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Specifying measurement errors for required lifetime estimation performance

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ABSTRACT

Lifetime estimation based on the measured health monitoring data has long been investigated and applied in reliability and operational management communities and practices, such as planning maintenance schedules, logistic supports, and production planning. It is known that measurement error (ME) is a source of uncertainty in the measured data considerably affecting the performance of data driven lifetime estimation. While the effect of ME on the performance of data driven lifetime estimation models has been studied recently, a reversed problem—"the specification of the ME range to achieve a desirable lifetime estimation performance" has not been addressed. This problem is related to the usability of the measured health monitoring data for estimating the lifetime. In this paper, we deal with this problem and develop guidelines regarding the formulation of specification limits to the distribution-related ME characteristics. By referring to one widely applied Wiener process-based degradation model, permissible values for the ME bias and standard deviation can be given under a specified lifetime estimation requirement. If the performance of ME does not satisfy the permissible values, the desirable performance for lifetime estimation cannot be ensured by the measured health monitoring data. We further analyze the effect of ME on an age based replacement decision, which is one of the most common and popular maintenance policies in maintenance scheduling. Numerical examples and a case study are provided to illustrate the implementation procedure and usefulness of theoretical results.

1. Introduction

Reliable and accurate lifetime estimates for key engineering assets have long been a hot research topic attracting increasing attention in reliability and operational research communities and practices. Because estimating the lifetime is important and fundamental for maintenance schedules and logistic supports of assets, which can lead to the extension of the asset life and lifecycle cost reduction (Derman et al., 1984; Bayus, 1998; Wang, 2002; Pecht, 2008; Elwany et al., 2011). In particular, accurate lifetime estimation can lead to timely and efficient maintenance and logistic planning to reduce the extra costs due to unscheduled maintenance (Scanff et al., 2007). Therefore, the effectiveness of maintenance decisions and logistic planning relies heavily on the performance of the estimated lifetime of the asset.

Traditionally, if the past failure data of the assets from either fields or experiments are available, the lifetime can be estimated from the failure data by using likelihood-based inference methods (Kalbfleisch and Prentice, 2002; Lawless, 2002). However, for expensive and highly reliable assets, failure data are scarce or limited. In practice, most failures of assets arise from a degradation mechanism at work and there are measurable characteristics that can be observed to deteriorate over time, such as the drift of gyros in the inertial navigation platforms and the length of fatigue cracks in rotating bearings (Si et al., 2012). Therefore, health monitoring data for these characteristics obtained from routine condition monitoring (CM) is a feasible and low-cost alternative used for the lifetime estimation task. However, perfect measurements in practical cases are impossible and the measured health monitoring data are inevitably contaminated by the uncertainty during the measurement process (Meeker and Escobar, 1998). It is noted that, in many cases, degradation (e.g. fracture, cracks, and electronic charge trapping) cannot be directly or perfectly measured but is correlated to other measurable parameters, which may be able to reflect the degradation condition of the monitored asset (Gu et al., 2009; Kumar et al., 2010; He et al., 2011; Huynh et al., 2012). Here the term "*degradation*" refers to the deterioration process of a certain characteristics of an asset with time. Examples can be either performance degradation (e.g. light output from an LED) or some measures of actual physical degradation (e.g., the length of a fatigue crack, the drift

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of a gyro, and the account of erosion), which are closely correlated with the underlying physics-of-failure of the asset. Therefore, throughout this paper, we used the term "measured data" to represent the actually measured health monitoring data which are associated with the hidden degradation of the asset.

As a source of uncertainty, measurement error (ME) resulting from the noise, disturbance, non-ideal measurement instruments, etc., exists in almost all measurement processes (Kolle and O'Leary, 1998; Oxtoby et al., 2003; Dieck, 2006; Huynh et al., 2012). Hence any investigation of the lifetime estimation problem via degradation modeling must take the ME into account. From an engineering point of view, the study of ME to reveal sources contributing to its variation or the characterization of the distribution of ME has been well considered (see e.g., Whitmore, 1995; Meeker and Escobar, 1998; Peng and Tseng, 2009). A variety of literature has addressed various aspects of the relationship between the ME and parameter estimation in the degradation models and the applications of lifetime estimation in maintenance, including Lu and Meeker (1993), Upadhyaya et al. (1994), Meeker and Escobar (1998), Wang (2002), Huynh et al. (2012), etc. Recently, Peng and Tseng (2009) investigated the effect of ME on lifetime estimation based on a Wiener process with a random drift coefficient. Si et al. (2011) presented a comprehensive survey of degradation data-based methods in the context of remaining useful life estimation.

The above-mentioned studies with respect to the effect of ME on performance characteristics of lifetime estimation could be the solution to the problem of "*the performance of lifetime estimation due to the ME*". Here we call this problem as a forward problem which focuses on the estimation from the measured data such as parameter estimation, structure identification, reliability estimation, and lifetime estimation, while the specification of ME is fixed. However, a reversed problem of "*the specification of the ME range in order to achieve a desirable lifetime estimation performance*" has not been addressed in the literature. This problem is related to the usability of the measured data for estimating the lifetime and is called an inverse problem in this paper. It aims at specifying the ME characteristics to achieve the desired lifetime estimation performance. If the performance of ME does not satisfy certain requirements, the desirable performance of the estimated lifetime cannot be ensured. In other words, the inverse problem seeks to obtain the limitations to the ME in lifetime estimation under a given desired performance.

As a matter of fact, the inverse problem has its practical background, and reliability practitioners or users in maintenance decision and logistic scheduling are often interested in the various facets of the inverse problem. First, a practitioner in practice may make maintenance decisions based on the specified performance characteristics of lifetime estimation. He or she would like to expect accurate lifetime estimation in order to plan maintenance and other logistic support activities in a timely and cost-effective way. As discussed earlier, the higher quality the measured data has, the better performance the lifetime estimation has. Hence if the measured data with ME are used for such lifetime estimation task, he or she may wonder how to specify the allowable limits to the distribution-related parameters (e.g. bias and standard deviation) of ME in order to avoid unacceptable deterioration in the performance of lifetime estimation. Secondly, to ensure a desired performance for lifetime estimation based on the measured data, the ME should be controlled so that the performance of lifetime estimation can be maintained. This refers to the design of the device that takes the measurements. Thirdly, when the lifetime estimated from the measured data with ME is used for maintenance decision, the practitioner may wonder what effect of ME will have on the final decision, because inaccurate lifetime estimation can lead to the increase of extra costs due to unscheduled maintenance. For example, Scanff et al. (2007) provided a business case study using Eurocopter's data from manufactures of two standard microelectronic subsystems in commercial helicopter to predict the lifecycle cost impact of using prognostics and health management. The results indicated that modeling failure data as a Weibull distribution was cost-effective as opposed to those whose failure data are represented by an exponential distribution. This resulted from the fact that most lifetimes of assets were not exponential. Together with these discussions, it can be concluded that the inverse problem has its practical implication for engineering practices in the fields of maintenance schedules and logistic supports requiring lifetime estimation from the measured condition monitoring data, and can be regarded as the necessity analysis of ME for the required lifetime estimation performance. However, all these very practical problems are not presented and addressed in the literature.

In this paper, we will consider such a reverse problem and attempt to give some initial answers based on a Wiener process-based degradation model (WPDM), commonly used for modeling degradation processes where the asset operates in time-invariant environments and thus the rate of degradation can be approximated as a constant for simplicity. We note that such rate can be time-dependent and nonlinear (e.g. Si et al., 2012), but it is not the focus of this paper. WPDMs are popular degradation models which have been widely studied and applied in a variety of contexts such as LED lights, rotating bearings, and gyros drifts, and have tractable mathematical properties (Ye, 1990; Whitmore, 1995; Tseng et al., 2003; Crowder and Lawless, 2007; Ye et al., 2012; and a review Si et al., 2011). As indicated before, we consider that the actual degradation is unobservable, but some measured data which are related to the degradation are available. Specifically, we consider a WPDM affected by the ME for lifetime analysis and develop some expressions for permissible bias and variance of the ME under required lifetime estimation performance. In order to answer the aforementioned questions, the properties of the estimated lifetime considering the effect of ME under WPDM are derived first. Then, we define some measures to characterize the difference between lifetime estimations without/with considering the ME. Through these measures, we formulate some requirements on the ME for the sake of achieving certain required performance of lifetime estimation. Based on the obtained results, we further analyze the effect of ME on an age based replacement decision, which is one of the most common and popular maintenance policies in maintenance scheduling (Barlow and Hunter, 1960), and often used as a benchmark model for demonstration. Finally, numerical examples and a case study are provided to illustrate the implementation procedure and usefulness of the theoretical results, where we also consider a comparison of condition-based replacement policy. The results indicate that, by specifying the ME range given a desirable lifetime estimation performance, it is possible to mitigate the conservativeness of maintenance decision so that the effectiveness of the replacement decision can be improved such as extending the operation cycle and reducing the long run average cost per unit time.

The rest of the paper is organized as follows. In Section 2, we provide the fundamental results of WPDM for lifetime estimation. In Section 3, the properties of WPDM with ME are derived. In Section 4, given the required performance characteristics for lifetime estimation, we analyze the allowable bias and standard deviation of ME. In Section 5, we analyze the effect of ME on an age based replacement decision. Numerical examples and a case study are provided in Section 6. We draw conclusions in Section 7.

2. Properties of the WPDM

In this paper, let $\{X(t), t \geqslant 0\}$ denote the stochastic degradation process which is correlated with the underlying physics-of-failure