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A Generic Bayesian Approach to Real-Time Structural Health Prognostics

Byeng D. Youn[1] and Pingfeng Wang[2]
Department of Mechanical Engineering, University of Maryland at College Park
College Park, MD 20742, USA

This paper presents a decision-centered lifetime and reliability prognostics using a generic Bayesian framework. This generic Bayesian framework models and updates sensory degradation data, remaining life, and reliability using non-conjugate Bayesian updating mechanism. Thus, it continuously updates lifetime distributions of degraded system in real-time. Furthermore, the generic Bayesian framework eliminates dependency of evolutionary updating process on a selection of distribution types for the parameters of a sensory degradation model. The Markov Chain Monte Carlo (MCMC) technique is employed as a numerical method of non-conjugate Bayesian updating framework. While accounting for variability in loading conditions, material properties, and manufacturing tolerances over the population of system samples, different reliabilities will be identified for different samples. So, reliability distribution for an engineering system can be obtained and updated in a Bayesian format. The proposed Bayesian methodology is generally applicable for different degradation models and prior distribution types. The proposed methodology is successfully demonstrated with 26 resistors for the lifetime and reliability prognostics.

I. Introduction

To support critical decision-making processes such as maintenance replacement and product design, engineering systems composed of multiple components, complex joints, and various materials, such as distributed manufacturing facilities, electronic devices, advanced military systems, require sensory health monitoring and prognosis [1]. While interpreting data acquired by smart sensors and distributed sensor networks, and utilizes these data streams in making critical decisions, research on real-time diagnosis and prognosis which provides significant advancements across a wide range of application. Maintenance and life-cycle management is one area that is positioned to significantly benefit in this regard due to the pervasive nature of design and maintenance activities throughout the manufacturing and service sectors. Maintenance and life-cycle management activities constitute a large portion of overhead costs in many industries [2]. These costs are likely to increase due to the rising competition in today's global economy. In the manufacturing and service sectors, unexpected breakdowns can be prohibitively expensive since they immediately result in substantial risks (e.g., lost production, substantial maintenance cost, and poor customer satisfaction). In order to reduce and possibly eliminate such risks, it is necessary to accurately assess the current state of system degradation and precisely evaluate the remaining life of degrading components. Two major research areas have tried to address these challenges: reliability analysis and condition monitoring. Although reliability analysis and condition monitoring are seemingly related, reliability analysis focuses on population-wide characteristics while condition monitoring deals with component-specific properties. Furthermore, both fields of research have evolved separately. Research in the reliability analysis area can be broadly classified into two subcategories. One category focuses on quantification of reliability and statistical analysis of time-to-failure data, such as [3]–[5] while the other deals with the development of physics-based models (e.g., fatigue, wear, corrosion) and finite-element methods aimed at reliability-based design optimization (RBDO) [6-9]. In contrast, condition monitoring research uses sensory information from functioning system to assess their degradation states. Some of the applications of condition monitoring include condition monitoring of bearings [10]–[12], machine tools [13], transformers [14], engines [15], and turbines [16] among many others. Most of the research in this field focuses on system diagnosis and fault classification. Some research utilizes condition monitoring information for performing prognosis [17]–[21]. However, these efforts focus on the characterizing individual

[1] Assistant professor, corresponding author, bdyoun@umd.edu.
[2] Graduate Student, pfwang@umd.edu.

components with little or no utilization of reliability information.

This paper presents a decision-centered lifetime and reliability prognostics using a generic Bayesian framework. This decision-centered prognostics framework will benefits both maintenance and product design decisions by providing highly confident lifetime and reliability information. This generic Bayesian framework models and updates sensory degradation data, remaining life, and reliability using non-conjugate Bayesian updating mechanism. The lifetime prognostics tool continuously updates lifetime distributions of degraded system in real-time. The decision-centered prognostics tool takes into account variability over the operational time and population of samples. The variability over time is due to unpredictability in future sensory data at a given time and measurement errors, whereas that over the population results from uncertainties in material properties, manufacturing tolerances, and loading conditions. While considering the variability over the operational time, remaining life distribution for a single sample of the system can be continuously updated in real-time. Non-conjugate Bayesian updating is proposed to eliminate dependency of evolutionary updating process on a selection of distribution types for the parameters of a sensory degradation model. The Markov Chain Monte Carlo (MCMC) method is employed for the numerical method of non-conjugate Bayesian updating framework. While accounting for variability in loading conditions, material properties, and manufacturing tolerances over the population of system samples, different reliabilities will be identified for different samples. So, reliability distribution for an engineering system can be obtained and updated in a Bayesian format. The proposed Bayesian methodology is generally applicable for different degradation models and prior distribution types. The proposed methodology is successfully demonstrated with 26 resistors for the lifetime and reliability prognostics.

II. Related Work

In this section, relevant literature related to system degradation modeling and real-time life and reliability prognostics will be reviewed. The goal of real-time health prognostics is to predict the remaining life of a system (or component) based on a real time health condition. For that purpose, a stochastic degradation model must be developed to model system degradation and predict the remaining life in a statistical manner. The degradation model contains a multiple of stochastic parameters and they will be continuously updated in real time.

In the literature, different stochastic degradation models have been developed to model various degradation phenomena of systems or components. Doksum and Hoyland [22], Lu [23], and Whitmore *et al*. [24] used a Wiener diffusion process for a degradation model. In this approach, it is assumed that one key degradation measure governs failure and takes the statistical model to be a Wiener diffusion process $\{W(t)\}$ with statistical parameters, mean and variance. Bagdonavicius and Nikulin [25] modeled the degradation by a Gamma Process and include possibly time-dependent covariates. In their study, the influence of covariates on degradation was modeled and estimation of reliability and degradation characteristics from data with covariates was considered. Lu and Meeker [26], Boulanger and Escobar [27], Tseng, Hamada and Chiao [28], Hamada [29], Chiao and Hamada [30], and Meeker, Escobar and Lu [31] considered degradation path models. Degradation in these models is modeled by the process $S(\mathbf{u},t)$, where t is time and $\mathbf{u}$ is a multidimensional random vector. By fitting the model parameter vector $\mathbf{u}$ with the degradation data measured, the lifetime and reliability of the systems or components were then studied. Suzuki, Maki and Yokogawa [32] used linear degradation models to study the increase in a resistance measurement over time. Dowling [33], Meeker and Escobar [34] used convex degradation models to study the growth of fatigue cracks. Meeker and Escobar [34] also used concave degradation models to study the growth of failure-causing conducting filaments of clorine-copper compound in printed-circuit boards. Carey and Koenig [35] used similar models to describe degradation of electronic components. Lu and Meeker [34] developed an exponential pattern model to study the life distribution over a population of components, and recently, Gebraeel et, al. [18] applied similar exponential pattern degradation with stochastic process of modeling random error term to study the residual life of single operating device of ball bearings. Besides the stochastic degradation models, some models are developed based on the artificial intelligent technique. Chinnam [36] presents a neural network based model for online estimation of component reliability. Gebraeel et, al. [37] also used the neural network based approach to study the component remaining life distribution and applied on the case study of rolling bearing prognostics.

Once the degradation model is obtained for a given degradation signal, health prognostics of systems or components can be further studied. Lu and Meeker [26] considered the case in which the life distribution of a population of devices is to be computed using degradation information obtained from a randomly selected set of devices and illustrated various methods for computing life distributions with various random coefficient models. Tseng *et al.* [28] combined random coefficient models for luminosity degradation with experimental design to identify manufacturing settings that provide slow rates of luminous degradation of fluorescent lamps. Doksum and Hoyland [22] developed a maximum likelihood estimator of inverse Guassian life models for units subject to accelerated stress testing. In their study, accumulated decay is modeled as a Wiener process with drift and diffusion dependent on and changing with the stress level. They illustrated how to use test data to estimate the mean life under normal stress levels. Whitmore and Schenkelberg [38] used a Wiener process to model degradation data collected from accelerated testing, developed methods for estimating the parameters of time and stress transformations and apply their methods on a case study on self-regulating heating cables. Lu *et al.* [39] presented methods for forecasting system performance reliability for systems with multiple failure modes. In their investigation, time series forecasting was used to develop a joint density function for the performance measures. This joint density is then integrated to obtain a reliability function that can be used to assess the system reliability. Lu *et al.* [40] developed a method for real-time estimating the conditional performance reliability for an individual operating component. In their study, sampled measurements are treated as a realization of a stochastic process, and exponential smoothing is used to develop a conditional distribution of the performance variable.

Although different methods have been developed for the purpose of prognostics as listed above, they are all model dependent and only applicable for certain or few degradation models being used. In this paper, a generic Bayesian framework for decision-centered lifetime and reliability prognostics is developed, which employs the non-conjugate Bayesian updating technique and is generally applicable to any stochastic degradation models with random model parameters. For demonstrative purpose, we employ a quadratic exponential pattern degradation model modified from Gebraeel *et al.* [37] and Lu *et al*. [26]. In the study of Gebraeel *et al.* [37], the Bayesian semi-conjugate updating model is used for updating the model parameters and the predicted remaining life distribution has its closed analytical form due the intentionally constructed conjugate properties of the Bayesian updating model. However, there are two obvious drawbacks of this approach. First, prior distributions for the model parameters must be specified as certain distribution types, for example, lognormal distribution and normal distributions, to guarantee the conjugate property to be held. This specification of prior distributions will substantially limit the application of this approach. Second, since the posterior distribution of the model parameters have strong correlation, the updating mechanism can only be applied once and thus cannot be applied for real-time applications.

To make the Bayesian updating technique generally applicable to a broad range of engineering problems, the generic Bayesian framework employs a non-conjugate Bayesian updating mechanism with Markov Chain Monte Carlo (MCMC) technique. The proposed methodology is able to predict the remaining life distribution at any time of early degradation stage and to update the distribution in real time with continuously evolving signals. The reliability of the system or components considering the population variability is evaluated at an early degradation stage and updated with more testing specimens involved. Details of the proposed method will be discussed in the next section with the modified exponential pattern model as an example.

III. A Generic Bayesian Framework for Prognostics and Health Management

To consistently model diverse degradation signals from different engineering applications, the generic Bayesian framework is proposed in this section. This framework uses non-conjugate Bayesian updating to eliminate dependency of evolutionary updating process on a selection of distribution types in the sensory degradation data model. The MCMC method will be employed for the numerical method of non-conjugate Bayesian updating framework.

A. Bayesian Updating

As mentioned previously, the degradation signals can continuously be obtained either through embedded sensor network or online monitoring facilities. To effectively extract the valuable information about the health condition of the monitored components or systems, the generic Bayesian framework employs the Bayesian technique for updating the model parameters with evolving sensory degradation signals. This subsection gives a brief introduction of the Bayesian updating technique.

Let X be a random variable with probability density function $f(x, \theta)$, $\theta \in \Omega$. According to the Bayesian point of view, θ is interpreted as a realization of a random variable Θ with a probability density $f_\Theta(\theta)$. The density function expresses what one thinks about the occurring frequency of Θ before any future observation of X is taken, that is, a prior distribution. Based on the Bayes' theorem, the posterior distribution of Θ given a new observation X can be expressed as

$$f_{\Theta|X}(\theta \mid x) = \frac{f_{X,\Theta}(x,\theta)}{f_X(x)} = \frac{f_{X|\Theta}(x \mid \theta) \cdot f_\Theta(\theta)}{f_X(x)} \tag{1}$$

The Bayesian approach is used for updating information about the parameter θ. First, a prior distribution of Θ must be assigned before any future observation of X is taken. Then, the prior distribution of Θ is updated to the posterior distribution as the new data for X is employed. The posterior distribution is set to a new prior distribution and this process can be repeated with evolution of data sets. This updating process can be briefly illustrated in Fig.1.

To update the degradation model parameters using the Bayesian updating technique, the likelihood function $f_{X|\Theta}(x|\theta)$, which combines a new degradation signal with the prior information of model parameters, is quite essential. However, for algebraic convenience, existing researches mostly focus on seeking the conjugate or semi-conjugate models [22, 23]. Conjugate models of Bayesian updating are quite valuable for uncertainty modeling with continuously evolving signals due to its closed form of the posterior distribution. However, only limited conjugate or semi-conjugate models are available and, thus, updating results strongly depend on selection of the models. To overcome such difficulty, non-conjugate Bayesian updating framework must be developed but its computation is quite complicated. The MCMC methods will be used for the non-conjugate Bayesian updating procedure, which will be introduced in the later subsection.

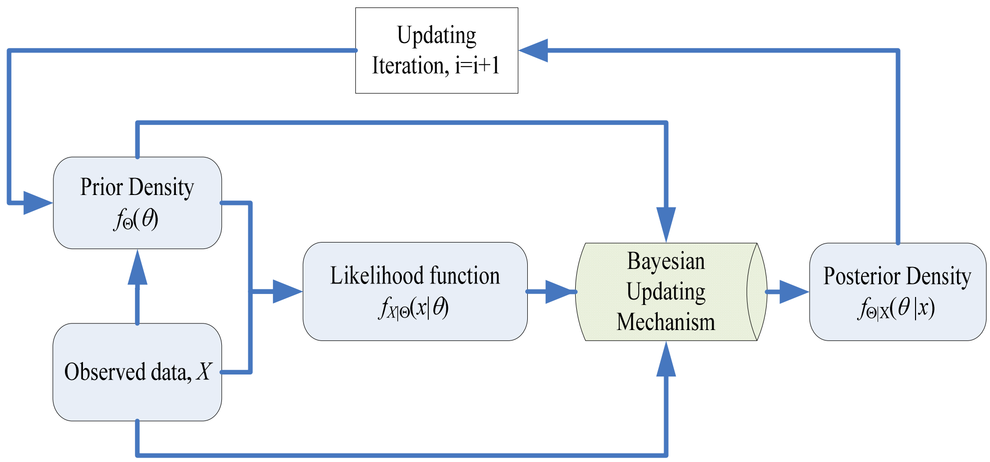

Fig. 1 Process of Bayesian Updating

B. A Generic Bayesian Framework

As shown in Fig. 2, the generic Bayesian framework contains three critical steps: (1) updating the model parameters based on the prior information and a new sensory degradation signal; (2) updating the lifetime distribution; (3) updating the reliability distribution. The framework is illustrated in Table 1.

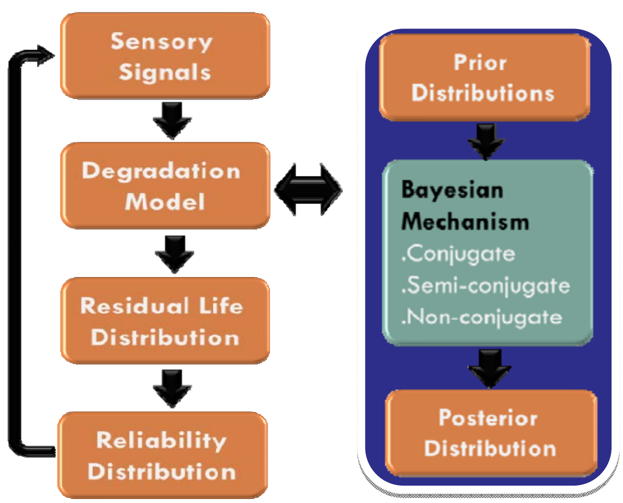

Fig. 2 A Generic Bayesian Degradation Prognostics Framework

Table 1 Procedure of the Decision-Centered Prognostics

STEP1	Selecting an appropriate degradation model and specifying model parameters and prior distributions
STEP2	Building a likelihood function with the prior distributions and new sensory signal
STEP3	Updating the joint probability distributions of the model parameters with a prior model information and degradation signals by non-conjugate Bayesian updating technique
STEP4	Updating the lifetime distribution based on the updated degradation model parameters
STEP5	Calculating the reliability of component (or system) life due to the variability of the test samples.

Note that Step 2 to Step 4 can be repeated until the lifetime distribution can be continuously updated with the evolving degradation signals. In the following, the detail procedure will be explained with an exponential degradation family. For the demonstration purpose, a quadratic exponential degradation model can be used as

$$S(t_i) = S_0 + \delta \cdot \exp(\alpha t_i^2 + \beta t_i + \varepsilon(t_i) - \frac{\sigma^2}{2}) \tag{2}$$

where $S(t_i)$ represents the degradation signal at time t_i; S_0 is a known constant; δ, α, and β are stochastic model parameters and ε represents the random error term which follows normal distribution with zero mean and σ^2 deviation.

Step 1: Prior distributions are required to be specified for the model parameters δ, α and β. Gebraeel *et al.* [36] successfully applied the Bayesian updating technique to the similar model by constructing a semi-conjugate Bayesian updating model. By assuming that δ and β follow lognormal and normal prior distributions, respectively, normal posterior distributions for both δ' and β with a certain correlated coefficient will be obtained through the Bayesian updating process, where $\delta'=\ln\delta - \sigma^2/2$. As the model parameters were updated, the degradation signal $S(t_i)$ is proven to be a normal distribution and the lifetime distribution can then be obtained if a failure threshold D is predetermined.

Although the semi-conjugate Bayesian updating model constructed by Gebraeel *et al.* [18] can simplify the computation for the posterior distribution and thus obtain a closed form remaining life distribution, however, there are two obvious drawbacks of this approach. First, prior distributions for the model parameters must be specified as certain distribution types, for example, lognormal distribution and normal distributions, to guarantee the conjugate property to be held. This specification of prior distributions will substantially limit the application of this approach. Second, since the posterior distribution of the model parameters have strong correlation, the updating mechanism can only be applied once and thus cannot be applied for real-time applications. To make it generic to update the degradation models, different prior distributions may be preferred for different model parameters. In such situations, non-conjugate Bayesian updating framework is more desirable because it can update parameter distributions for any given prior distributions.

Step 2: For the purpose of demonstration, the model in Eq. (2) is considered. It is more convenient to work with the logged signal at time t_i which will be denoted as $L(t_i)$, as

$$\begin{aligned} L(t_i) &= \ln(S(t_i) - S_0) = \ln\delta - \frac{\sigma^2}{2} + \alpha t_i^2 + \beta t_i + \varepsilon(t_i) \\ &= \delta' + \alpha t_i^2 + \beta t_i + \varepsilon(t_i) \end{aligned} \tag{3}$$

where $\delta'=\ln\delta - \sigma^2/2$. Suppose a new sensory signal, $L_i = L(t_i)$, be observed as $L_1, L_2, \ldots, L_k$ at times $t_1, t_2, \ldots, t_k$. Since the error terms, $\varepsilon(t_i)$, i= 1,2, …, k, are iid normal random variables, the following likelihood function can be obtained for given observations as

$$\begin{aligned} & f\left(L_1, L_2, \cdots, L_k \mid \delta', \alpha, \beta\right) \\ & \sim \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^k \cdot \exp\left(-\sum_{i=1}^{k}\left(\frac{L_i - \delta' - \beta t_i - \alpha t_i^2}{2\sigma^2}\right)\right) \end{aligned} \tag{4}$$

Step 3: If the prior distributions for δ', α and β are provided, for example, $\pi_0(\delta', \alpha, \beta)$, the joint posterior distribution for these parameters can be expressed as

$$f\left(\delta^{'},\alpha,\beta\,|\,L_1,L_2,\cdots,L_k\right)$$
$$\sim\left(\frac{1}{\sqrt{2\pi}\sigma}\right)^k\cdot\exp\left(-\sum_{i=1}^{k}\left(\frac{L_i-\delta^{'}-\beta t_i-\alpha t_i^2}{2\sigma^2}\right)\right)\times\pi_0\left(\delta^{'},\alpha,\beta\right) \tag{5}$$

As shown in Eq.(5), the posterior joint distribution of model parameters δ', α, and β strongly depends on selection of the joint prior distributions $\pi_0(\delta', \alpha, \beta)$. Thus it is not reasonable to use a conjugate or semi-conjugate Bayesian model, which gives a closed form posterior distribution for each parameter. In this circumstance, non-conjugate Bayesian updating framework is more desirable because it can update parameter distributions for any given prior distributions. The MCMC method can generate N sets of Markov Chain samples for the stochastic model parameters from the joint posterior distribution in Eq. (5).

Step 4: The life distribution information can be obtained when a failure threshold D is specified for the degradation signal. By plugging N sets of parameters data, the life data can be determined by solving the N sets of quadratic equations as

$$T_i=\text{roots}\left(\alpha T^2+\beta_i T+\delta^{'}_i+\varepsilon_i-D=0\right)$$
$$i=1,2,...,N. \tag{6}$$

When predicting the system life using Eq. (6), the random error term, ε, should not be ignored. Moreover, the life T_i is the positive real root of the quadratic equation. The sample size, N, can be increased because solving the quadratic equation in Eq. (6) N times is trivial. The life data, T_1, T_2, …, T_N, can be used for creating the life distribution. As sensory signal evolves over time, the life distribution can be updated in real-time by repeating Step 2 to Step 4.

Step 5: The reliability of the component or system can be calculated when the lifetime distributions are obtained with multiple testing specimen. As most life distributions are obtained, the generic Bayesian framework is used for updating reliability distribution of the component or system.

C. Markov Chain Monte Carlo (MCMC) Method

It is extremely difficult to compute the exact analytical form of the posterior distribution for the model parameters since the normalization factor (the denominator in Eq. (1)) of the posterior distribution requires complicated and multi- dimensional integration. Although it is hard to obtain the posterior distribution directly, it is feasible to draw relevant samples. So, MCMC method provides a mechanism to draw samples from the complicated posterior distribution. This study uses the Metropolis-Hastings algorithm for MCMC method. The algorithm generates a Markov chain in which each state X^{t+1} for δ', α and β depends only on the previous state X^t. The algorithm also uses a proposal density $Q(X', X^t)$, which depends on the current state X^t, to generate a new state X'. This proposal is 'accepted' as the next value ($X^{t+1} = X'$) if u drawn from $U(0,1)$ is satisfied. The MCMC method for non-conjugate Bayesian model is summarized in Table 2. More details regarding MCMC can be found in ref. [41].

Table 2 MCMC Method for Non-Conjugate Bayesian Model

Algorithm A Metropolis-Hastings sampler for the quadratic exponential pattern model
(1) Initialization of Parameters, $X^1 = [\delta_0, \alpha_0, \beta_0]$, set t =1.
(2) Propose $X' = Q(X', X^t)$
(3) Draw $u \sim U(0, 1)$
(4) Calculate $a = \{P(X')\cdot Q(X^t\|X')\}/\{P(X^t)\cdot Q(X'\|X^t)\}$
(5) If $a > u$, $X^{t+1}= X'$; *else*, $X^{t+1}= X^t$
(6) *If* $t<N$, set $t = t+1$, go Step (2); else , stop.

This study uses the multi-variant normal sample generating function for $Q(X', X^t)$ and $P(X)$ is the function proportional to the joint posterior density function in Eq.(5).

IV. Application of Proposed Bayesian Methodology

In this section, we apply the proposed decision-centered prognostics with the quadratic exponential degradation model presented above to the degradation signals of 26 resistors. They have run to failure under accelerated testing conditions. We first briefly describe our experimental setup and experimental data obtained. We then describe how the proposed decision-centered prognostics is implemented to predict life and reliability based on sensory signals, as developed in Section 3. We also evaluate the predictive ability of these models and discuss the results of these experiments.

A. Experiment Setup and Degradation Signals of Resistors

In this study, 26 identical resistors are employed in the accelerated life testing. Figure 3 shows the experiment setup. In this experiment, regulated power supply is used to provide fixed current to the tested resistor and the voltage is measured and recorded by a DAQ system from National Instruments. Voltage signal is measured at frequency of 100 Hz. Data for these 26 tested resistors are shown in Fig. 4.

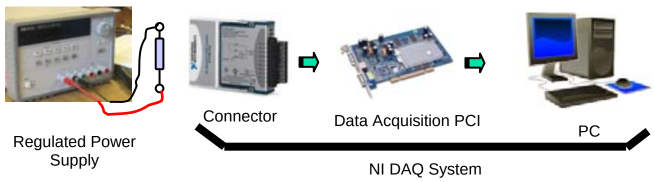

Fig. 3 Experiment Setup for Resistor Degradation Testing

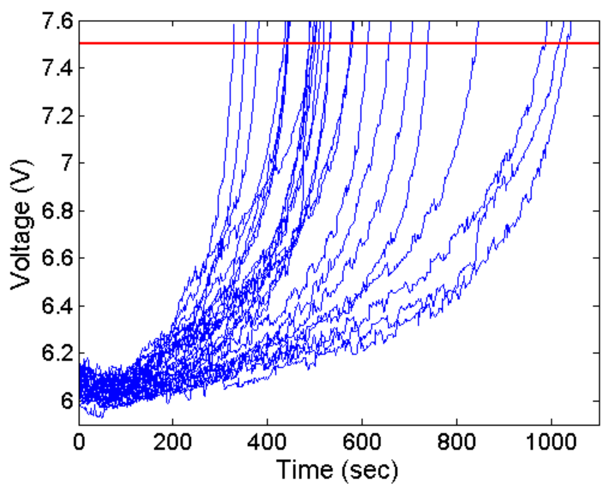

Fig. 4 Degradation Voltage Signal for 26 Tested Resistors

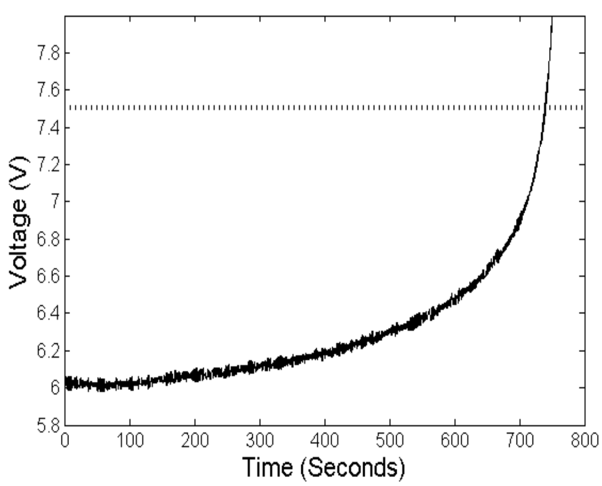

Fig. 5 Voltage Degradation Signal for Resistor 6

B. Life Prognostics

For the prognostics of the resistors, the proposed generic Bayesian framework is applied to a single resistor. The voltage is used for a degradation signal. The threshold of resistor failure is defined to be 7.5 V as shown in Fig 4. The voltage degradation curve for the resistor is shown in Fig. 5 where the dotted line in the figure is the predefined failure threshold $V_f = 7.5$ V.

Prognostics for this resistor are carried out at around 300, 400, 500, 600 and 650 seconds. Figure 6 shows the mean, 5- and 95-percentile predicted remaining life and the true remaining life at different prognostics times. Figure

7 shows the prognostics results with 3 sets of figures. The first figure set in the first row shows the sensory degradation signals (red) at five updating times. The second figure set in the second row shows the Markov chain samples generated from joint posterior distribution of the stochastic parameters, δ' and β. It is evident that the joint posterior distribution is correlated non-Gaussian and the distribution type changes over time. The third figure set in the third row displays the predicted remaining life distributions at five updating times. It is apparent that (1) the predicted remaining life distribution is centered at around the true remaining life of the resistor; (2) the confidence of the life prediction is enhanced as more degradation signals are involved in the prognostics process. In other words, the variation of life distribution is narrower. Finally it converges to the true remaining life when the resistor is close to its time-to-failure.

C. Reliability Prognostics

As shown in Fig. 4, the sensory signals have enormous variability over the population of the testing specimen. Such variability is mainly due to variability in material properties and loading conditions over the population. Therefore, different resistors own different life distributions, which result in. variability results in different reliabilities. However, it is common that the number of the testing specimen is restricted due to limited resources, such as cost, time, and facilities. Due to the lack of reliability data, reliability can be subjective and uncertain. Thus, the Bayesian updating technique can be used for modeling the reliability of the resistors while employing Bayesian binomial inference. The reliability of the resistors is modeled as a beta distribution [42]. All 26 degradation signals of the resistors are employed in this study.

Suppose the resistor is designed to satisfy 400-second life during this accelerated testing. Based on the predicted remaining life distribution from life prognostics at early degradation stage, the reliability for each resistor can be obtained by

$$R_i = \Pr\left(T^{(i)} > 400\right)$$

where $T^{(i)}$ is the time-to-failure (or life) for i^{th} resistor. For this Bayesian updating process, the non-informative prior distribution, which is uniform distribution for reliability over [0, 1], is used. As the reliability prognostics progressively produces the reliability data, R_1, R_2, …, R_N, the posterior distribution is obtained as a Beta distribution with two parameters as

$$\alpha = \alpha_0 + \sum_{i=1}^{N} R_i \quad \beta = \beta_0 + \sum_{i=1}^{N} (1 - R_i)$$

where α_0 and β_0 are the parameters of a prior distribution. For non-informative prior distribution, α_0 =1 and β_0 = 1.

Figure 8 shows the updating process of the reliability distribution while considering progressively more resistors. The first figure set in the first row displays the voltage sensory signals of the resistors being progressively obtained. The second figure set in the second row illustrates the updated reliability distributions with evolving sensory signals. Among 26 resistors, the first four groups are composed of six resistors and then the last group consists of eight resistors. The non-informative prior distribution with the first set of reliability data, R_1, R_2, …, R_6, generates the posterior reliability distribution, which is shown in the first figure of the second row (Fig. 8). Repeating Step 2 to Step 5 progressively updates the reliability distribution continuously, as shown in Fig. 8.

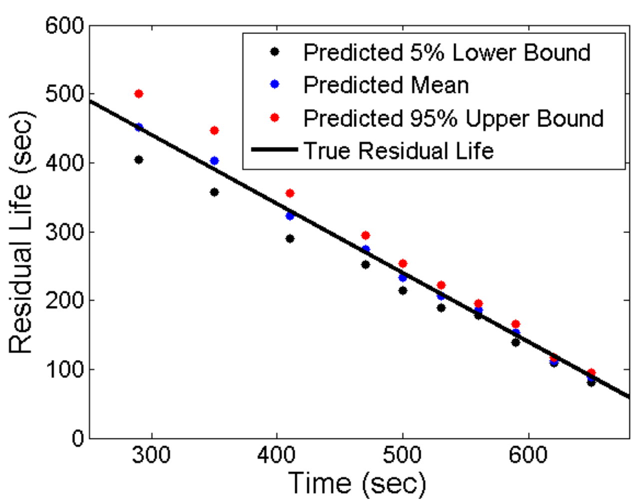

Figure 6 Predicted Residual Life and Actual Resistor Residual Life

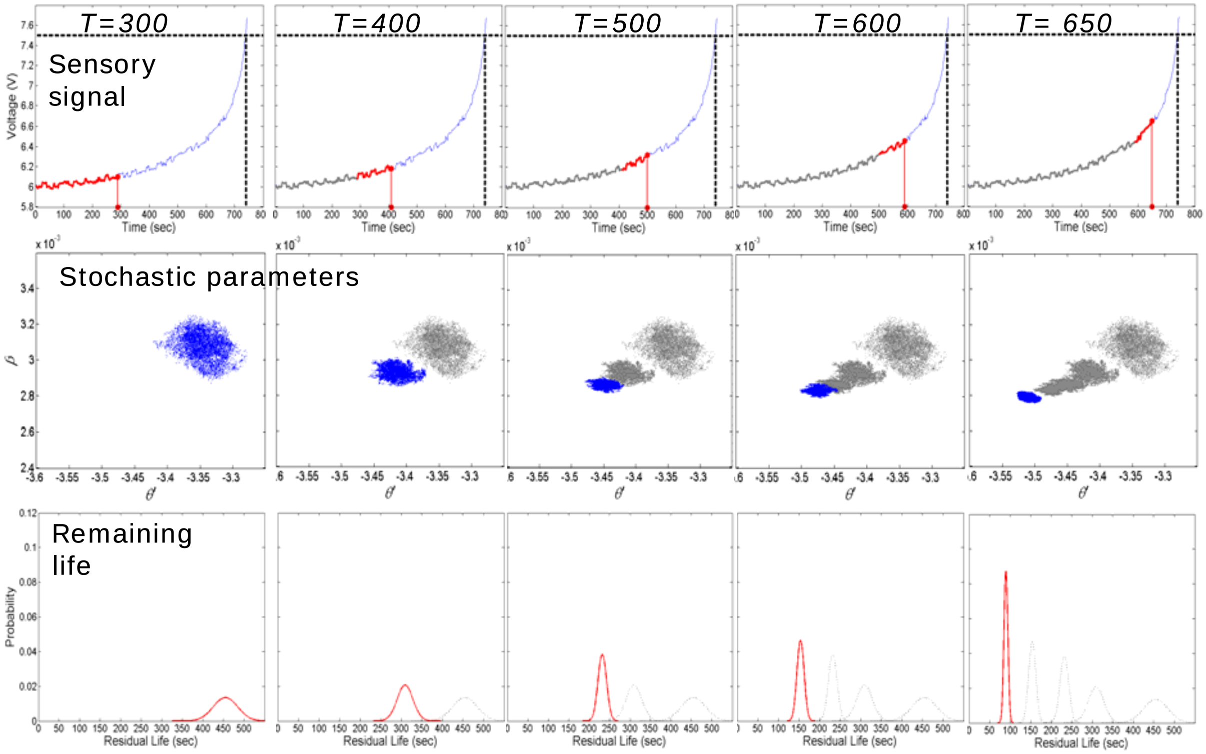

Figure 7 Real-Time Prognostics Results for the Sixth Resistor Degradation Signal

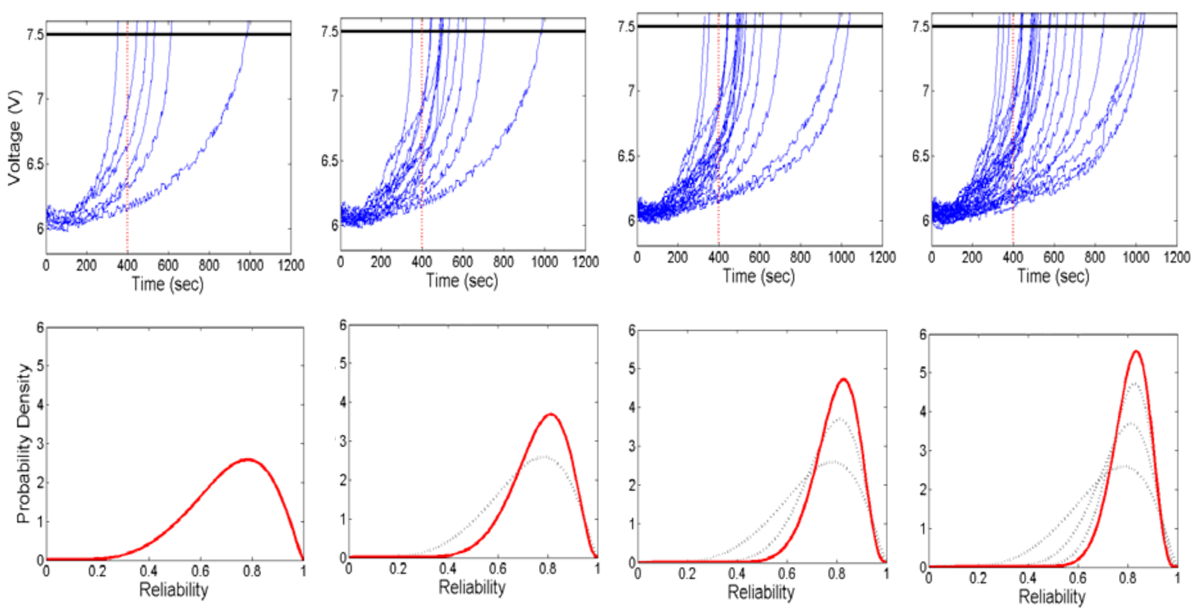

Fig. 8 Reliability Updating Considering Population Variability of Resistors

V. Conclusion

This paper presents a decision-centered health prognosis for confident life and reliability prediction of engineering components or systems. The decision-centered health prognosis is composed of two prognostics tools: (1) life prognostics and (2) reliability prognostics. For these prognostics tools, a generic Bayesian framework is proposed, which models a sensory degradation signal, predicts remaining life and reliability in real-time. Non-conjugate Bayesian updating mechanism is proposed for the life prognostics tool, whereas conjugate mechanism is used for the reliability prognostics tool. This technique enables to eliminate dependency of the evolutionary updating process on selection of distribution types for the parameters of sensory degradation model. The MCMC method is employed for non-conjugate Bayesian updating mechanism. While accounting for variability in loading conditions, material properties, and manufacturing tolerances over the population of system samples, different reliabilities will be identified for different samples. However, it is expected that reliability data is insufficiently given due to limited testing resources. So, reliability distribution for a system can be obtained and updated in a Bayesian format. Although the quadratic exponential degradation model is employed in this study, the proposed generic Bayesian framework for degradation signal modeling, remaining life prediction, and reliability evaluation is generally applicable for different degradation models and prior distribution families. The proposed methodology is successfully demonstrated with 26 resistors for the life and reliability prognostics.

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