Reliability Engineering and System Safety 152 (2016) 38–50

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Remaining useful life prediction based on noisy condition monitoring signals using constrained Kalman filter

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ARTICLE INFO

Article history:
Received 2 July 2015
Received in revised form
22 December 2015
Accepted 25 February 2016
Available online 4 March 2016

Keywords:
Remaining useful life
Condition monitoring signals
Constrained Kalman filter

ABSTRACT

In this paper, a statistical prognostic method to predict the remaining useful life (RUL) of individual units based on noisy condition monitoring signals is proposed. The prediction accuracy of existing data-driven prognostic methods depends on the capability of accurately modeling the evolution of condition monitoring (CM) signals. Therefore, it is inevitable that the RUL prediction accuracy depends on the amount of random noise in CM signals. When signals are contaminated by a large amount of random noise, RUL prediction even becomes infeasible in some cases. To mitigate this issue, a robust RUL prediction method based on constrained Kalman filter is proposed. The proposed method models the CM signals subject to a set of inequality constraints so that satisfactory prediction accuracy can be achieved regardless of the noise level of signal evolution. The advantageous features of the proposed RUL prediction method is demonstrated by both numerical study and case study with real world data from automotive lead-acid batteries.

1. Introduction

Remaining useful life (RUL) prediction is essential to ensure the overall system reliability and to design a successful maintenance strategy. Therefore, significant research efforts have been devoted to RUL prognosis [8,19]. Moving forward from the traditional time-to-failure analysis, contemporary RUL prognosis emphasizes on the prediction of failure event on an individual unit based on the condition monitoring (CM) signals, also referred as degradation signals in some applications [36]. The CM signals are the observable indicators that can be used to infer the unobservable underlying health status of a system, e.g., internal resistance of the automotive battery or bearing vibration measurements of a gearbox. Thus, many prognostic algorithms based on the CM signal observations are proposed recently [7,6,28,32,25].

The RUL prognostic algorithms that utilize the CM signals can be generally classified into two categories based on the definition of the failure. In the first category, the failure of a system is defined as the time when the CM signal surpasses a pre-specified failure threshold [15]. Often, this type of failure is called the soft failure because the failure is determined by a user-defined threshold [34]. In the second category, the value of the CM signal does not determine the failure occurrence directly, rather, influences the occurrence probability [13]. This type of failure is called hard failure [8,36]. In both classes of prognostic method, a mixed effects model is typically used to model the evolution of CM signals. Furthermore, to facilitate the accurate RUL prediction for a specific unit, the parameters of the mixed effects model are updated through Bayesian inference framework [7,36]. Specifically, first, the initial population-level mixed effects model is fitted at the offline stage, which reflects the average behavior of multiple units and provide the prior information. Then, the model updating is conducted in the online stage based on both prior information and the newly collected CM signals from the specific unit to obtain the posterior information. As a result, the posterior contains unique characteristics of the specific unit of our interest. The Bayesian updating has been investigated intensively and it is generally agreed that the model updating is the key for satisfactory RUL prediction accuracy [26].

Although the mixed effects CM signal model and the online Bayesian model updating have shown its efficacy in various applications, one issue has not been sufficiently addressed in the existing literature. The CM signals (or degradation signals) are indicators of the unobservable health status of a unit or system. Thus, CM signals should be inherently monotonic because the underlying health condition is always deteriorating unless some maintenance actions have been performed [3,37]. Indeed, most of prognostic methods based on CM signals implicitly assume the monotonicity of the signal. For instance, in the soft failure prognosis, the failure is defined by the time when CM signal passes the

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http://dx.doi.org/10.1016/j.ress.2016.02.006
0951-8320/

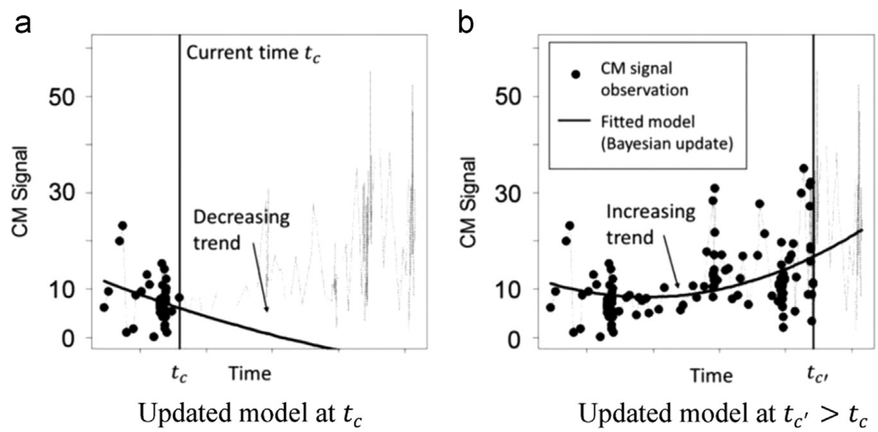

Fig. 1. Illustration of Bayesian updating with violation of monotonicity.

failure threshold. Clearly, if the updated signal evolution path shows a decreasing trend in time, the predicted signal would never pass the threshold. Thus, the RUL prediction becomes infeasible [14]. Because the signal observations are subject to random disturbances such as the sensor noise, the conventional Bayesian updating method used in the existing literatures cannot guarantee the monotonic trend of the updated CM signal. Recently, recursive filtering methods such as Kalman and particle filters have been actively investigated for the RUL prognosis [20,33,38,5]. Those methods are good examples of adopting sequential Bayesian inference to update the CM signal path modeled by, for instance, Weiner process [33]. To some extent, stochastic filters can serve as a noise-remover. However, despite of advantageous features, existing filter-based RUL prognostic methods do not have the control over the state space because they are built upon the conventional Bayesian inference framework. Thus, they may still produce counter-intuitive posterior state estimates and hinder reasonable RUL prediction when severe noise is present. This phenomena is illustrated in Fig. 1.

Fig. 1 shows a CM signal for an automotive lead-acid battery collected from an example unit. From Fig. 1(a), the updated model at time t_c violates the monotonicity principle and exhibits a decreasing trend in time. The trend becomes increasing when more signal observations are cumulated as shown in Fig. 1(b). However, the trend is still not monotonic. Thus, the fitted model based on the conventional Bayesian model updating method does not accurately reflect the true underlying degradation process of the unit.

Even though the abovementioned issue has been recognized in many applications, it has not been thoroughly studied in the existing RUL prognosis literature. Typically, when the CM signals show a high level of noise and the RUL prediction is infeasible, the prediction is skipped at that time and the algorithm waits for more CM signal observations to accumulate until the prediction becomes feasible again [14]. In some cases, the signals with a high level of noise are pre-processed prior to the modeling via signal smoothing techniques such as exponential smoothing [1]. However, these methods do not truly solve the issue and cannot guarantee the monotonicity of the CM signals.

To fill this research gap, we propose an effective online model updating method by using the constrained Kalman filter (CKF) approach. The conventional Bayesian model updating is replaced by the CKF procedure so that the undesirable parameter space for the CM signal model can be excluded. In this way, CKF can not only guarantee the monotonicity of the signal but also incorporate specific domain knowledge of the degradation process. To the best of our knowledge, no existing work has been reported on integrating the CKF method into an online failure prognosis framework to deal with the issue of non-monotonicity of the predicted CM signal. A comprehensive simulation study and a real world case study on the RUL prognosis for automotive lead-acid battery demonstrate the effectiveness of the proposed approach. In addition to above-mentioned contribution, we also proposed a new method of realizing the CKF algorithm. Among several variants of CKF approaches, the probability density function (PDF) truncation approach is known to be effective for enforcing double-sided inequality constraints [27]. The PDF truncation method truncates the posterior distribution obtained by the conventional unconstrained KF at the edges of the inequality constraints to ensure that the final estimates would lie within the specified constrained space and many promising results have been reported [18]. However, the existing PDF truncation methods either depend on a complex variable decomposition [23] or a computationally expensive Monte Carlo approach [27]. Due to such limitations, these methods are less appealing for online real time prognosis. To overcome those limitations and to facilitate efficient online prognosis, we propose a new approach for the PDF truncation by directly using the moment generating function (MGF) that is computationally efficient.

The paper is organized as follows. In Section 2, the CM signal model and the corresponding online updating method based on the proposed CKF is introduced. Then, the RUL prognostic framework with CKF is described in Section 3. A numerical study that reveals meaningful insights of the proposed method is discussed in Section 4. In Section 5, a case study with real world application of RUL prognosis for automotive lead-acid batteries is presented which shows the practical benefit of the proposed method. Lastly, Section 6 summarizes the contributions of the proposed method and concludes the paper.

2. Modeling noisy CM signals based on the constrained Kalman filter

In this section, one of the most popular methods for modeling the CM signal, a mixed effects model, is reviewed. The conventional online Bayesian model updating based on the mixed effects model is presented accordingly. Then, the constrained Kalman filter (CKF) method is described.

2.1. Review of CM signal models and the online Bayesian model updating

To model the CM signal evolution, the mixed effects model has been widely used in RUL prognosis literature due to its flexible model structure [7]. The mixed effects model allows each unit to have its own parameter. In other words, the model assumes that each unit has its own signal propagation path. The mixed effects