frac{(T_{h1} - T_{c2}) - (T_{h2} - T_{c1})}{\log\left(\frac{T_{h1}-T_{c2}}{T_{h2}-T_{c1}}\right)} \tag{1}$$

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

where LMTD is the log-mean temperature difference; T is the temperature for the hot leg inlet ($h1$), hot leg outlet ($h2$), cold leg inlet ($c1$), and cold leg outlet ($c2$); Q is the heat rate; A is the surface area of heat transfer; and U is the heat transfer coefficient. The LMTD, heat rate, and heat transfer coefficient are referred to as features since they are calculated from measured signal values. An example of a calculated heat transfer coefficient from the real data is shown in Fig. 4.

Similar to the process for the heat exchanger signals, parameters of the heat transfer are sampled from the feature cycles and used to develop distributions representing initial degradation, rate of degradation, and noise level. The time before degradation onset was not sampled due to difficulties identifying the precise point of onset. In order to create influence of maintenance action on the heat transfer parameters, the values sampled from the real data heat transfer features are divided into two groups. The parameters can then be sampled from the different groups based on the maintenance action desired: flush or clean. After the appropriate noise is added, the resulting maintenance-based heat transfer features look like the example in Fig. 5.

While this process of generating maintenance-dependent heat transfer paths could be used to develop prognostic models, the heat transfer features may or may not accurately represent changes seen in the temperature signals due to the fact that the heat transfer is sampled from the distribution parameters rather than calculating directly from the signals. To improve this process, the inlet hot and cold leg temperatures, as well as the heat transfer coefficients, are passed to a kernel regression model and used to predict the outlet temperatures (Fig. 6).

The multivariate kernel model is used as an error correction model to capture relationships between input and output data. This heteroassociative regression model is similar to a general regression neural network [9]. General regression neural network is a nonparametric model, which makes it flexible for a variety of uses. Its simplicity also helps improve understanding of the differences between model uncertainty and data uncertainty, making it extremely useful for exploratory research involving relative model performance. In this study, kernel regression is used to capture relationships between predictor and response variables so that typical equipment responses can be recreated under the influence of equipment and signal degradation. This kernel model is trained on the real data, and evaluated for the sampled cycles so that the relationships between the signals are retained in the newly generated data. Since the input temperatures are not influenced by degradation, it makes sense to directly simulate these temperatures and use them in the model. By doing this, the resulting outlet temperatures also reflect the influence of maintenance action seen in the generated heat transfer coefficient. Rather than using the output temperatures and the simulated input temperatures to recalculate the heat transfer coefficient and use this feature in the prognostic model, the LMTD of the temperature signals was used. This means that the parameter used in the prognostic model to predict the TTF of the equipment is dependent only on the simulated inlet temperatures and model outlet temperatures, and does not require a simulated mass flow rate signal.

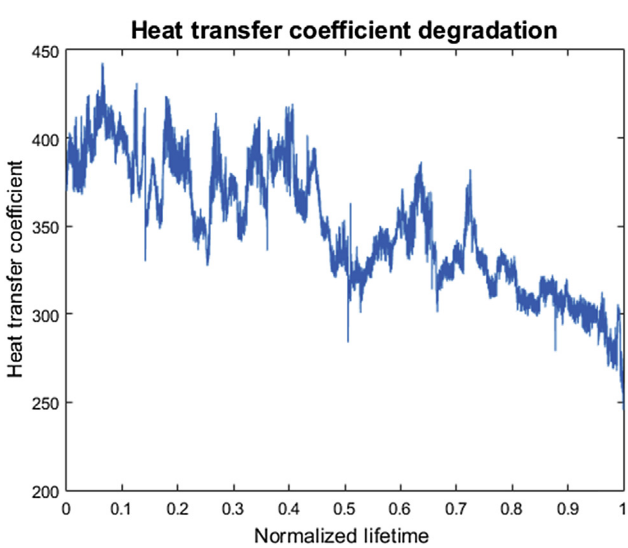

Fig. 4. Heat transfer coefficient of the heat exchanger under the influence of fouling degradation.

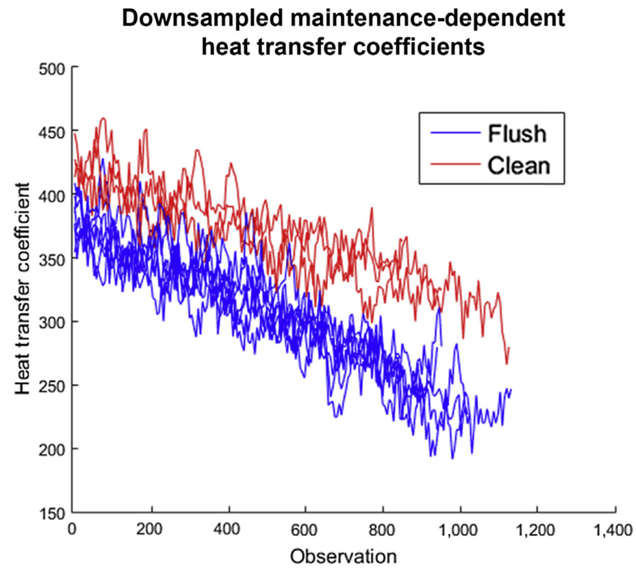

Fig. 5. Example of sampled heat transfer coefficient features.

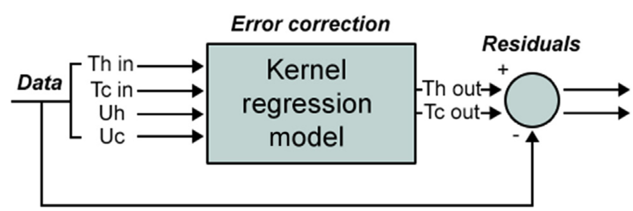

Fig. 6. Kernel regression model for a heat exchanger system.

In order to establish when a cycle is considered "failed," a threshold must be applied to the LMTD of each generated cycle. This threshold corresponds to a generalized efficiency of the heat exchanger system under the influence of fouling degradation. For the generated cycles, all are normalized so that the range of all cycles is between 0 and 1; the threshold was chosen arbitrarily at a 0.45 degradation level for all cycles regardless of maintenance action. Observations after this point are removed from the model and assumed to have an RUL of zero. Cycles that do not reach the threshold are treated as censored cases. The RUL is calculated as the difference between the current observation and the predicted TTF. An example of generated prognostic parameters (LMTD) with the applied threshold is provided in Fig. 7.

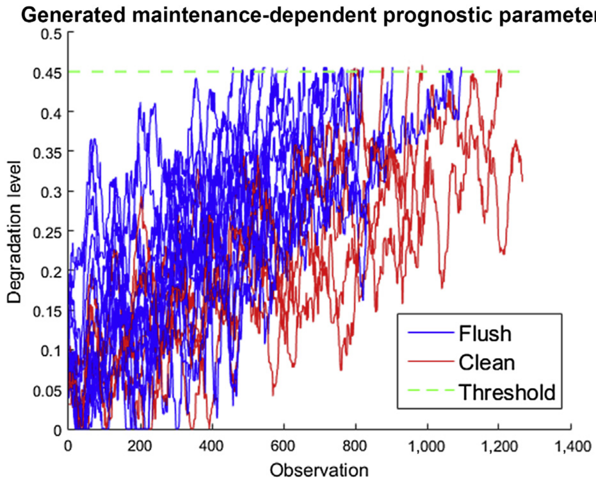

Fig. 7. Simulated prognostic parameters with threshold at a 0.45 degradation level.

In this figure, observations are designed to represent a sample every 15 min. This means that cycle life ranges from approximately 5 days to 15 days. One observation that can be made about the generated prognostic parameters is the amount of noise present in the degradation paths. Since the simulated signals contain correlated process noise, the prognostic parameter amplifies the noise, resulting in large fluctuations of the LMTD feature. Since industrial heat exchangers operate on longer maintenance cycles, these parameters can be smoothed, as it does not make physical sense for the heat exchanger efficiency to fluctuate so rapidly for the given time scale. The primary interest is in the underlying changes to degradation on a macro level.

To evaluate the influence of maintenance actions on prediction capabilities, two types of prognostic models were chosen. The first is a Weibull model, which is a traditional reliability model commonly used to estimate the TTF for average equipment under average conditions and is referred to as a Type I prognostic model. More information on Weibull models can be found in the work of Weibull [10]. The second model used is a general path model (GPM), which maps the degradation path of the prognostic parameter for each cycle and attempts to quantify a general representative path for the system based on the historic failure cycles. This allows the GPM to predict TTF for the specific heat exchanger equipment under specific conditions, i.e., a Type III prognostic model. More information on the GPM and its uses in prognostics can be found in the works of Lu and Meeker [11], and Coble and Hines [12]. For this system, a quadratic GPM fit was used to model the generated failure cycles. For the heat exchanger system, Type II models are not used.

In order to fully understand how maintenance-dependent modeling influences Type I and III prognostic model prediction accuracy, three degradation models are developed. As a baseline, a single degradation model is developed that does not consider maintenance. This maintenance-independent model is used to compare the relative prediction accuracy with that of maintenance-dependent models. For maintenance-dependent modeling, two models are used: one for flush actions and one for full cleaning. Prediction accuracies are not directly comparable between the maintenance action-specific models, but each can be used to assess the prediction improvement compared with the maintenance-independent model prediction accuracy baseline. Since this division of modeling is used for both Type I and Type III prognostic models, a total of six models are developed and evaluated.

For each of the six models, half of the generated cycles are used to train the models and the other half are used to evaluate the prediction accuracy. As a metric for prediction accuracy, the mean absolute error (MAE) is used. MAE is defined by Eq. (3).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|p_i - y_i| \tag{3}$$

where p is the prediction, y is the actual value, and n is the number of observations in the cycle being predicted. This is an average error over each observation of the cycle. Other measures of prognostic predictive performance can be used [13,14], but this simple measure is sufficient for this application.

4. Results

While the primary objective of the research is to identify the influence of maintenance-dependent modeling on prognostic model prediction accuracy, it is equally important to discuss the results of data simulation. Comparisons of the real and simulated data are shown for the input signals (and heat transfer features) in Fig. 8.

The results are fairly similar when comparing the cycles generated by sampling from real data parameter distributions with

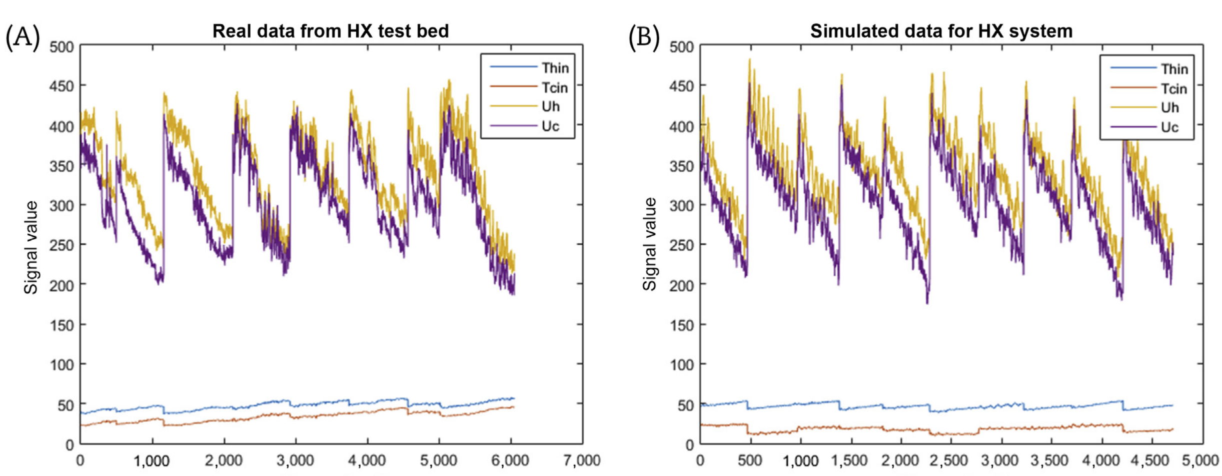

Fig. 8. Comparison of real and simulated data. (A) Real heat exchanger data. (B) Simulated data. HX, heat exchanger.

Table 2
Type I prognostic model results.

Maintenance-independent combined MAE (No. of observations)	Maintenance–dependent flush MAE (No. of observations)	Maintenance–dependent clean MAE (No. of observations)
459.2	205.0	104.2

MAE, mean absolute error.

Table 3
Type III prognostic model results.

Maintenance-independent combined MAE (No. of observations)	Maintenance–dependent flush MAE (No. of observations)	Maintenance–dependent clean MAE (No. of observations)
170.5	90.0	78.0

MAE, mean absolute error.

the original dataset. The reason for differences in the relationship between the temperature signals is the method of sampling. In the real data, the correlation between the temperature signals is very high; due to random sampling of the signal parameters used in the generated data, this strong relationship between the signals is partially lost. Data could be sampled in a correlated manner, but the method used provides a conservative result.

For the results of applying the Type I Weibull model to the datasets, multiple batches were run and aggregated into an average prediction score. The results of the maintenance-independent and maintenance-dependent Type I prognostic modeling are provided in Table 2.

The average cycle length is approximately 1,000 observations; therefore, the combined model can predict the TTF with roughly 46% prediction error. While this is typically considered as an inaccurate model, the purpose of this research is to compare the accuracy of the maintenance-independent model with that of the maintenance-dependent models. In addition, most models see improvement in prediction accuracy as they get closer to failure. The models developed in this work are evaluated along the total lifecycle; therefore, error improvement may change if compared during specific phases of equipment life. It is important to have higher prediction accuracy near the end of life, which should be an area of future research for maintenance influence on prognostic accuracy. For the flush and clean models, the prediction error is reduced from 46% to 21% and 10%, respectively. Type I models are prone to high uncertainty; therefore, it is typically assumed that Type I models will not perform well for systems with large variance in failure times. This is one of the driving motivations behind using Type III models for more complex systems. For the heat exchanger system, the results of applying Type III models are given in Table 3.

Again, the average cycle is approximately 1,000 observations, resulting in a maintenance-independent model prediction error of 17%. This is significantly reduced from 46% prediction error in the maintenance-independent Type I model. Comparing this result with the prediction errors for maintenance-dependent models, the flush and clean models had prediction errors of approximately 9% and 8%, respectively. This is a reduction of more than 40% compared with the maintenance-independent model.

5. Conclusions

The purpose of this study was to determine how the influence of maintenance actions on system degradation influences modeling ability to predict equipment failures. By generating operating cycles for a heat exchanger system with two possible maintenance actions, these cycles could be grouped according to maintenance conducted and prognostic models were developed. The importance of integrating maintenance information with process data is quantified by comparing maintenance-dependent models with a single prognostic model independent of the maintenance conducted. By comparing models, the results of this research show that, for this case, prognostic model prediction accuracy can be improved by 40% or more when maintenance action-dependent models are used. These results validate the theory that increasing model specificity through maintenance data assimilation may result in improvements to prognostic model performance.

Conflicts of interest

No conflict.

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