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Satellite lithium-ion battery remaining useful life estimation with an iterative updated RVM fused with the KF algorithm

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Abstract Lithium-ion batteries have become the third-generation space batteries and are widely utilized in a series of spacecraft. Remaining Useful Life (RUL) estimation is essential to a spacecraft as the battery is a critical part and determines the lifetime and reliability. The Relevance Vector Machine (RVM) is a data-driven algorithm used to estimate a battery's RUL due to its sparse feature and uncertainty management capability. Especially, some of the regressive cases indicate that the RVM can obtain a better short-term prediction performance rather than long-term prediction. As a nonlinear kernel learning algorithm, the coefficient matrix and relevance vectors are fixed once the RVM training is conducted. Moreover, the RVM can be simply influenced by the noise with the training data. Thus, this work proposes an iterative updated approach to improve the long-term prediction performance for a battery's RUL prediction. Firstly, when a new estimator is output by the RVM, the Kalman filter is applied to optimize this estimator with a physical degradation model. Then, this optimized estimator is added into the training set as an on-line sample, the RVM model is re-trained, and the coefficient matrix and relevance vectors can be dynamically adjusted to make next iterative prediction. Experimental results with a commercial battery test data set and a satellite battery data set both indicate that the proposed method can achieve a better performance for RUL estimation.

1. Introduction

Since a lithium-ion battery was firstly used in a United Kingdom satellite called STRV-1d, it has been widely used in many spacecraft including satellites and deep-space detectors. A significant improvement on satellites' total weight reduction is achieved with the huge advantages of gravimetric energy density and volumetric energy density. Lithium-ion batteries have

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become the third generation of aerospace application power storage batteries.[1]

As one of the most critical component, a lithium-ion battery is an inevitable sub-system of a spacecraft.[2] The battery energy storage not only is the solitary power source while a spacecraft operating in a shadow phase, but also provides extra peak power while some high-power payloads working or changing the running orbit. Accurate Remaining Useful Life (RUL) estimation can help realizing the condition-based maintenance schedule and optimizing the task schedule. This is also essential for future autonomous maintenance and autonomous health management. In addition, with the high requirement of the spacecraft long lifetime, i.e., 8–10 years for low-earth orbit satellites, battery RUL estimation can provide more decision-making information for a ground reliability assessment. In particular, for those low-cost and long-lifetime space applications or urgent launching missions, a sufficient on-ground degradation or lifetime test is not permitted.

Besides aerospace applications, lithium-ion batteries have become a crucial part for almost all industrial systems. Performance degradation identification, capacity fade modeling, and RUL estimation have drawn much attention in reliability engineering. Especially, lithium-ion battery RUL estimation has become a research hotspot in the field of Prognostics and Health Management (PHM).

The approaches for lithium-ion battery RUL estimation can mainly be classified into two categories: model-based and data-driven methods. Model-based methods are generally achieved by building physical degradation models describing lithium-ion battery inner electrochemical reactions. Although complex models can always reveal how irreversible processes impact the performance degradation, model-based methods always involve too many parameters to represent complicated failure mechanisms properly. Furthermore, since a lithium-ion battery is a kind of dynamic nonlinear system, parameters are not consistent under different operating conditions and working loads, which makes it more difficult to identify the parameters. On the other hand, some electrochemical features, i.e., Solid Electrolyte Interphase (SEI),[3] Electrochemical Impedance Spectrum (EIS),[4] etc., can only be measured under strict conditions and by high-cost instruments. These testing approaches cannot satisfy the real applications. Thus, for RUL estimation approaches used on spacecraft, it is difficult to find proper dynamic parameters to match the special in-orbit operating conditions for model-based methods.

Data-driven methods estimate the RUL based on historical data and monitoring data. Many data-driven methods have already been applied in battery RUL estimation. Liu et al.[5] optimized an AutoRegressive (AR) model by combining a nonlinear degradation function to estimate the battery RUL. Liu et al.[6] utilized Artificial Neural Networks (ANNs) whose network weights are adaptively optimized using the Recursive Levenberg–Marquardt (RLM) method to predict RUL. Lu et al.[7] proposed a geometrical approach to model the li-ion battery capacity, and four geometrical features were utilized to present the slight changes in the performance degradation. Xing et al.[8] fused an empirical exponential and a polynomial regression model to predict the remaining useful performance of lithium-ion batteries. Yan et al.[9] introduced an LS-FDP framework for prognosis, and Lebesgue Sampling (LS) was applied for "execution only when necessary". Some other data-driven methods, such as the Naïve Bayes (NB) model,[10] the Markov Chain Mote Carlo approach,[11] the Support Vector Machine (SVM),[12,13] the Particle Filter (PF),[14–17] Gaussian Process Regression (GPR)[18], etc., are all widely used in battery RUL estimation. The Relevance Vector Machine (RVM) algorithm is also adopted in battery RUL prediction with high learning capability and easy training process.[19] The RVM represents a generalized linear model under the Bayesian framework,[20] so it can provide uncertainty management ability which is valuable for lithium-ion battery health management.[21]

Saha et al.[22] firstly attempted to use the RVM in battery prognostics, in which the RVM-PF approach provided the uncertainty presentation with a probability density function. Wang et al.[23] applied the RVM to acquire relevance vectors to indicate the battery capacity fading and cycle life. A three-parameter conditional capacity degradation model was established at the same time. Widodo et al.[24] proposed a battery health assessment framework based on a sample entropy of the discharge voltage. The RVM algorithm was used to predict the RUL and provide the uncertainty presentation. Li et al.[25] developed a multistep-ahead prediction model based on the mean entropy and the RVM was applied for the State of Health (SoH) and RUL prediction. Liu et al. [15] optimized the RVM with an incremental learning strategy to satisfy the requirements of dynamic training and on-line learning capabilities. Zhang et al.[26] weakened the noise during a battery test by using wavelet and estimated the RUL with the RVM optimized by differential evolution. Hu et al.[27] used the RVM to learn the relationship between the capacity and its charge-related features. An RVM regression model trained offline was used to infer the unknown capacity from a set of charge-related characteristics.

As mentioned above, the RVM has been widely used in lithium-ion battery RUL estimation. However, its poor performance of long-term prediction is the challenging issue that has limited its applications.[28] The statistical filtering algorithm is also applied to estimate battery RUL, but in real applications, the measurement equation is hard to determine owing to the dynamic feature of a lithium-ion battery. A fusion framework is proposed in this paper to solve the above two bottlenecks. Single-step prediction is conducted once the RVM model be trained. The predicted estimator is considered as the measurement value in the Kalman Filter (KF). The estimator is optimized and the uncertainty involved is filtered by a state-space equation. The training data set is extended with this optimized observer, and the model is retrained with this updated training data set. The main contribution in this paper can be summarized as follows: (A) to improve the poor performance of long-term prediction, we propose an iterative updated method for the RVM. The training data set is updated when the prediction value is optimized by the KF. Then the model is re-trained to obtain new relevance vectors and coefficient matrix. The capacity for next cycle is predicted after the update; (B) a data-driven method is applied as the measurement equation applied in the statistical filtering method. With this fusion framework, a state-space model can be established. Then, the KF can fuse the prediction value with the physical degradation model to get an optimized capacity prediction.

The rest of this paper is organized as follows. Section 2 introduces the principle of the RVM algorithm and the KF algorithm briefly. In Section 3, the proposed hybrid strategy for battery RUL prediction is described in detail. Experimental results are shown in Section 4 based on a commercial battery

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