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Prognostics uncertainty reduction by fusing on-line monitoring data based on a state-space-based degradation model

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ABSTRACT

The objective of this study is to develop a state-space-based degradation model and associated computational techniques to reduce failure prognostics uncertainty by fusing on-line monitoring data. A key problem in failure prognostics for an individual system under actual operating conditions is uncertainty management. In this study, the various uncertainty sources in failure prognostics are analyzed, and an appropriate uncertainty quantifying and managing mechanism is proposed, accounting for both the item-to-item variability and the degradation process variability. The method is demonstrated on a crack growth data set, and the results show that the proposed prognostics method has the ability to provide a failure time prediction with less uncertainty by fusing sensor data, which are beneficial for risk assessment and optimal maintenance decision-making.

1. Introduction

Modern engineering systems, such as aero engines and nuclear power plants, must be run safely and economically throughout their entire life cycles. As a result of intense financial pressure on life cycle cost (LCC), much attention is being paid to the operational and support activities that contribute to a large portion of the life cycle total ownership cost. In this climate, the industrial and military communities are concerned with a system's Residual Useful Life (RUL) under actual operating conditions or in-service reliability, with the goals of maximizing equipment up-time and minimizing maintenance and operating costs [1,2].

Prognostics usually focuses on the prediction of the failure time or the Remaining Useful Life (RUL) of a system or component in service by analysis of data collected from sensors. In a statistical manner, the failure time distribution (probability density of the failure time) may be estimated first, then any other reliability indexes or RUL can be obtained at the basis of the failure time distribution. Failure can be defined as the point in time when the system degradation reaches a predefined level. This definition makes it possible to use a degradation model to make inferences about failure time.

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However, regardless of how well we know a system, failure time is random, and the prediction of failure has some uncertainty arising from the system's materials, environment, and loading variability. A trustworthy failure time prediction with less uncertainty would be preferred for risk-based decision making for maintenance or replacement in operation. Inappropriate uncertainty quantifications and representations will reduce the value of failure prognostics. Therefore, a key issue in prognostics is to quantify and manage the uncertainties inherently associated with failure time prediction [3–5]. Here, we use the phrase "manage uncertainty" to refer to our attempt to reduce uncertainty by using sequentially available health monitoring data [3].

The uncertainty associated with the stochastic degradation process has been addressed in the field of structure reliability analysis [6–8]. First-/second-order reliability methods have been used to compute the failure probabilities. Additionally, manual inspection results have been included in the model through Bayesian updating [9,10]. In practice, many system failures can be linked to an underlying physical or chemical degradation process, such as fatigue crack growth, corrosion, or wear [11,12]. Direct monitoring or measuring of the hidden degradation state is difficult, or even impossible in some cases. However, with the advance of on-line condition monitoring technologies, such as the emerging Structure Health Monitoring (SHM), other on-line monitoring data, which are statistically related to the unobservable degradation state, may be available. Compared to manual inspections, on-line condition monitoring system may provide frequent observations of a system by an array of sensors, allowing us to determine the current health state of the system as well as to reduce the prognostics uncertainty by fusing the mass of on-line monitoring data.

The objective of the paper is to develop a mechanism to reduce the system failure prognostics uncertainties by fusing the noisy on-line monitoring data available. It will focus on identifying the latent degradation process of an individual system under actual operating conditions using sensor data, followed by statistically predicting the degradation trend as well as the failure time. In this framework, we use a State-Space Model (SSM) to model the stochastic degradation process with observation information. Some research on state-space-based degradation models has already been developed for residual life prognostics [13–20]. The use of an SSM and a stochastic filtering technique for condition-based maintenance applications was initially proposed by Wang [13,14]; then it was further explored for engine wear prediction with oil-based monitoring data [15,16]. Myotyri et al. [17] used a discrete SSM to predict the remaining lifetime of a component using condition monitoring measurements. Cadini et al. [18] extended Myotyri's work by adopting a continuous SSM to estimate the failure probability of a component subject to degradation for condition-based component replacement. Both Myotyri et al. and Cadini et al. assumed that model parameters were known and did not discuss parameter estimation issues. Orchard and Vachtsevanos proposed an on-line particle-filtering-based framework for fault diagnosis and failure prognosis based on a nonlinear SSM [19]. Zhou et al. [20] developed Monte Carlo-based algorithms to estimate the SSM parameters and remaining useful life. However, the uncertainty associated with the parameters was often ignored and the mean values of the estimated parameters were adopted for degradation prediction [19,20]. In fact, there is always some degree of uncertainty regarding the unknown parameters, depending on the sample size. The use of a probability distribution to quantify the knowledge about these parameters would be better than simply assuming that they are known deterministically.

The paper is organized as follows. Section 2 introduces some basic modeling and computational techniques. Section 3 is focused on the transformation from degradation prediction to time-to-failure distribution, given a predefined failure threshold. The proposed method is demonstrated on crack growth data in Section 4. Finally, Section 5 offers concluding remarks.

2. State-space model for latent degradation process modeling

2.1. State-space-based degradation model

Assuming that a population of homogeneous items degrades under a regular usage profile in service, if all manufactured items are identical and operate under exactly the same conditions and environment, then all items will fail at exactly the same time [11]. However, in practice, due to the lack of precision in manufacturing processes (variability in the component geometry or dimensions) and differences in the quality of material and in the initial degradation level, variability is introduced into the failure time. We refer to such variability between each individual item as item-to-item variability, which is introduced due to random variations across the population. Different applications and environmental conditions between items can also contribute to item-to-item variability. Another type of variability comes from variations within the degradation process for a given single item that may be caused by varying the operating and environmental conditions during its life cycle. Thus, it is necessary to model the stochastic behavior within the individual degradation process over time by a stochastic process [21]. This means that even knowing the present exact degradation state does not necessarily ensure a certain (or deterministic) prediction in the future. We refer to this type of variability as process variability.

Ideally, a stochastic degradation model should consider all the variability mentioned above in a systematic manner, in order to produce a confident prediction of failure time with the least possible uncertainty. In this study, we adapt the SSM to describe the dynamics of the degradation process for in-service reliability analysis. One advantage of SSM is that computations can be done recursively to incorporate new data. This is an advantage when data arrive sequentially, and on-line inferences, such as on-line condition monitoring or in-service reliability assessments, are required in practice. SSM assumes that there is an unobserved state of interest that evolves over time and that observations of the state are made at