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An improved non-Markovian degradation model with long-term dependency and item-to-item uncertainty

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ABSTRACT

It is widely noted in the literature that the degradation should be simplified into a memoryless Markovian process for the purpose of predicting the remaining useful life (RUL). However, there actually exists the long-term dependency in the degradation processes of some industrial systems, including electromechanical equipments, oil tankers, and large blast furnaces. This implies the new degradation state depends not only on the current state, but also on the historical states. Such dynamic systems cannot be accurately described by traditional Markovian models. Here we present an improved non-Markovian degradation model with both the long-term dependency and the item-to-item uncertainty. As a typical non-stationary process with dependent increments, fractional Brownian motion (FBM) is utilized to simulate the fractal diffusion of practical degradations. The uncertainty among multiple items can be represented by a random variable of the drift. Based on this model, the unknown parameters are estimated through the maximum likelihood (ML) algorithm, while a closed-form solution to the RUL distribution is further derived using a weak convergence theorem. The practicability of the proposed model is fully verified by two real-world examples. The results demonstrate that the proposed method can effectively reduce the prediction error.

1. Introduction

Remaining useful life (RUL) prediction is an effective technology to reduce the maintenance costs for practical systems [1–3]. According to the monitoring data, the key idea lies in estimating the probability density function (PDF) of RUL by analyzing the first hitting time (FHT) with a given failure threshold. Ahmadzadeh and Lundberg [4] reviewed the recent studies about RUL prediction and summarized them into four types, that is, physics, experimental, data-driven, and hybrid methods. Some related works can be further found in [5–13]. Among these categories, data-driven methods only need to establish a stochastic model to fit the observations without any assumption of physical parameters or additional expertise, and thus are more commonly used for the prediction.

As far as we know, most of the existing data-driven methods are limited to various types of memoryless Markovian degradation models [14], including Markov chains [15–19], Wiener processes [20–25], and Gamma processes [26–30]. Wang et al. [16] presented a continuous hidden Markov model to describe the degradation states of tool wear, and predicted the RUL of the system based on the milling force signal. Considering the influence of different operating conditions, Al-Dahidi et al. [19]

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established a homogeneous semi-markov model, and directly used a Monte Carlo method to infer the future degradation states. For a Wiener degradation process with a nonlinear diffusion term, Si et al. [20] obtained an approximate analytical solution of the RUL using a time-space transformation method. Lei et al. [21] considered the measurement uncertainty in the mechanical systems, which was simply represented by a zero-mean Gaussian random variable, and then built a state-space model for predicting the RUL, according to the statistical properties of the Wiener process. Wang et al. [22] studied the limitation of standard Brownian motion (BM), and further developed a generalized Wiener process degradation model containing the temporal uncertainty. Van Horenbeek and Pintelon [26] proposed a dynamic predictive maintenance strategy via the RUL prediction results of a stationary Gamma degradation process. To deal with the noise factors, Le Son et al. [30] used the Gibbs sampling method to estimate the hidden degradation states of a non-homogeneous Gamma process, and approximated the RUL distribution for predictive maintenances.

Although the above models can be used to obtain the RULs, the long-term dependencies among the monitoring data indeed exist in some practical industrial processes, and have a great impact on the evaluation of the degradation states. Generally speaking, there are two kinds of correlation forms, namely, positive correlation and negative correlation. The former implies the future degradation states tend to follow the previous direction, while the latter mainly leads to an opposite tendency. The root of this phenomenon can be briefly boiled down to the interaction with environments [31]. Because a Markovian process is completely memoryless, the traditional Markovian models cannot describe such dynamic systems. Therefore, one major issue is to establish a degradation model with the property of long-term dependencies.

Fractional Brownian motion (FBM) is a typical kind of continuous non-Markovian stochastic process with stationary but dependent increments, and introduces the long-range correlation structure [32–34]. The correlation function of FBMs is characterized by the Hurst exponent H, which satisfies $0 < H < 1$. Based on different values of H, FBMs can be divided into three types, that is, $0.5 < H < 1, 0 < H < 0.5$, and $H = 0.5$. The first two types reveal the statistical fractal features of positive and negative correlations, respectively. Specifically, the third type of FBM signal degenerates into an ordinary BM. Compared with the random walk, the fractal feature is more common in practice. Indeed, the FBM has been widely used in the fields of finance, geography, and signal processing. For instance, because of the persistent heat conduction, the temperature degradations in a blast furnace often present the positive correlation. Note that the mechanical vibration signals usually seem to be negatively correlated, but long-term dependencies still exist in the hidden degradations such as the fatigue crack growth of bearings. From the above analysis, the FBM is an alternative choice to model the degradations of practical systems.

In our previous work [35], we first presented a non-Markovian degradation model, in which the long-term dependencies are described by a simple FBM. Because the Monte Carlo simulation method costs a large amount of computation, Zhang et al. [36] further gave an approximated PDF of the RUL based on the same FBM model. However, these works are quite preliminary, and only consider one single degradation process. Different from the strategy of replacing the diffusion term with an FBM, some other existing literatures also consider the long-term dependency by introducing an age- and state-dependent function into the degradation models in recent years [37–39]. Guida et al. [37] first presented a new kind of discrete-time continuous-state Markov model with a nonnegative finite-valued function relying on both the current age and the current state, for the purpose of estimating the unknown transition probability density. Li et al. [38] proposed a more general Wiener process-based stochastic degradation model, in which the traditional age-dependent drift term was replaced with an age- and state-dependent function. Zhang et al. [39] took into account the long-term dependency from both the drift coefficient and the diffusion coefficient simultaneously, and established a novel nonlinear degradation model for the RUL prediction of complicated systems.

These two kinds of modeling methods are all available for describing the long-term dependency of the degradation processes. Actually, some significant limitations exist in the strategy of changing the drift term into an age- and state-dependent function. On the one hand, it is difficult to choose a reasonable form of the drift term without any prior knowledge of the degradation process. On the other hand, the degree of long-term dependency cannot be measured directly by a simple age- and state-dependent function. Instead, FBM has long been considered to be a natural mathematical tool in modeling the non-Markovian stochastic processes with self-similarity and long-term dependency. Based on a nonlinear transformation of BM, FBM can simply construct a correlation structure among the degradation states, in which the degree of long-term dependency is quantitatively analyzed by the Hurst exponent. Therefore, using an FBM as the diffusion term seems to be more general and effective in response to the uncertainty of practical degradation processes, from the perspective of mathematical principle and physical significance.

Interestingly enough, the long-short term memory (LSTM) also provides a feasible scheme for the problem of long-term dependency. In the literature, Hochreiter and Schmidhuber [40] first proposed the idea of LSTM for the purpose of improving the storage ability of traditional recurrent backpropagation, in other words, addressing the structure of long-term dependency. As a kind of peculiar recurrent neural network (RNN), LSTM is capable of adding or removing state information recursively on the basis of its special network architecture including the memory cells, the constant error carrousel (CEC), along with several gate units. Recently, a few researches on LSTM-based RUL prediction have come to publicity [41–43]. By using a variation of LSTM, i.e., the long-short term memory-based encoder-decoder (LSTM-ED) model, Malhotra et al. [41] constructed an unsupervised health index (HI) to indicate the healthy state of the system, and then utilized the HI curve matching technology to predict the RUL. Yuan et al. [42] aimed at using multiple LSTM neural networks to establish an effective system of fault diagnosis and RUL prediction for aero engines, with the consideration of complex operations as well as hybrid degradations. Wu et al. [43] employed vanilla LSTM neural networks for characterizing the dependency, and further applied it to the high-precision prognostics for engineered systems.