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An improved unscented particle filter approach for lithium-ion battery remaining useful life prediction

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ABSTRACT

Lithium-ion rechargeable batteries are widely used as power sources for mobile phones, laptops and electric cars, and gradually extended to military communication, navigation, aviation, aerospace and other fields. Accurate remaining useful life (RUL) prediction of lithium-ion battery plays an important role in avoiding serious security and economic consequences caused by failure to supply required power levels. Thus, the RUL prediction for lithium-ion battery has become a critical task in engineering practices. With its superiority in handling nonlinear and non-Gaussian system behaviors, the particle filtering (PF) technique is widely used in the remaining life prediction. However, the choice of importance function and the degradation of diversity in sampling particles limit the estimation accuracy. This paper presents an improved PF algorithm, that is, the unscented particle filter (UPF) based on linear optimizing combination resampling (U-LOCR-PF) to improve the prediction accuracy. In one aspect, the unscented Kalman filter (UKF) is used to generate a proposal distribution as an importance function for particle filtering. In the other aspect, the linear optimizing combination resampling (LOCR) algorithm is used to overcome the particle diversity deficiency. It should be noted that the step coefficient K can affect the performance of LOCR algorithm, and the fuzzy inference system is applied to determine the value of step coefficient K. According to the analysis results, it can be seen that the proposed prognostic method shows higher accuracy in the RUL prediction of lithium-ion battery, compared with the existing PF-based and UPF-based prognostic methods.

1. Introduction

In recent years, lithium-ion batteries are successfully used in many consumer electronics (e.g., mobile phones, laptops and electric cars), and gradually extended to military communication, navigation, aviation, aerospace and other fields [1]. The main reason of this success is that they offer prominent advantages in power supply. Compared with the traditional batteries such as lead-acid, nickel-cadmium or nickel-metal-hydride cells, lithium-ion battery has lower weight, higher power density, higher operating voltage, wider temperature range and longer cycle life [2]. For example, with the same capacity, the weight of lithium-ion battery is half of nickel cadmium or nickel-metal hydride batteries, and the operating voltage of lithium-ion battery is three times that of nickel cadmium or nickel-metal hydride batteries. However, failures of lithium-ion batteries may have a wide range of possible hazards because of their extensive usage.

For power equipment and systems, failures of lithium-ion batteries can lead to their performance degradation, and even lead to task failures and casualties [3]. For example, Samsung Galaxy Note 7 has caused a number of explosions because of lithium-ion battery failures, resulting in serious economic loss and adverse social impact. Samsung lost around $17 billions in its global recall of 2.5 million Galaxy Note 7. In the field of aerospace, power system failure is a critical cause of task failure. For example, in 1999, the abnormal internal impedance of the battery led to the failure of the US space test [4]. Consequently, the safety and reliability of lithium-ion battery has become a focus of attention in engineering practices.

In order to ensure and improve the safety and reliability of lithium-ion battery, a lot of research has been conducted on battery health monitoring [3–5]. In these research, the prognostic and health management (PHM) methods play a major role [6–7]. The implementation of prognostics and health management can help people understand battery state-of-charge (SOC) and state-of-health (SOH), which provide useful information to battery management systems (BMSs). The SOC and SOH are two aspects of lithium-ion battery PHM. The SOC estimates remaining energy of battery as it is being used. Accurate SOC estimation can balance differences between individual cells, optimize charge and discharge strategy, and prevent overheating, overcharge

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and over discharge. Gebel et al. [8] determined the SOC of a lithium iron phosphate cell using classification methods based on frequency domain data. Piller et al. [9] summarized the commonly used SOC determination methods and established the relation between different methods and the most common applications. The SOH estimates general health condition and ability to deliver specified performance compared with a new one by collecting measures/estimates of different internal battery physical parameters. Guha et al. [10] considered the internal resistance growth of a battery as the aging parameter, and an empirical model was developed based on electrochemical impedance spectroscopy (EIS) test data. Jha et al. [11] developed the SOH estimation and RUL prediction with very high accuracy and precise confidence bounds by integrating the benefits of particle filter and bond graph model.

Though significant progress has been achieved on battery SOC and SOH techniques, it still remains difficult to accurately predict the remaining-useful-life of a battery from the estimations. Therefore, in order to improve battery management system, a lot of research on lithium-ion battery RUL prediction has been conducted. According to battery degradation mechanism, some battery degradation models were proposed for the RUL estimation. Chao et al. [12] presented a new particle filter framework for the RUL prediction of lead-acid battery by incorporating battery's electrochemical model, in which model parameters that reflect the degradation of battery were seen as state variables. Guha et al. [10] put forward a method for the RUL estimation of lithium-ion battery based on the internal resistance growth model using the particle filtering approach, in which the internal resistance growth of a battery have been considered as the aging parameter. Xu et al. [13] proposed a hierarchical model to characterize lithium-ion battery degradation by examining detailed discharging voltage profiles in different discharging cycles. Li et al. [14] developed a simplified multi-particle model via a predictor-corrector strategy and quasi-linearization, which enables researchers to accelerate the processes of the battery design, aging analysis and RUL estimation. Si et al. [15] proposed an adaptive and nonlinear prognostic model to estimate battery RUL using a system's history of observed data to date. Feng et al. [16] found two markers of a battery's maximum releasable capacity decay, named as time-to-voltage saturation and time-to-current-saturation, and proposed an RUL prediction method based on a damage-marker bivariate degradation model. Wang et al. [17] proposed a conditional three parameter capacity degradation model and combined it with a relevance vector machine to estimate the remaining useful life of lithium-ion battery.

In addition to the above mentioned methods, the improved Kalman filter and support vector machine are also commonly used to predict the RUL of battery. Hu et al. [18] proposed a multiscale framework with EKF for SOC and capacity estimation, which comprises two ideas: (i) a multiscale framework to estimate SOC and capacity that exhibit time-scale separation and (ii) a state projection scheme for accurate and stable capacity estimation. Zheng et al. [19] put forward a novel method, which is developed using unscented Kalman filter (UKF) with relevance vector regression and applied to the RUL and short-term capacity prediction of battery. Compared with the Kalman filter, the UKF can better depict the nonlinearity of the state equation with higher estimation accuracy. Khelif et al. [20] estimated the RUL at any time instant of the degradation process by establishing a direct relation between sensor values or health indicators using a support vector regression (SVR). Li et al. [21] proposed a grey support vector machine model by integrating the improved grey model with the support vector machine to predict the battery RUL.

However, since battery life generally demonstrates non-linear and non-Gaussian property, the Kalman filter is sometimes insufficient to handle it, and the particle filter is another option that has been utilized in the lithium-ion battery's RUL estimation. In addition, the fusion method based on model-driven and data-driven techniques is a hotspot for the RUL prediction, and a lot of research has been conducted. For example, Miao et al. [22] utilized the empirical degradation model and the unscented particle filter algorithms to predict the battery remaining useful life, and achieved a very good result. Hu et al. [23] employed the Gauss–Hermite particle filter to project the capacity fade to the end-of-service value and captured the uncertainty in the RUL prediction. Li et al. [24] proposed a mutated PF technique to approximate the posterior probability density function (PDF) of system state, in which a novel mutation approach is proposed to search extended areas of the prior PDF using mutated particles to make more comprehensive exploration of the posterior PDF. Sbarufatti et al. [25] proposed a method for predicting the end-of-discharge of lithium-ion battery, which stems from the combination of particle filter and radial basis function neural network. Dong et al. [26] utilized a filter algorithm known as the Support Vector Regression-Particle Filter (SVR-PF) to predict the lithium-ion battery's SOH and RUL. Wang et al. [27] constructed a state-space model for the lithium-ion battery capacity to assess capacity degradation and made use of a spherical cubature particle filter to solve the state-space model. Liu et al. [28] developed an improved particle learning (PL) framework to predict the RUL of lithium-ion batteries, in which the kernel smoothing algorithm is fused into PL to keep the variance of parameter particles invariant during recursive propagation with the battery prediction model. Jiang et al. [29] established the multiple τth-order state equation which could really reflect electronics degradation process by training Least Squares Support Vector Regression via electronics historical failure data. It can be used in particle filter to predict the electronics status, remaining useful life or other performances. Su et al. [30] established a new data-driven prognostic method based on the interacting multiple model particle filter, which can be used to determine the remaining useful life of lithium-ion battery and the probability distribution function of the associated uncertainty. Zhang et al. [31] proposed an improved unscented particle filter method for lithium-ion battery RUL prediction based on Markov chain Monte Carlo (MCMC), which used the MCMC to solve the problem of sample impoverishment in UPF algorithm.

The improved particle filtering methods described above partially reduced the problem of particle degradation and particle diversity deficiency, and achieved good result in the RUL estimation of lithium-ion battery. However, the problems of particle degradation and particle diversity deficiency are still challenging issues in the RUL estimation. The work presented in this paper is an improvement on the particle filter from the aspects of importance function selection and resampling technique to more accurately predict the RUL of lithium-ion battery. On one hand, the UKF is used to generate a proposal distribution as an importance function for particle filtering. Miao et al. [22] verified that the results obtained by the UPF algorithm are better than those of standard particle filter algorithm in the RUL estimation of lithium-ion battery. On the other hand, a linear optimizing combination resampling algorithm is used to overcome the particle diversity deficiency. Zou et al. [32] confirmed that the LOCR algorithm partly overcomes the loss of diversity in particles and improves the precision of PF.

The organization of the paper is as follows. Section 2 introductions the concepts of the standard PF, UKF. Section 3 presents the process of the LOCR and U-LOCR-PF. Section 4 describes the lithium-ion battery life testing data that is used in this paper and establishes the degradation model. Section 5 gives the comparison results of the standard PF, UPF and U-LOCR-PF, respectively. Conclusions are drawn in Section 6.

2. Unscented particle filter

Particle filter is a statistical filtering technique based on the Monte Carlo method and recursive Bayesian estimation. The essence of particle filter is the approximate probability distribution of discrete random measures composed of particles and their weights, and the discrete random measures are updated according to the algorithm. Unscented particle filter uses UKF as a proposal distribution, which is used to generate an importance function for particle filter. To better