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A particle filtering and kernel smoothing-based approach for new design component prognostics

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ABSTRACT

This work addresses the problem of predicting the Remaining Useful Life (RUL) of components for which a mathematical model describing the component degradation is available, but the values of the model parameters are not known and the observations of degradation trajectories in similar components are unavailable. The proposed approach solves this problem by using a Particle Filtering (PF) technique combined with a kernel smoothing (KS) method. This PF–KS method can simultaneously estimate the degradation state and the unknown parameters in the degradation model, while significantly overcoming the problem of particle impoverishment. Based on the updated degradation model (where the unknown parameters are replaced by the estimated ones), the RUL prediction is then performed by simulating future particles evolutions. A numerical application regarding prognostics for Lithium-ion batteries is considered. Various performance indicators measuring precision, accuracy, steadiness and risk of the obtained RUL predictions are computed. The obtained results show that the proposed PF–KS method can provide more satisfactory results than the traditional PF methods.

1. Introduction

Prognostics is an engineering discipline which is mainly focused on the estimation of the future degradation path, remaining useful life and potential risk associated to an equipment [1]. Technical approaches of prognostics can be broadly categorized into data-driven and model-based [1–5]. Model-based prognostic methods use mathematical representations of the equipment degradation evolution in order to predict the equipment Remaining Useful Life (RUL) [6–9]. They usually require the knowledge of the values of the model parameters, which are typically estimated considering the results of experimental tests or by observing the degradation behaviors of similar components. In practice, the whole model-based prognostics process is divided into an off-line and an on-line phase. During the off-line phase, a mathematical model of the equipment degradation is built using the available physical knowledge on the involved degradation mechanisms and historical degradation data. Some statistical or artificial intelligence methods are, then, applied to the available historical data in order to estimate model parameters. For example, in [10] the authors used an adaptive-network-based fuzzy inference system and robust relevance vector machine to build the steelmaking process model which reduced the effect of noise and outliers in the historical data; in [11], a combined relevance vector machine and exponential regression method was used to estimate the ball bearings degradation and predict its RUL based on real world vibration-based degradation data; in [12,13], the authors used artificial neural networks combined with optimization algorithms to estimate the State-of-Charge of batteries. During the on-line phase, the acquired degradation measurements or condition monitoring data are used to adapt the degradation model to the current degradation situation and to predict the equipment RUL. For example, vibration data were used in [14] to predict the RUL distribution of bearings and the RUL distribution of Gyros were estimated using data collected during the testing process in [15].

The novelty of the present work is that we consider, within the framework of model-based prognostics, a case in which a mathematical model of the degradation process is available but the true model parameter values are unknown, and there are no data available for estimating them related to the degradation of similar components. These situations are typically encountered for safety-critical and high-value components which are characterized by very high reliability, unique or new design material composition. For these kinds of components, performing run-to-fail tests is too expensive or not feasible.

In such cases, the model parameters can be estimated by resorting to (i) expert knowledge, with uncertainty possibly expressed in the form of interval of values and (ii) a sequence of data collected during the component operating life until the present time. In this setting of

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very limited available information, the objective is to jointly estimate (i) the parameters of the degradation model, (ii) the remaining useful life of the component. For doing this, one has to handle the following sources of uncertainty (i) measurement uncertainty, (ii) intrinsic randomness of the degradation process, (iii) uncertainty in the model parameters and (iv) uncertainty on the future operational and environmental conditions.

In model-based prognostics, the problem of predicting the component RUL is typically tackled in two sequential steps: (1) estimation of the component degradation state at the present time and (2) prediction of the future evolution of the component degradation.

Step (1) is typically handled by resorting to filter methods such as Kalman Filter [16–18], used in cases of linear degradation models and Gaussian noise, and PF, used in cases of non-linear degradation models and/or non-Gaussian noise. Examples of applications of the PF methods to non-linear degradation problems can be found in [19–22]. Notice that all these works assumed that the model parameter exact values were known. In principle, also the uncertainty on the model parameters values can be treated by adopting Bayesian filtering methods where the dimension of the state vector is extended by including also the elements for the unknown parameters [23–25]. The problem of joint estimation of system state and model parameters had been addressed in [25,26] considering Bayesian filtering approaches. For the application of fault detection, an approach to estimating the model parameters and the system state was discussed in [26]. In the context of prognostics, with few model parameters to be estimated, Bayesian approaches had been presented in [27–29]; however, these prognostic approaches had not been developed for cases with several model parameters and very poor knowledge on their prior distributions. In particular, it has been shown that in those cases in which the true parameter values are located in the tail of the prior distributions or the prior distributions are characterized by large variances with respect to the parameter typical ranges, most particles weights tend to very small values after the Bayesian updating. Under such situations, traditional PF methods will suffer a serious particle impoverishment [30]; thus, in order to get satisfactory estimates, one would need to use a very large number of particles, with the consequence of increasing computational efforts, and rendering this solution unfeasible in practical cases.

Alternatively, the problem of particle impoverishment has been addressed by adding an artificial evolution to the particles in order to maintain their diversity [23,31]. However, it has been shown that adding an artificial evolution causes an increase of the variance of the particles, which may obstacle the convergence of the population towards the true model parameter values [25]. Furthermore, the variance of the artificial noise is a further hyper-parameter to which the estimation results are very sensible, and which may be difficult to set in the context of the information available in the present work.

In this work, in order to overcome the problem of particle impoverishment in a case in which few available degradation measurements are available, we consider a method for parameter estimation based on a kernel smoothing technique. The method was proposed in [25] in a completely different problem context and is here extended to a prognostics problem. The main advantage of the method is that it can solve the problem of impoverishment without the side effects of variance increase (i.e. without adding extra artificial noise on particles).

Once the equipment degradation state at the present time and the model parameters have been estimated, it is necessary to predict the future evolution of the equipment degradation trajectory (step 2). Notice that this requires going beyond the traditional use of filtering methods, since it involves future time horizons in which no measurements are available for the Bayesian updating. This issue is addressed by adopting a procedure proposed in [32] based on the simulation of the future evolution of the particles describing the component degradation state at the present time.

The main contribution of this work consists in the proposal of a systematic method for on-line RUL prognostics of degrading equipment in the cases that (1) the true values of the parameters in the degradation model are unknown and/or affected by large uncertainties; (2) historical operation data of degradation of similar equipments are unavailable. From the methodological point of view, the novelty consists in the application of a kernel smoothing procedure to a prognostic problem which requires the prediction of the future evolution of the component degradation. The developed method for model parameters estimation and RUL prediction is applied to a numerical case study regarding the degradation of a Lithium-ion battery. Various performance indicators measuring precision, accuracy, steadiness and risk of the obtained RUL predictions are considered.

The remainder parts of the paper are organized as follows. Section 2 illustrates the problem statement. In Section 3, the PF approach to prognostics is briefly recalled, whereas in Section 4, we introduce the PF–KS method for the joint estimations of the degradation state and the model parameters. Sections 5 and 6 describe the prediction of the future degradation evolution and the component RUL. Section 7 shows a numerical application of the proposed method to the prognostic of the RUL of a Lithium-ion battery. In Section 8, we draw some conclusions and suggest potential future work.

2. Problem statement

The objective of the work is to develop a prognostic method for RUL prediction of a degrading component, and related uncertainty. The following sources of information are considered available:

- A degradation model for the mathematical representation of the evolution of the equipment degradation. The mathematical model is typically obtained from a physical understanding of the degradation mechanism. In this work, we assume that the physical model can be formulated as a first order Markov Process:

  $$x_t = g(x_{t-1}, \mathbf{p}_{t-1}, \gamma) \tag{1}$$

  where $g(x, \mathbf{p}, \gamma)$ is the recursive transition function, x_t is an indicator of the equipment degradation state at time t, $\mathbf{p}$ is the vector of the model parameters, whose true values are unknown, γ is the process noise which represents the degradation process uncertainty. Model parameters and process noise are assumed to be constant during the life of the component.
- The measurement equation which links the degradation state x and its measurements. It is typically represented by a possibly non-linear function h

  $$z_t = h(x_t, \sigma_m) \tag{2}$$

  where z_t is the measurement of x_t at time t and σ_m is the measurement noise.
- Degradation measurements $z_t (t = 1, 2, \ldots, T)$, collected during the operating life of the component, until the present time T. For simplicity, we assume that measurements have been performed at regular intervals from $t=1$ (in arbitrary units).
- A failure threshold defining the maximum acceptable degradation state: the equipment is considered failed when its degradation exceeds the failure threshold. In this work, we assume that the failure threshold value is known [33].

Notice that degradation measurements performed on identical or similar components are considered to be not available. On the contrary, we assume the availability of a prior estimate of the probability density functions (PDF) of the initial degradation state $p(x_0)$ and the model parameters $p(\mathbf{p}_0)$ based on expert judgment.