Progress Towards Prognostic Health Management of Passive Components in Advanced Reactors – Model Selection and Evaluation

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Abstract—This paper presents recent progress towards developing a prognostic health management framework for passive components of advanced reactors (AR). The focus of this paper is on lifecycle prognostics for passive components using a Bayesian prognostic algorithm that provides a natural framework for incorporating different sources of variability and uncertainties inherent in the operations of AR. High-temperature creep damage, a prototypic failure mechanism in AR materials, is used as the context for this research. A Bayesian model selection approach is implemented to select the appropriate creep degradation model at any given time, using relevant sensor measurements reflecting the material degradation state. The model selection approach, based on reversible jump Markov chain Monte Carlo methods, is integrated with Bayesian particle filter-based prognostic framework. The proposed approach is evaluated using strain measurements obtained from accelerated creep testing of stainless steel specimens. Results indicate feasibility of the proposed approach in accurately identifying the creep degradation stage from the available measurements at a given time. Effect of uncertainties in material degradation model and measurement noise on the performance of the prognostic algorithm is also investigated.

Keywords- advanced reactor prognostics; prognostic health management; reversible jump MCMC; Bayesian model selection; particle filter; high-temperature creep

I. INTRODUCTION

The term “advanced reactors (AR)” generally encompasses all non–light-water-cooled reactor concepts. These reactor concepts are being considered as a longer-term option for meeting electrical generation and process heat needs in the United States [1]. The relative lack of experience in operating advanced reactors under variable demand environments (when compared to operating experience with the current fleet of light-water-cooled reactors under baseload generation conditions) is expected to present a significant challenge in their wide-scale deployment. This is compounded by limited knowledge of physics-of-failure mechanisms of advanced materials proposed for use in structural components in advanced reactor environments (high temperatures, fast neutron fluxes, potentially corrosive coolant chemistry, and longer exposure times due to extended periods between maintenance and refueling outages).

Prognostic health management (PHM) systems are expected to play a vital role in the safe and economic operation of AR under such circumstances by ensuring early warning of material damage accumulation in structural components. This will pave the way for condition-based maintenance activities with a positive impact on safety and operating economics of AR.

The lifecycle of structural components (often termed passive components) used in AR transitions from fabrication and installation to operation, with degradation accumulation and failure generally determining end-of-life. Degradation in materials and components also follows a lifecycle, going from precursor formation to initiation of microscopic cracks followed by coalescence and macro-crack growth to failure. Repairs or other mitigation activities will change the time horizon for each of these lifecycle stages, as do changing operational conditions such as unanticipated contamination of the primary system coolant, which can cause and accelerate component degradation.

PHM systems for passive components employ material degradation models to predict remaining useful life (RUL). The appropriate degradation models may change over the lifecycle of a component. An effective PHM system for advanced reactors should be able to adapt or adjust its prognostics methodology to the stage the component or degradation is in its lifecycle [2]. For passive components, this requirement may be posed in terms of degradation growth lifecycle and is fundamentally one of Degradation Rate model selection based on available data. This formulation is particularly useful where classical population-statistics–based approaches for prognostics may not be viable, as the volume of historical failure data necessary to develop reliability models may not be available for long-lived passive structures such as reactor vessels or piping. Often, different models may also be more appropriate (e.g., more accurate, more precise, or suitable to runtime requirements) during different stages of component degradation [3].
This paper addresses the issue of lifecycle prognostics for passive components, by formulating the problem as one of model selection within the context of a Bayesian prognostic algorithm. To provide context, the paper uses high-temperature creep damage as the prototypic degradation mechanism for structural materials in AR. This paper briefly provides an overview of the Bayesian prognostic algorithm that is based on particle filtering and probabilistic model selection approach. This is followed by results of application of the proposed approach to measured strain data from accelerated creep testing of stainless steel specimen.

II. BAYESIAN PROGNOSTICS AND MODEL SELECTION USING A MARKOV CHAIN MONTE CARLO APPROACH

Bayesian state-space approaches to prognostics typically use the following two mathematical models [4]:

- Degradation Rate model: represents the degradation accumulation rate (i.e., the degradation level at the next time instant given the degradation level at all times up to and including the present time), and
- Measurement Physics model: represents the quantitative relationship between the measurement and the degradation state at the present time instant.

Mathematically, the Degradation Rate model defines the relationship between degradation levels \(x_k\) and \(x_j\ (k > j)\) and is a representation of the evolution of damage in the material with time. The model may also include information on stressor history; that is,

\[
x_k = f(x_j, \sigma_k, \sigma_{k-1}, \ldots, \sigma_j, \eta_{k-1})
\]

where \(\sigma_k, \sigma_{k-1}, \ldots, \sigma_j\) are stressor values at times \(k, k-1, \ldots, j\) with \(j < k\). In (1), \(\eta_{k-1}\) represents the uncertainty in the state transition model and is typically represented by a probability density function (PDF). The Measurement Physics model relates the degradation level to the measurements \(z_k\) at the present time instant:

\[
z_k = h(x_k, v_k)
\]

with \(v_k\) representing the level of uncertainty in the relationship between the material condition and the measurement. As with \(\eta_{k-1}\), \(v_k\) is generally represented by means of a PDF. These two models are used to compute the conditional probability density of the degradation state at the present time, conditioned on all measurements up to and including the present time. A recursive approach is used, with the Degradation Rate model, to estimate degradation state \(x_k\) at future time instants and compute the likely time-to-failure, from which the RUL is estimated along with confidence bounds for the estimate [5-7].

While several options are available, in this study we use the particle filter as our recursive algorithm because of its applicability to nonlinear models, and the ability to accommodate non-Gaussian distributions for the uncertainties in (1) and (2) [5, 6, 8].

Given this basic framework for prognostics, the dynamic model selection methodology, where the PHM algorithm switches between different Degradation Rate models, becomes a driver for accuracy of the RUL prediction. Again, several options for model selection are available that are based on either Bayesian or non-Bayesian approaches [9]. Both of these approaches in general rely on estimating a specific model selection criterion to select the best model from a given set. In this study, we chose to use an automatic reversible jump Markov chain Monte Carlo (RJMCMC) algorithm [10, 11] to evaluate posterior Degradation Rate model probabilities at each measurement update. This approach allows for transition from one Degradation Rate model to the other using a pre-defined set of model transition probabilities.

Fig. 1 shows the schematic of the overall approach integrating the automatic RJMCMC method [10, 12] and particle filtering algorithm [5] to estimate material damage evolution over time. We begin with a set of damage progression models that capture the distinctive stages of degradation growth. Using the RJMCMC, the posterior probabilities for each of the damage progression models are evaluated as each measurement becomes available. The model may be applied with the particle filter to estimate growth of degradation in the material and compute the RUL. In practice, however, a slightly different approach is used, where each of the models is used for estimating degradation growth, and a weighted average of the results is computed. The weights in this procedure are the model posterior probabilities obtained using the automatic RJMCMC algorithm at the latest measurement update time index.

The RJMCMC algorithm provides a structured mechanism for computing the likelihood of a Degradation Rate model given the data. Specifically, if models \(M = \{M_1, M_2, \ldots, M_{n\text{models}}\}\) [11] are a finite set of models from which the choice of model \(M_i^{(k)}\) at time index \(k\) is to be made, the problem may be described as one of determining the probability of \(M_i^{(k)}\) (and its parameters) given the measurements, i.e., \(p(M_i^{(k)} | z_k)\). While a standard MCMC simulation using the Metropolis-Hastings (M-H) algorithm [13] can be used for this purpose, it imposes the restriction that all models in set \(M\) have their parameters belonging to the same dimensional space. Green [12] has

![Figure 1. Schematic of material state estimation using automatic RJMCMC and particle filtering method.](image-url)
proposed an RJMCMC approach, which removes this restriction and allows trans-dimensional moves (moves across models with varying dimensional parameters) within the standard MCMC simulation. In turn, this simplifies the evaluation of model posterior probabilities by using only one simulation instance for the entire model set $M$.

To summarize, the problem of Degradation Rate model selection for lifecycle prognostics may be addressed using the following process:

- At a given time step, obtain relevant measurement data that is sensitive to the degradation.
- Determine the appropriate current phase of degradation (for instance, primary, secondary, or tertiary creep) by using information from available measurements.
- Using the RJMCMC approach, determine the likelihood of each Degradation Rate model and its associated model parameters.
- Project the degradation growth to future time instants over a given time horizon using each Degradation Rate model within the particle filter.
- Using the likelihood information as weights, compute the weighted average of the projected degradation-growth trajectories.
- As the component ages, repeat the steps above to update the lifecycle prognostics Degradation Rate model and parameter selection as more measurements become available.

III. PROGNOSTICS FOR HIGH-TEMPERATURE CREEP

In this study, we use high-temperature creep damage as a prototypic degradation mechanism relevant to ARs, and apply a Bayesian PHM algorithm augmented with the RJMCMC approach to model selection.

High temperatures (usually in excess of 550°C) and variable loading profiles may cause a structural component to fail catastrophically due to thermal creep, when accumulated over long time frames (several years). Thermal creep degradation is plastic deformation that occurs in materials under stress at high temperatures. Unlike the deformation of materials under stress at low temperatures, which is independent of time, deformation from creep is a function of time, temperature, and stress [14]. The creep strain rate in most materials is non-linear and sensitive to operating temperatures, load conditions, and microstructure of the material, posing a challenge to accurately detecting and monitoring damage progression.

In general, the evolution of creep appears over three distinct phases [15, 16] from fault onset to rupture: primary, secondary, and tertiary. In the primary (or transient) phase, the rate of creep strain decreases with time. In the secondary phase, the strain rate is approximately constant. The strain rate increases rapidly in the tertiary phase until material rupture or failure. Several models have been proposed to describe the primary, secondary, or tertiary phase of creep [17]. Some of these models have been proposed to describe two phases in a unified model [18]. The most appropriate model for each phase of creep depends on the material properties and environmental conditions.

Given the different stages that thermal creep goes through, it becomes imperative for PHM systems to correctly identify the appropriate material degradation model, as well as its transitioning from one Degradation Rate model to another over the lifecycle of a component.

IV. EXPERIMENTAL SET-UP

A laboratory-scale thermal creep test bed was designed and built for acquiring measurement data for evaluating the proposed algorithms. A series of measurement campaigns are ongoing for evaluating multiple nondestructive evaluation (NDE) measurement methods for sensitivity to different stages of creep progression [19]. In this study, we use some of the preliminary data on creep strain measurements for evaluating the algorithms.

The laboratory-scale creep test system consists of a mechanical load frame, furnace, 5-ton actuator, power supply, and control system [see Fig. 2(a)]. The control system encompasses the electronics that run the system, including the motor drive for the stepper motor that is used in conjunction with the actuator. The load frame is the base for mounting the other components. The control system enables active control of load and temperature through the use of a programmable logic controller (PLC), which also enables real-time data acquisition of key parameters (load, temperature, displacement). Key control parameters (such as test speed and furnace control settings) may be adjusted to accommodate various test scenarios and provide the ability to simulate both steady-state and variable-loading scenarios (where the load and/or temperature are varied according to some predetermined function) that are characteristic of typical ARs. Creep specimens fabricated from 304-grade stainless steel are used to generate validation data in these studies. A schematic of the creep specimens used is shown in Fig. 2(b).

Figure 2. (a) Creep test system for prognostic algorithm validation, (b) stainless steel specimen schematic (dimensions in mm: 50.8 × 50.8 × 6.35) used for accelerated thermal creep experiments, and ultrasonic sensor locations along the axial direction of the specimen.
The test bed allows specimens to be removed after a defined amount of time and measured using advanced NDE techniques [20]. Specimens can be re-inserted for inducing additional creep damage if needed. Measurements include ultrasonic, eddy current, magnetic Barkhausen, and creep-strain measurements that provide the true state (level of accumulated creep strain). Initial (or baseline) measurements using multiple NDE methods were completed on several creep specimens, including on a specimen set aside as a reference or verification standard. The relative change in the measurements provides an understanding of the sensitivity of the NDE technique, and can be related back to the level of accumulated creep strain in the specimen. Note that inferring the present state of material degradation from the measured sensor response is equivalent, in the case of creep damage, to estimating the level of accumulated creep strain in the specimen. For this reason, we used the measured creep strain measurements directly for the purposes of evaluating the prognostics algorithms.

V. RESULTS AND DISCUSSIONS

Fig. 3(a) shows the experimental strain measurements obtained from accelerated thermal aging of a stainless steel specimen. The strain values are calculated from the measured longitudinal displacements of the crosshead of the load frame [shown in Fig. 2(a)] divided by the gage length of the specimen. The measured strains were observed to rise quite rapidly during the first two hours of testing as the specimen temperature and applied load increased to their final values, and the specimen was exposed to steady temperatures and loads. Data from this time period was discarded for the prognostic analysis in this study. After this stage, natural creep progression follows, with the primary and secondary stages of creep damage seen in the data. Specifically, it can be observed from Fig. 3(a) that there are two distinct stages of creep progression—a rapid increase in creep strain until about 4 hours into the test, followed by a somewhat linear increase in strain after that until the end of the data set at 15 hours. For the purposes of this study, the creep strain after 15 hours is assumed to indicate end-of-life, based on this test duration (additional studies beyond this limit are ongoing).

The end-of-life threshold for creep strain at t = 15 hours is shown in Fig. 3(b). Fig. 3(b) also shows strain measurements selected at an interval of one hour, which will be used as the intermittent measurements for updating Degradation Model predictions. The figure also shows the model-fits from two distinct Degradation Models for characterizing primary and secondary stages of creep progression [21, 22]. Model parameters are fitted with the experimental strain measurements and can be mathematically described as:

- **Primary stage (Degradation Model 1):**
  \[ \dot{\varepsilon} = a_1 \left[ 1 - \exp(-a_0 k) \right]; \quad t < 6; \quad a_1 = 0.0012; \quad a_0 = 0.7936. \]

- **Secondary stage (Degradation Model 2):**
  \[ \dot{\varepsilon} = a_1 k + a_0; \quad 4 < t; \quad a_1 = 0.0756e - 3; \quad a_0 = 0.9757e - 3. \]

It should be mentioned that the experiments were not carried out until failure of the specimen. As a result, the tertiary stage of creep damage (rapid accumulation of creep strain leading to failure) is not observed from the experimental data.

To validate the algorithms, we examined the process uncertainty by varying the model parameters for both primary and secondary stages of creep progression. The shaded regions in Figs. 3(c) and 3(d) are obtained by random sampling from the following assumed distribution of the model parameters.

- **Primary stage (Degradation Rate Model 1):**
  \[ \{a_1, a_0\} \sim N(0, \sigma_{\text{primary}}^2); \quad \sigma_{\text{primary}} = 1.5 \times 10^{-3}. \]

- **Secondary stage (Degradation Rate Model 2):**
  \[ \{a_1, a_0\} \sim N(0, \sigma_{\text{secondary}}^2); \quad \sigma_{\text{secondary}} = 5 \times 10^{-4}. \]

As can be observed, most of the experimental data (>95%) lies within the shaded region in Figs. 3(c) and 3(d). Thus, these distributions may be used to characterize process uncertainty in the primary and secondary stages of creep progression.

The automatic RJMCMC algorithm as described in [10, 11] is used to obtain posterior probabilities for the two Degradation Rate models described above, based on experimental measurements of creep strain. The model transition probabilities are assumed to be equally likely from any model to any other model:

\[ \text{Model Transition Probability: } T = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix} \]  \hspace{1cm} (3)

Further, we assume that the prior probabilities for each model are uninformative:

\[ P_{\text{Primary}} = 0.5; \quad P_{\text{Secondary}} = 0.5 \]  \hspace{1cm} (4)

Given this problem setup, the parameters used for the MCMC and particle filter are as follows. The total number of samples in the Markov chain \( N_{\text{total}} \), and the number of burn-in samples, \( N_{\text{burn}} \), at each measurement time index \( k \) are set to 75000 and 25000, respectively. Failure of the material due to high-temperature creep is assumed to occur when the accumulated creep strain reaches or exceeds 3.75%; we further assume that this level of creep strain occurs at the end of the secondary stage at \( t = 15 \) hrs.

Fig. 4 shows the state trajectories obtained using the particle filtering approach based on the sampling importance resampling (SIR) algorithm [5] with 2000 particles, when integrated with the Degradation Rate model selection and averaging procedure. The measurement and process noise terms are assumed to be zero-mean Gaussian distributions. Figs. 4(a), (b), and (c) show the predicted trajectories of creep progression as intermediate measurements become available. Fig. 4(d) shows the estimated trajectory using all available data. The state trajectory is observed to be influenced by each new available measurement; this is likely due to relatively small measurement noise term as compared to the process noise term. This causes the particle filter algorithm to place higher confidence on the measurements rather than on the Degradation Rate (process) models. The shaded area in Fig. 4...
represents the 95% credibility intervals as estimated using the modified particle filtering algorithm.

![Figure 3](image-url)

**Figure 3.** (a) Experimental strain measurements on stainless steel specimen under accelerated thermal creep, (b) strain measurements for model prediction update and identified creep models, process uncertainty quantification for (c) primary stage, and (d) secondary stage.

Fig. 5 shows the posterior probabilities of the two Degradation Rate models after each available measurement. The posterior probabilities are shown for two different levels of noise, to determine the sensitivity of the model selection procedure to various uncertainties. Also shown are the RUL values, which are estimated by taking the difference between the time index corresponding to the current measurement and the time index when the creep strain is estimated to reach end of life.

The posterior probabilities indicate the ability of the proposed approach to identify the appropriate model, and account for various uncertainty levels. Because the true time to failure is known (15 hours, in this example), the error in the estimated RUL may be used as an indicator of the performance of the algorithm. Results from the present data set indicate that the algorithm overestimates the RUL somewhat (as seen in Figs. 5(c) and (d); however, the error in RUL appears to be a function of the amount of uncertainty in the data, with higher levels of noise (uncertainty) introducing higher uncertainty into the estimated RUL [Figs. 5(b) and (d)]. Thus, accurate characterization of process uncertainties and measurement noise is important for reliable and robust performance of prognostics algorithms.

**VI. CONCLUSIONS**

This paper describes a Bayesian framework based Degradation Rate model selection approach for predicting material degradation evolution over time using available measurements. An automatic RJMCMC procedure along with an SIR-based particle filtering algorithm is proposed in this paper. The framework is evaluated using strain measurements obtained on stainless steel specimens subjected to high-temperature creep. A laboratory-scale test bed has been built for obtaining data for evaluating (and eventually validating) prognostic algorithms. Results to date using this data indicate that the proposed Bayesian framework can be used to identify distinct stages of creep progression. However, the accuracy of the prognostic result is dependent on the ability to quantify the sources of uncertainties within the Measurement model and Degradation Rate model used within the Bayesian prognostic methodology. Additional evaluation using nondestructive measurement data sets from the test bed is ongoing. Future work will examine extending this work to prognostics when multiple, competing physical models are present at each stage of damage progression. Further, future research will also explore the ability to integrate prognostic results from multiple PHM systems to estimate the health of the overall component or subsystem.
Figure 4. Creep strain progression estimated using model averaging procedure and SIR particle filtering algorithm, with (a) 2 measurements, (b) 3 measurements, (c) 8 measurements, and (d) measurements till threshold. Process noise: $\mathcal{N}(0, \sigma_{\text{process}}^2); \sigma_{\text{process}} = 1e-4$, Measurement noise: $\mathcal{N}(0, \sigma_{\text{measurement}}^2); \sigma_{\text{measurement}} = 5e-5$. 
Figure 5. Model posterior probabilities for two models 'Model 1': Primary stage, 'Model 2': Secondary stage and RUL estimation for different process and measurement noise terms; (a) and (c) Process noise: $N(0, \sigma^2_{\text{process}}); \sigma_{\text{process}} = 1e-4$, Measurement noise: $N(0, \sigma^2_{\text{measurement}}); \sigma_{\text{measurement}} = 5e-5$; (b) and (d) Process noise: $N(0, \sigma^2_{\text{process}}); \sigma_{\text{process}} = 1e-4$, Measurement noise: $N(0, \sigma^2_{\text{measurement}}); \sigma_{\text{measurement}} = 5e-5$.

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