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Remaining useful life estimation for deteriorating systems with time-varying operational conditions and condition-specific failure zones

Li Qi, Gao Zhanbao, Tang Diyin *, Li Baoan

School of Automation Science and Electrical Engineering, Beihang University, Beijing 100083, China

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Abstract Dynamic time-varying operational conditions pose great challenge to the estimation of system remaining useful life (RUL) for the deteriorating systems. This paper presents a method based on probabilistic and stochastic approaches to estimate system RUL for periodically monitored degradation processes with dynamic time-varying operational conditions and condition-specific failure zones. The method assumes that the degradation rate is influenced by specific operational condition and moreover, the transition between different operational conditions plays the most important role in affecting the degradation process. These operational conditions are assumed to evolve as a discrete-time Markov chain (DTMC). The failure thresholds are also determined by specific operational conditions and described as different failure zones. The 2008 PHM Conference Challenge Data is utilized to illustrate our method, which contains mass sensory signals related to the degradation process of a commercial turbofan engine. The RUL estimation method using the sensor measurements of a single sensor was first developed, and then multiple vital sensors were selected through a particular optimization procedure in order to increase the prediction accuracy. The effectiveness and advantages of the proposed method are presented in a comparison with existing methods for the same dataset.

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1. Introduction

The discipline of prognostic and health management (PHM) brings about the idea of using monitoring techniques and data analysis methods to assess the reliability of a system in its life cycle and to determine the occurrence of failure. Estimating the remaining useful life (RUL) is considered as the core and always a major challenge in PHM. Once accurate prognostic results are available, appropriate health management actions such as maintenance and logistical support are able to perform

* Corresponding author. Tel.: +86 10 82338693.
E-mail addresses: 15210585903@163.com (Q. Li), gaozhanbao@buaa.edu.cn (Z. Gao), tangdiyin@buaa.edu.cn (D. Tang), superlba@163.com (B. Li).

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in time. For aircraft or aerospace vehicles, accurate RUL estimation not only means much to the cost savings, but more importantly, it is of great significance in ensuring system reliability and preventing disaster. The current techniques for RUL estimation can be roughly classified into physical-based approaches, data-driven approaches and their combinations. For complex systems such as nuclear power systems, aircraft engines, flight control systems, etc., it is too complicated to map their precise physics to their exact failure mechanisms, thus data-driven approaches are good alternatives to accomplish the prognostic tasks.

Many data-driven approaches for RUL estimation employ data fitting methods including machine learning and statistical-based methods to model the system deterioration process. When developing an appropriate degradation model to predict the system's future behavior, the uncertainty underlying the deterioration process is an important issue that should be taken into serious account. The existing methods have broadly presented two ways to describe the uncertainty in a degradation model. One is using probabilistic methods, in which the deterioration phenomenon is considered to have certain random behavior which is often characterized by probability laws, e.g., normal distribution[1–4], or by stochastic models, e.g., Wiener processes[5–7], Gamma processes[8,9], inverse Gaussian processes[10,11], etc. The other can be referred to as parameter updating strategies, which updates the models parameter by newly available data acquired from currently functioning individuals. Gebraeel et al.[6] developed a Bayesian method to update the stochastic parameters of exponential degradation models using real-time condition monitoring information. Variations of this work have been investigated in many literatures, e.g., Elwany[12], Bian[13], You[14] and Si et al.[15] Following the Bayesian-based updating principals, Ye and Chen[10] developed an updating procedure for inverse Gaussian processes; Si et al.[7] proposed a Bayesian recursive filter to update the drift coefficient in the Wiener process, and further, this recursive filter was improved in the study of Si et al.[16] to deal with a general nonlinear degradation model. Besides Bayesian-based updating approaches, many other updating approaches have also been reported, e.g., Chen et al.[17] utilized both the current observations and the future prediction results obtained by support vector machine to update the system model parameters.

Various reasons may contribute to the uncertainties in a deterioration process; however, with all kinds of reasons, the influence of time-varying operational conditions (or environmental conditions) has not received enough attention. As noted by Bian et al.,[18] most degradation models assume that the operational conditions are invariant, or without affecting the deterioration process. However, this is not always true in real engineering applications. The operational conditions usually vary with environmental changes or operating mode conversions, and in most cases, they exerted non-trivial effects on the process of deterioration. Examples can be found in inertial navigation systems[19], flight control systems[20], smart power grids[21] and other smart structures.

In recent years, a few probabilistic methods considering the effect of operational conditions on degradation processes have been proposed. Liao and Tian[22] developed a Bayesian updating technique for Wiener process-based degradation models to accommodate piecewise constant operating conditions. Bian and Gebraeel[23] proposed a tangent approximation method to estimate RUL for a Wiener process-based degradation model under a continuous deterministic environmental profile. To deal with dynamic environmental conditions, Kharoufeh and Cox[24] considered a random environment characterized by a continuous-time Markov chain, and Kharoufeh et al.[25] further extended this method to semi-Markov-based random environment. Si et al.[26] predicted residual storage life for systems with switches between the working state and the storage state, considering a continuous-time Markov chain to describe the state sojourns and switches. In above methods, the quantified effect of operational conditions on degradation processes only comes from specific operational conditions, but the effect resulted from the transition between different operational conditions has not been included. Among limited contributions which combine both effects, Bian et al.[18] studied a complex situation in which the failure rates are determined by environmental conditions, and the degradation signal exhibits upward or downward jumps at environment transition epochs. In their model, the jump magnitudes are supposed to be deterministic quantities and the degradation rates are the main factor in deterioration. However, in some situations, the jump magnitude is more of a random variable than a deterministic quantity, and it leads the deterioration trend especially when the operational condition changes frequently.

In this paper, we will focus on estimating RUL using probabilistic methods for degrading systems under time-varying operational conditions and subject to equidistant condition monitoring. The dynamics of the time-varying operational conditions will be considered and described by a discrete-time Markov chain (DTMC). The influence from both the operational conditions and the transitions of operational conditions on degradation processes will be quantified and incorporated in the degradation model. In order to validate our RUL estimation method, we use 2008 PHM Conference Challenge Data[27], a mass run-to-fail dataset simulated from a model of a realistic large commercial turbofan engine, to present our algorithm, to analyze the results, as well as to compare the proposed method with other existing approaches for the same dataset. We select several benchmark methods dealing with this data for comparison purposes: similarity-based regression approach by Wang et al.,[28] neural networks approach by Heimes[29] and Peel[30], and Wiener process-based approach by Son et al.[31] Our method is different from all existing methods dealing with this dataset in at least three aspects. Firstly, instead of using fusion methods to eliminate different influences resulted from different operational conditions, we quantify these differences according to different operational conditions and different transitions of operational conditions. Secondly, we consider condition-specific failure zones instead of a general failure threshold. To our knowledge, we are the first to consider different failure mechanisms according to different operational conditions. Not only does our illustrative example present such pattern, but also this consideration is more realistic and appropriate in many real applications. For example, a degraded system may not be capable of operating under harsh conditions, but it may operate safely under mild conditions. Thirdly, although sensor measurements from various sensors are available, our proposed method enables RUL estimation using each single sensor, which allows us to develop an optimization procedure to select the sensors that contribute most to the accuracy of prognostics.

The remainder of the paper is organized as follows. In Section 2, the 2008 PHM Conference Challenge Data is

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