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Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter

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HIGHLIGHTS

- Battery State-of-Health is estimated by the health condition parameters.
- Propose capacity degradation parameters to analyze capacity degradation online.
- Propose the RUL prediction model to predict the RUL and update its distribution.
- A novel support vector regression-particle filter algorithm is used in the research.

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ABSTRACT

Lithium-ion batteries are used as the main power source in many electronic and electrical devices. In particular, with the growth in battery-powered electric vehicle development, the lithium-ion battery plays a critical role in the reliability of vehicle systems. In order to provide timely maintenance and replacement of battery systems, it is necessary to develop a reliable and accurate battery health diagnostic that takes a prognostic approach. Therefore, this paper focuses on two main methods to determine a battery's health: (1) Battery State-of-Health (SOH) monitoring and (2) Remaining Useful Life (RUL) prediction. Both of these are calculated by using a filter algorithm known as the Support Vector Regression-Particle Filter (SVR-PF). Models for battery SOH monitoring based on SVR-PF are developed with novel capacity degradation parameters introduced to determine battery health in real time. Moreover, the RUL prediction model is proposed, which is able to provide the RUL value and update the RUL probability distribution to the End-of-Life cycle. Results for both methods are presented, showing that the proposed SOH monitoring and RUL prediction methods have good performance and that the SVR-PF has better monitoring and prediction capability than the standard particle filter (PF).

1. Introduction

Lithium-ion batteries are a source for major or supplementary power in many kinds of devices, they are quickly becoming the most common power source for Electric Vehicles (EV) [1]. Remaining Useful Life (RUL) of a battery is defined as the useful life left on the battery at a particular time of operation. RUL estimation is essential to the Condition Based Maintenance (CBM) and health management of the battery [2]. It is important to find a reliable and accurate approach to monitor the Lithium-ion battery State-of-Health (SOH) and predict the RUL, to provide timely maintenance and replacement of the battery system [3–4].

Many studies in the field of Lithium-ion battery health condition estimation are principally based on the development of prognostics tools [5–8]. Regression algorithms such as Support Vector Machine (SVM) [9] and Relevance Vector Machine (RVM) [10] were applied to Lithium-ion battery health condition analysis, which have been able to estimate the degradation trend of battery performance. Meanwhile, Kalman Filters [11–14] were used by some researchers to study battery health due to their capability to estimate the battery state parameters from experimental data. Moreover, a Particle Filter (PF) is able to deal with more general system models than a Kalman Filter, consequently it has also been applied to battery SOH monitoring and RUL prediction [15–18]. The PF estimated value and probability distribution of the RUL are good indicators of Lithium-

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ion battery related maintenance [16–18]. Especially, Saha et al. [17] focused on battery SOH monitoring and RUL prediction by using the battery impedance data extracted from Electrochemical Impedance Spectroscopy (EIS), which provided an approach for the application of the PF in the field of Lithium-ion battery health prognostics. The impedance of Lithium-ion battery provides important data for the estimation of battery degradation [19]. The correlation between the Lithium-ion battery impedance and capacity was observed in several studies [20,21].

In the light of these previous works, the correlation between battery capacity and impedance [20,21] provides new parameters for analyzing the battery capacity degradation. These capacity degradation parameters should be estimated through an online process so the real time battery health condition can be monitored. Similar parameters have been estimated by the linear regression algorithm by Takeno et al. [20].

Moreover, the battery RUL can be predicted by projecting the PF algorithm estimated capacity degradation trend out until the capacity reaches the End of Life (EOL) criterion. The probability distribution parameters at the last time step of online updating are treated as the final RUL distribution [15–18]. However, the RUL prediction is a multi-step ahead prediction process, a few more cycles should be processed after the online updating stops, so the probability distribution parameters of the RUL are not updated when the time step changes.

In this study, a method for battery SOH monitoring is developed to analyze the proposed capacity degradation parameters online and build a novel RUL prediction model which is able to update the RUL probability distribution parameters. Moreover, a Support Vector Regression-Particle Filter (SVR-PF) algorithm is implemented in the research to improve the standard PF against the degeneracy phenomenon. The RUL prediction is based on the SOH monitoring results and the percentage of nominal capacity is used to represent the battery SOH.

The rest of this paper is organized as follows: Section 1 reviewed the related literature and introduced the general content of the paper. Section 2 introduces the basic algorithms of the PF and SVR-PF. Section 3 describes the battery data and the circuit model. In section 4 the estimation of battery health condition parameters and the modeling of the lithium-ion battery are introduced. Section 5 presents the new RUL prediction method. In section 6 the simulation results are shown to test the performance of the proposed SOH monitoring and RUL prediction methods and compare the estimation and prediction capability between the SVR-PF and the standard PF. The conclusions are given lastly in section 7.

2. Particle filter and support vector regression-particle filter

2.1. Particle filter

Particle filter (PF) is a general algorithm based on the recursive Bayesian estimation [22], which uses the Monte Carlo method to draw samples (also called particles) from a posterior distribution and assigns a weight to each particle [23].

Compared to the Kalman Filter which only focuses on linear systems and Gaussian noise [24], a particle filter focuses on a more general situation where the system can be nonlinear and the noise distribution can be non-Gaussian. The system state space model for PF is:

$$\begin{cases} x_k = f(x_{k-1}, v_{k-1}) \\ z_k = h(x_k, n_k) \end{cases} \tag{1}$$

where the system states are represented by x_k, either the measurements or the system outputs is represented by z_k and the system noise and measurement noise are represented by v_{k-1} and n_k respectively, which both can be either Gaussian or non-Gaussian.

Suppose we know the prior distribution $p(x^i_{0:k-1}|z_{1:k-1})$ and have already drawn N samples from the posterior distribution from system (1). The approximation of the posterior distribution is:

$$p(x_{0:k}|z_{1:k}) \approx \sum_{i=1}^{N} w^i_k \delta\left(x_{0:k} - x^i_{0:k}\right) \tag{2}$$

where the samples (i.e., the particles) are represented by $\{x^i_k\}$ and the sample weights are represented by $\{w^i_k\}$ which have $\sum_i^N w^i_k = 1$. A higher weight indicates a higher probability of a sample. $\delta()$ is the Dirac-Delta function.

It is hard to sample directly from a posterior distribution, therefore we use another technique known as Importance Sampling, which draws samples from the importance distribution and has this form:

$$q(x_{0:k}|z_{1:k}) \approx \sum_{i=1}^{N} \delta\left(x_{0:k} - x^i_{0:k}\right) \tag{3}$$

If the importance distribution (3) is substituted into (2), the weight update is given by:

$$w^i_k = \frac{p\left(x^i_{0:k}|z_{1:k}\right)}{q\left(x^i_{0:k}|z_{1:k}\right)} \tag{4}$$

If the importance distribution (3) can be decomposed to:

$$q(x_{0:k}|z_{1:k}) = q(x_k|x_{0:k-1}, z_{1:k})q(x_{0:k-1}|z_{1:k-1}) \tag{5}$$

We can have the weight renew equation based on Bayesian estimation:

$$\begin{aligned} w^i_k &= \frac{p\left(z_k\middle|x^i_k\right)p\left(x^i_k\middle|x^i_{k-1}\right)p\left(x^i_{0:k-1}|z_{1:k-1}\right)}{q\left(x^i_k\middle|x^i_{0:k-1}, z_{1:k}\right)q\left(x^i_{0:k-1}|z_{1:k-1}\right)} \\ &= w^i_{k-1}\frac{p\left(z_k\middle|x^i_k\right)p\left(x^i_k\middle|x^i_{k-1}\right)}{q\left(x^i_k\middle|x^i_{0:k-1}, z_{1:k}\right)} \end{aligned} \tag{6}$$

where the likelihood function is represented by $p(z_k|x^i_k)$ and the state transfer distribution is represented by $p(x^i_k|x^i_{k-1})$. If system (1) follows the Markov process, the weight renew Equation (6) can be simplified to

$$w^i_k = w^i_{k-1}\frac{p\left(z_k\middle|x^i_k\right)p\left(x^i_k\middle|x^i_{k-1}\right)}{q\left(x^i_k\middle|x^i_{k-1}.z_k\right)} \tag{7}$$

If we choose state transfer distribution to be the importance distribution:

$$q\left(x^i_k\middle|x^i_{k-1}, z_k\right) = p\left(x^i_k\middle|x^i_{k-1}\right) \tag{8}$$

The weight update equation can be simplified to (9) in which the likelihood function $p(z_k|x^i_k)$ and the prior weights are used to update the new weights [25]:

$$w^i_k = w^i_{k-1}p\left(z_k\middle|x^i_k\right) \tag{9}$$

Resampling is used to avoid the problem of degeneracy of the PF algorithm. Without resampling, after a few iterations, some of the