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Specification analysis of the deteriorating sensor for required lifetime prognostic performance

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ABSTRACT

Lifetime prognostic based on the degradation data has been widely investigated and adopted for reliability assessment and maintenance policy. However, the measurement error (ME) is usually inevitable, which leads to the bias of lifetime estimation and erroneous evaluation of the safety risk. In this paper, we mainly focus on an inverse issue: how to specify the sensor's performance (i.e., the ME range) for satisfying a given requirement of the lifetime estimation. Under this consideration, we first analyze the probability distribution functions of the lifetime estimation with/without the ME based on Wiener process degradation model. Then a distance measure based on the relative entropy is formulated to evaluate the difference between these two lifetime estimations. Furthermore, the permissible ranges of the time-dependent and time-independent ME are attained under a given allowable bias of lifetime estimation according to the proposed distance measure. In addition, the influence of the ME on maintenance policy is discussed. Finally, numerical examples and a case study are provided to illustrate.

1. Introduction

Lifetime estimation (or remaining useful life estimation, RUL estimation), an important way for evaluating systems' health, has been widely applied to many industrial systems and gained much attention [1, 2, 3]. Accurate lifetime estimation can provide an important evidence for maintenance decision, and further can decrease the property loss and avoid casualties caused by the system's failure [4, 5, 6, 7, 8]. Particularly, statistical data-driven approach, an effective way to achieve a precise lifetime estimation, has been well exploited in numerous researches [9, 10]. In general, two kinds of the observed data are available for the statistical data-driven approach in practice, i.e., failure-time data and degradation-path data [11, 12]. Correspondingly, there are two general methods for lifetime estimation: failure-time data analysis and degradation-path data modeling [11, 13]. Compared with the former, lifetime estimation based on the degradation-path data modeling can predict the future failure and achieve the same accurate results with much fewer testing samples. What should be noticed is that under the framework of the statistical data-driven approach, the degradation path is regarded as a stochastic process such as Wiener process, Gamma process, Inverse Gaussian process and so on. Accordingly, its lifetime and RUL are defined as random variables rather than the fixed value, which can reflect the uncertainty and randomness of the estimated lifetime better. Thus, we mainly focus on the lifetime estimation based on the statistical degradation-path model in this paper.

Traditionally, if the degradation data of the deteriorating system are available, then we can model the degradation path and then its lifetime could be derived. However, due to the system's characteristics, measurement procedure, operator's skill, environment changing, and other factors, perfect measurement is impossible in practice, which means that the measurement error (ME) is inevitable [14, 15]. Hence, the effect of the ME should be considered for the lifetime estimation based on degradation-path data. By now, many researchers have addressed a variety of approaches to identify the ME and the parameters of degradation model [14, 15, 16, 17, 18]. In 1995, Whitmore [15] first investigated how to deal with the degradation model with the ME, where the randomness of the ME was described as a Gaussian random variable. Following his work, Tang et al. [17], Ye et al. [14, 19] studied how to estimate the lifetime based on different degradation model with the ME. It should be noticed that all the above-mentioned researches mainly focused on how to model the degradation data affected by the ME and then estimate the lifetime based on the proposed model. As Si et al. clarified in [20], these works could be regarded as a forward problem including degradation modeling and ME identification, lifetime estimation based on the actual degradation model, and uncertainty analysis of the results owing to the ME. The forward problem aims at the issue how to eliminate the effect of the ME, and obtain the accurate

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Acronyms and abbreviations

Notation

AIC	Akaike information criterion
BM	Brownian motion
FPT	first passage time
MLE	maximum likelihood estimation
PDF	probability density function
CDF	cumulative distribution function
PHM	prognostics and health management
RUL	remaining useful life
ME	measurement error
RUL	remaining useful life
KL	Kullback Leibler
$B(\cdot)$	standard BM
T	lifetime
$X(t)$	degradation state at time t
x_k	observation of at the k-th observing time
$\boldsymbol{X}_{0:k}$	available observations of $\{X(t), t \le 0\}$ up to t_k
ξ	threshold of $\{X(t), t \le 0\}$
$f_T(t)$	PDF of the lifetime T
μ	the drift coefficient
σ_B	the diffusion coefficient
$\hat{\mu}$, $\hat{\sigma}_B$	the estimates of μ, σ_B from the observed data without the ME
$\hat{\mu}'$, $\hat{\sigma}_B'$	the estimates of μ, σ_B from the observed data with the ME
T_ϵ	the pseudo lifetime
$f_{T_\epsilon}(t)$	the PDF of the pseudo lifetime

lifetime estimation. On the contrary, the inverse problem aims at the issue how to specify the ME characteristics for satisfying a given lifetime estimation performance.

In fact, the inverse problem is also interesting and meaningful for practical engineering. Specially speaking, when we make maintenance decision based on the performance of the lifetime estimation, accurate result can provide significant and effective evidence for timely and cost-effective logistic support activities. So if there are inevitable ME existing in the observed data, we may wonder how to specify the allowable range of the ME for satisfying the acceptable performance of the lifetime estimation. That is to say, the ME should be limited in a certain permissible range, which refers to sensor's performance and the design of the measurement system. Furthermore, due to the unscheduled maintenance and increased costs caused by the inaccurate lifetime estimation, we may wonder what the influence of the ME on the maintenance decision is. For example, Scanff et al. analyzed the lifecycle cost impact of health management for two microelectronic subsystems in commercial helicopter, and found that the result with the correct lifetime was cost-effective compared with the incorrect lifetime [21]. In conclusion, the reverse problem is of great importance in maintenance schedule, and it can be also treated as the specification analysis of the sensor subject to the prearranged performance of the lifetime estimation. What should be noticed is that if the ME of the sensor can be identified or calibrated online, the reverse problem is unnecessary since the effect of the ME can be eliminated for lifetime estimation. In this case, the accuracy of the lifetime estimation can be ensured so that the unscheduled maintenance could be avoided. Unfortunately, many sensors cannot be identified or calibrated online after they have been put into operation such as the thermocouple in the blast furnace. Therefore, it is much essential to investigate how to realize the specification analysis of these sensor. Under this consideration, we mainly focus on the reverse problem with the sensor that cannot be identified online. As to its inverse problem, only a few researchers have paid an attention to it. For example, Si et al. [20], and Tang et al. [22], discussed the specification of the ME based on linear Wiener Process, and further analyzed the effect of the ME on maintenance policy. In their works, if the required performance of the lifetime is given, the allowable range of the ME can be obtained based on their approaches.

However, there are two problems still needing to be further studied. In the above-mentioned researches and other relative studies, the ME is usually assumed as a time-independent random variable [15, 16, 23, 24]. In fact, the MEs of many sensors will change over time, e.g., the ME of the thermocouple will accumulate with aging [25, 26]. That is to say, the ME should be a time-dependent stochastic process rather than random variable in this case. On the other hand, in order to compare the difference between the lifetime estimations with/ without considering the ME, several measures combining variance and coefficient of the lifetime are formulated to quantify [20, 22]. It is noted that due to the property of statistical data driven approach, the lifetime should be a random variable rather than fixed value, which makes the applicability and availability of their measures limited. Besides, both of the above-mentioned papers compare the true lifetime with the first passage time that the process with ME reaches the given threshold. But in practice, it is more common to use the degradation model without considering the ME to fit the data with ME, and further obtain a pseudo lifetime estimation. So comparing the true lifetime estimation with the pseudo one is more appropriate and meaningful.

In this paper, we attempt to attain some results based on linear Wiener-process-based degradation model, which has been widely studied and used for degradation modeling in many deteriorating products. As discussed before, we consider that the true degradation process cannot be observed and only the collected degradation data with the ME are available. In this case, we concentrate on the influence of the ME on lifetime estimation and the permissible form of the ME under given allowable lifetime estimation performance. To deal with the aforementioned issues, we first investigate the influences of the time-independent/ time-dependent ME on parameters identification and lifetime estimation based on the Wiener process. It is noteworthy that the lifetime under the probabilistic framework should be a random variable rather than a fixed value. Then, we propose a measure to evaluate the difference between lifetime estimations with/ without considering the ME based on the relative entropy (i.e., Kullback Leibler distance), which can provide an effective way to measure the distance between two distributions [27]. Based on such measure, the required form of the ME is attained for satisfying a given distance which also reflects the required performance of lifetime estimation. In addition, we further analyze the effect of the time-dependent ME on maintenance decision based on the obtained results.

The remainder parts are organized as follows. In Section 2, the motivating examples and problem formulation are given. In Section 3, the influence of ME on lifetime estimation based on the Wiener process is derived. In Section 4, given the allowable bias of lifetime estimation, the acceptable forms of time-independent/ time-dependent ME are obtained. Two illustrative examples are presented to illustrate and demonstrate the proposed model in Section 5. This paper is concluded in Section 6.

2. Motivation and formulation

2.1. Motivating example of blast furnace

Example: Blast furnace is a typical large-scale complex system, and its wall will degrade inevitably over the time owing to the erosion of molten iron [28, 29]. If the furnace wall burn out, it will not only lead to the failure of the blast furnace, but also may cause disastrous accident. In practice, the thickness of the furnace wall is difficult to measure