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A method for remaining useful life prediction of crystal oscillators using the Bayesian approach and extreme learning machine under uncertainty

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ABSTRACT

A crystal oscillator is a typical frequency generating unit that is widely used in computers, neural chips, biosensors and other applications; thus, it is very important to estimate and predict its remaining useful life (RUL) precisely. However, there are few existing RUL prediction methods because the observed data involve various uncertainties, leading to the great limitation of RUL prediction in practical application. In this work, we propose an uncertainty RUL prediction method based on the exponential stochastic degradation model that considers the multiple uncertainty sources of oscillator stochastic degradation processes simultaneously. Next, based on Bayesian theory, a novel Bayesian-Extreme Learning Machine parameter-updating algorithm that combines the local and global similarity methods is presented and used to eliminate the effects of multiple uncertainty sources and predict the RUL accurately. The effectiveness of the method is demonstrated using the accelerated degradation tests of crystal oscillators. Through comparisons with the predicted results without uncertainty, the proposed method demonstrates its superiority in describing the stochastic degradation processes and predicting the oscillator's RUL.

1. Introduction

Crystal oscillators play a critical role in ensuring practical implementation of important operations, including frequency conversion, synchronization, and real-time clocks [1–4], and they have been widely used in computers [5], neuro-chips [6–8], biosensors [9–11], medical imaging [12] and other applications. As a core component of the benchmark frequency signal, its frequency stability and reliability are very important [13–17]. Therefore, the estimation of the remaining useful life (RUL) and the reliability of real oscillators have been important research subjects.

In the past years, two typical methods have been used to predict the RUL of crystal oscillators or other electronic products: physics-of-failure (PoF)-based approaches and data-driven approaches. PoF-based approaches [18–23] utilize a large amount of knowledge of a product's life cycle loading and failure mechanisms to undertake reliability design and assessment. They can accurately reflect the physical changes in the equipment and are the most effective prediction methods based on physical modeling. However, because the methods involve excessive physical parameters that are not always feasible, such models are usually particularly difficult to build precisely. In contrast, the data-driven approach [24–29] requires prognostic data that reflect the devices' degradation behavior derived from ordinarily observed operating parameters (electrical and non-electrical parameters, or time-domain and frequency-domain parameters) without the need of extensive knowledge on the devices. It avoids a complex physical modeling process and only requires prognostic data that reflect the devices' degradation behavior derived from ordinarily observed operating parameters without the need of extensive knowledge on the devices. However, because the prediction method lacks the physical information of the equipment, it cannot reflect the physical failure process of the equipment and has obvious limitations in the field of engineering application.

In recent years, much research has focused on estimating the distribution of the degradation amount, which utilizes a statistical viewpoint to model the degradation phenomenon and analyzes the degradation parameters based on the stochastic process. In contrast to the PoF-based and data-driven approaches, methods based on the stochastic process have the advantages of data-driven models and consider the degradation processes and degeneration distributions associated with the physical properties of the predicted object, so they have gradually attracted the attention of scholars. Zhai and Ye [30] proposed a new adaptive Wiener

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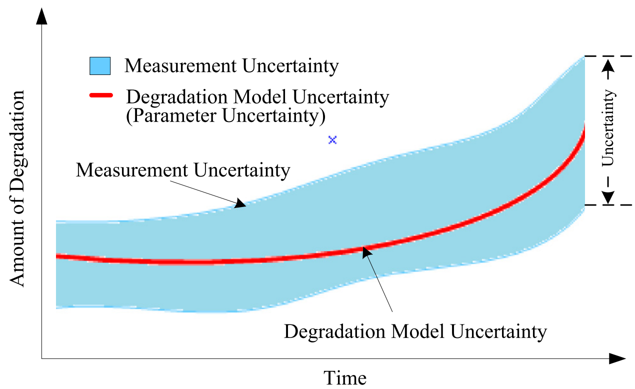

Fig. 1. Prediction process with degradation model uncertainty and measurement uncertainty.

process model that utilizes a Brownian motion for the adaptive drift. The new model shared the flexibility of the exiting Wiener model but avoided the difficulties in model estimation and RUL prediction. Pan et al. [31] presented a degradation modeling and RUL estimation approach based on use of the available degradation data for a deterioration system; they used an inverse Gaussian process with random effect to characterize the degradation process of the system. Wei and Xu [32] proposed a monitored degradation process with fluctuation that used a Gamma process combined with random measurement error, in which the gamma process was utilized to model the degradation process because of its monotonicity.

However, in practical application, because of the impacts of the system degradation process and the measurement error, it is inevitable to include degradation randomness and measurement uncertainty in the measurement data; such uncertainty is the greatest challenge of the RUL prediction method in practical engineering application. This method mainly includes measurement uncertainty, uncertainty of the degradation model and uncertainty of the prediction method. Fig. 1 shows a typical prediction process with degradation model uncertainty and measurement uncertainty.

Some researchers studied uncertainty evaluation and RUL prediction from the perspective of state estimation for the complex nonlinear and stochastic systems [33–40]. Shen and coworkers [33,34] studied the state estimation approach for uncertain systems with stochastic nonlinearities and the measurement noises. Ding et al. [35,36] studied the state estimation and control problem for a class of discrete-time stochastic nonlinear systems. Sankararaman [37] analyzed the significance, interpretation and qualification of uncertainty in prediction, with an emphasis on predicting the remaining life of the complex nonlinear and stochastic systems. Si et al. [38] presented a relatively general degradation model based on the Wiener process that characterized the three sources of variability contributing to the uncertainty of the RUL prediction (temporal variability, unit-to-unit variability and measurement variability) to incorporate the effect of three-source variability into RUL estimation. Guo et al. [39] presented a recurrent neural-network-based health indicator for predicting the remaining useful life of bearings that considered the uncertainty of the failure threshold. Rigamoti et al. [40] developed a local ensemble of Echo State Networks (ESNs) for predicting the RUL of an industrial component and estimating the associated uncertainty.

The above representative methods play a positive role in solving RUL prediction uncertainty. However, they mainly consider the uncertainty of the model parameters. The uncertainty of the degradation process, the uncertainty of the measurement and the uncertainty of the prediction method are not considered simultaneously. Therefore, these methods have still some limitations in practical applications of the RUL prediction.

This paper aims to address this issue by proposing a novel prediction method that considers the uncertainty of the degradation model, the uncertainty of the measurement and the uncertainty of the prediction method simultaneously. We use the Bayesian maximum likelihood method and the improved Optimally Pruned Extreme Learning Machine (iOPELM) for updating the parameters online, combining the local and global correction methods to eliminate the uncertainty of prediction model and achieving the real-time estimation of the potential degradation.

The major contributions of our study are the following aspects.

(1) A new uncertainty prediction model is constructed considering the multiple uncertainty sources of degradation processes simultaneously.
(2) The Bayesian-extreme learning machine parameter-updating algorithm combining the local and global similarity methods is developed to eliminate the effects of multiple uncertainty sources.
(3) A RUL prediction process is presented based on the uncertainty prediction model, including the data pre-processing, uncertainty degradation model construction, parameter updating, and RUL estimation.

The article structure is arranged as follows: characteristic parameters of crystal oscillators and the power law model are illustrated in Section 2; our approach and the uncertainty stochastic degradation model based on Bayesian-Extreme Learning Machine approach are shown in Section 3; Section 4 shows the application of the proposed method to the crystal oscillator and discusses the obtained results; and finally, in Section 5, some conclusions and remarks are drawn.

2. Investigation of the degradation indicators

2.1. Characteristic parameters of the crystal oscillators

The major parameters of the crystal oscillator include frequency stability, output power, and harmonic suppression; among them, frequency stability is most essential because it determines the accuracy of output signal directly. With an increase in the number of operational cycles, the internal performance of the oscillator degrades. External interference, such as temperature, acceleration, humidity, and ambient environment noise, and internal interference, such as thermal noise and shot noise, will cause the drift of the output frequency. Phase noise (PN) is the index of frequency stability that is usually expressed as a single-sideband power spectral density (SSB-PSD) figure. It consists of harmonic, spurious (parasite), and power supply ripple caused by the discrete spectrum. An oscillator propagates harmonic and cross modulation as a nonlinear component; the modulation of the output frequency thus exhibits sideband in the carrier frequency spectrum, i.e., PN.

Oscillator is composed of three parts: the amplifier, resonator and output buffer. The PN of the oscillator is the result of the interaction of the three parts. PN is easy to measure and can intuitively reflect the short-term stability, with diverse frequency components presented of the noise energy. In addition, the oscillator phase noise modulation power is much greater than the amplitude noise power; we usually omit the amplitude fluctuations. Therefore, measuring only the PN of the oscillator is suitable for determining its health status and predicting the RUL.

2.2. Power law model of phase noise

Previous studies [41,42] put forward simple models showing the relationship between the noise characteristics and the frequency spectrum. According to their models, a SSB-PSD can be