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Two novel mixed effects models for prognostics of rolling element bearings

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ABSTRACT

Rolling element bearings are widely used in various machines to support rotating shafts. Due to harsh working environments, the health condition of a bearing degrades over time. A typical bearing degradation process includes two phases. In Phase I, the health condition of the bearing is in normal and it exhibits a stable trend. In Phase II, the health condition of the bearing degrades exponentially. To analytically model the bearing degradation process, two novel mixed effects models are proposed in this paper. Each of the two mixed effects models is able to simultaneously model Phases I and II of the bearing degradation process. The main difference between the two mixed effects models is that different error assumptions including multiplicative normal random error and multiplicative Brownian motion error are respectively considered in the two mixed effects models. Consequently, two different closed-form distributions of bearing remaining useful life are derived from the two mixed effects models via Bayes' theorem once real-time bearing condition monitoring data are available. 25 sets of bearing degradation data collected from an experimental machine are used to illustrate how the two mixed effects models work. Comparisons are conducted to show that the mixed effects model with multiplicative Brownian motion error results in lower prediction errors than the mixed effects model with multiplicative normal random error for bearing remaining useful life prediction.

1. Introduction

Rolling elements bearings are widely used in various machines to support rotating shafts. Since these bearings often work in harsh working environments, they gradually degrade from a normal health condition to a failure condition [1]. In mechanical engineering, bearing performance degradation assessment aims to use a bearing health indicator constructed from analyses of vibration signals to evaluate the current health condition of a bearing [2]. The vibration signals are often used for analyses because they are easily collected by using an accelerometer attached to the casing of a bearing and they are sensitive to a bearing defect [3]. For example, when a bearing has a defect on the surface of either an outer race or an inner race, a transient is generated by a roller striking the defect. Because of rotation of a shaft, the transient is repetitively generated over time. Consequently, the intervals and amplitudes of the repetitive transients characterized by a bearing defect frequency [4] is helpful to identification of the bearing defect. Based on this phenomenon, the bearing health indicator can be constructed from the bearing defect frequency and its relevant signatures.

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In the past years, many signal processing and data mining based methods, such as wavelet filtering [5], self-organizing map [6], hidden Markov model [7], support vector data description [8], fuzzy c-means [9], Gaussian mixture models [10], comblet filtering [11], cyclic power spectrum [12], recurrent neural network [13], etc., were proposed to construct the bearing health indicator. These methods have their own advantages and disadvantages. The signal processing based methods [5,11,12] require expertise to accurately retain one of bearing defect related frequency bands for construction of the bearing health indicator. Moreover, the calculation time of the signal processing based methods is fast because fast signal processing algorithms and tricks are available. The data mining based methods [6–10] require historical bearing degradation data so as to use these historical data to train a normal model. Then, in the processing of bearing degradation, deviations from the trained normal model can be regarded as the health indicator. The data mining based methods require less expertise but their calculation time is extensive.

Even though these two kinds of methods are effective in describing bearing performance degradation over time, it should be noted that these methods can only be used to evaluate the current health condition of the bearing once real-time bearing condition monitoring data are available and they cannot be used to predict future health condition of the bearing, especially bearing remaining useful life (RUL) [14,15] that is defined as the period from the current time to the end of bearing lifetime. As a result, a statistical model is required to be analytically built for bearing RUL prediction. Lu and Meeker [16] presented several random coefficient models to calculate the life distribution of a population of devices. Following the work of Lu and Meeker, Gebraeel et al. [17] incorporated random coefficient models with real-time condition monitoring data via Bayes' theorem so as to posteriorly update the RUL distribution of a rolling element bearing. In this work, two different errors including multiplicative normal random error and multiplicative Brownian motion error were considered in the statistical modeling of bearing degradation. The results showed that the multiplicative Brownian motion error resulted in lower RUL prediction errors than the multiplicative normal random error. Inspired by the pioneered research work of Gebraeel et al. [17], many bearing prognostic methods have been proposed to predict bearing RUL [18,19]. Gebraeel et al. [20] replaced the independent assumption of random coefficients with the correlated assumption of random coefficients used in Ref. [17]. When historical bearing degradation data were not available, Gebraeel et al. [21] used the Bernstein distribution with failure time information to derive prior distributions required in Ref. [17]. Gebraeel et al. [22,23] developed a neural network-based degradation model to avoid the use of a specific statistical model for bearing prognostics. Bian and Gebraeel [24] proposed a parametric stochastic degradation model and derived the first-passage time for prediction of bearing RUL. Gebraeel and Pan [25] provided a strategy to make bearing prognostics work under dynamical environment conditions. Bian et al. [26] linked environment parameters with signal parameters so that prediction of bearing RUL can be conducted under dynamical environment conditions. Maio et al. [27] used a relevance vector machine to find relevance vectors and then extrapolated an exponential function established by fitting the relevance vectors to calculate bearing remaining useful life. Lei et al. [28] employed the analytical expression of the posterior estimation of the parameters of the statistical model proposed by Gebraeel et al. [17] to provide an importance function for standard particle filtering so as to improve bearing RUL prediction accuracies of the standard particle filtering.

It should be noted that most of the aforementioned statistical models are only effective in Phase II of bearing degradation, namely the exponential bearing degradation process after identification of the first change point of the bearing degradation. In other words, most of the aforementioned statistical models assumed that a bearing health condition has already entered Phase II and omitted the influence of Phase I on condition monitoring of bearings. Recently, Chen and Tsui [29] proposed a piecewise model consisting of two sub-models to model Phases I and II of the bearing degradation respectively. Because each of the two sub-models is applied to a certain phase of the bearing degradation, the piecewise model is not a unique model to model Phases I and II of the bearing degradation simultaneously. Besides, the discontinuity used in the piecewise model makes posterior estimation of the parameters of the piecewise model extremely difficult and time-consuming. Consequently, some underlying assumptions, such as independence of the parameters in both their priori and posteriori, and empirical Bayesian inference were adopted in Ref. [29] to simplify the posterior estimation of the parameters of the piecewise model. Additionally, it should be noted that in Ref. [29], only multiplicative normal random error was adopted in the piecewise model. In bearing prognostics, besides multiplicative normal random error, multiplicative Brownian motion error is another attractive error assumption in statistical modeling. To make the posterior estimation of the statistical model in Ref. [29] simple and extend the work to another situation in which multiplicative Brownian motion error is used for bearing prognostics, in this paper, two unique models, namely two mixed effects models, under the assumption of multiplicative normal random error and multiplicative Brownian motion error, are respectively proposed to model Phases I and II of bearing degradation.

The main contributions of this paper are summarized as follows. Firstly, we clarify none of the previous works [17,20–26,29] is a unique model to simultaneously describe Phases I and II of bearing degradation. Based on the two different errors including multiplicative normal random error and multiplicative Brownian motion error, two different mixed effects models are respectively proposed to simultaneously model Phases I and II of bearing degradation. Besides, the two-phase modeling with multiplicative normal random error [29] is extended to another situation, where multiplicative Brownian motion error is considered in the two-phase modeling. Secondly, based on the proposed mixed effects models, the closed-form distributions of RUL are derived once real-time bearing condition monitoring data are available. Moreover, since the closed-form distributions of RUL are available, the calculation time of RUL is fast. Thirdly, even though different proof procedures were adopted in Ref. [17] and this paper, the derived expressions of the posterior estimation of the parameters of the proposed statistical models can be mathematically reduced to the work of Gebraeel et al. [17] if only Phase II of bearing degradation