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Data-driven hybrid remaining useful life estimation approach for spacecraft lithium-ion battery

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ABSTRACT

Electrical power system (EPS) is one of the most critical sub-systems of the spacecraft. Lithium-ion battery is the vital component is the EPS. Remaining useful life (RUL) prediction is an effective mean to evaluate the battery reliability. Autoregressive model (AR) and particle filter (PF) are two traditional approaches in battery prognosis. However, the parameters in a trained AR model cannot be updated which will cause the under-fitting in the long term prediction and further decrease the RUL prediction accuracy. On the other hand, the measurement function in the PF algorithm cannot be obtained in the long term prediction process. To address these two challenges, a hybrid method of IND-AR model and PF algorithm are proposed in this work. Compared with basic AR model, a nonlinear degradation factor and an iterative parameter updating method are utilized to improve the long term prediction performance. The capacity prediction results are applied as the measurement function for the PF algorithm. The nonlinear degradation factor can make the linear AR model suitable for nonlinear degradation estimation. And once the capacity is predicted, the state-space model in the PF is activated to obtain an optimized result. Optimized capacity prediction result of each cycle is utilized to re-train the regression model and update the parameters. The predictor keeps working iteratively until the capacity hit the failure threshold to calculate the RUL value. The uncertainty involved in the RUL prediction result is presented by PF algorithm as well. Experiments are conducted based on commercial lithium-ion batteries and real-applied satellite lithium-ion batteries. The results have high accuracy in capacity fade prediction and RUL prediction of the proposed method. The real applied lithium-ion battery can meet the requirement of spacecraft. All the experiments results show great potential of the proposed framework.

1. Introduction

The electrical power system (EPS) [1] is one of the most critical subsystem of the satellites. Photovoltaics is always regarded as the main power source of the satellite. However secondary (rechargeable) battery plays an important role within the EPS. Secondary battery provides power during the satellites in launch phase and shadow phase, but also utilized to offer the peak power while high power loads working.

In 2000, the satellite (STRV-1d) launched by European Space Agency first utilized lithium-ion battery as its energy storage system From then on, seized with the outstanding advantages such as high gravimetric energy density and volumetric energy density, excellent property in low temperature application [2,3], it has been applied in more and more spacecraft and already considered as the third generation of the space battery [4].

As a kind of rechargeable battery, some irreversible reactions will occur during the charging and discharging [3], such as lithium deposition [5], electrolyte decomposition [6], active material loss [7], etc. These electrochemical reactions will cause the performance degradation and finally impact the reliability of the whole battery energy storage system. RUL prognosis is an effective way to guarantee the system safely and reliably. The RUL prediction result can provide the information on the time when the battery performance will hit the failure threshold and give the performance degradation curve. This information is helpful to make use schedule and realize condition based maintenance. Via this work, spacecraft can achieve reliable operation in orbit. On the other hands, RUL prognosis also provides useful information for ground life cycle test of spacecraft battery which is designed for a long life cycle. Normal degradation test will take long time to make the performance hit the failure threshold. RUL prediction may both reduce the cost of research and shorten the time of reliability test. Therefore lithium-ion battery RUL prediction has become a popular and challenging issue in spacecraft reliability design. Pervasive researches are conducted on the prognostics of performance degradation, capacity fade, RUL prediction, etc. Model-based method and data-driven methods are two essential approaches in battery's prognostics and health management [8].

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Model-based method is divided into two aspects, one is the empirical equation, such as NASA's capacity degradation function and bi-exponential equation. The other is the electrochemical principles, which estimate the capacity degradation via the quantitative change of some materials within battery, such as SEI growth, lithium dendrite growth, electrode metal dissolution, etc. Some physical models such as single particle model, pseudo-two-dimensional model, etc. are also considered as the electrochemical principles here. Although internal resistance is not the electrochemical products, it can reflect the battery degradation but it can't be obtained directly in real application. Thus we regard those internal resistance based method as the model-based method in this paper. Eddahech et al. [9] proposed an equivalent circuit model to predict the RUL and calendar aging based on the internal resistant during Electrochemical Impedance Spectroscopy (EIS), Remmlinger J. et al. [10] deduced an equivalent circuit model to identify the internal resistance and diagnostics the cell degradation in hybrid vehicle. EIS test is an efficient method to obtain the internal resistance. But in real application, due to the complex and critical testing condition, it's impossible to conduct EIS test while spacecraft working in orbit. Shim et al. [11] utilized the X-ray diffraction (SRD) on the cathode with a Siemens D-5000 machine to make a series of diagnostic studies. The experiment result showed that the lithium-ion battery capacity loss and impedance rise in the cathode are mainly caused by the reduction of SEI layer conductivity. The performance degradation will be quantized accurately by measuring the growth of SEI. However, for the spacecraft working in space or any other actual industrial applications, the instruments and observation operations are both unrealizable for SEI conductivity measurement. Another significant disadvantage should be considered is that parameters in physical model is hard to identify. Different operating conditions may fetch different parameters or even different models [12]. Zhang et al. [13] researched the influence of various operating conditions such as ambient temperatures, different discharging and charging current rates, etc. In summary, the common limitations of these model-based methods are (1) the test has to be conducted under exact conditions, (2) some measurements most conducted via invasive operation, (3) some instruments can't be utilized into real application and (4) the parameters in the model is hard to identify and may change along with the working condition. Space battery not only works as the only power source in shadow phase but also provides pulse power when orbital transfer and additional power when high power load working. Model-based methods are difficult both in parameter identification and test condition realization. In other words, realize battery prognosis only depend on model-based method may be difficult for online application.

Data-driven prognosis methods extract features from the monitoring data such as current, voltage, time, etc. Statistical and machine learning algorithms are used to track the degradation trend, fit the aging curve and estimate the RUL. Elaborate frameworks are proposed to predict the RUL of lithium-ion batteries. Lu et al. [14] proposed a geometrical approach to estimate the lithium-ion battery capacity. Four geometrical features are utilized to present the slight changes in the performance degradation. Yao et al. [15] fused an empirical exponential and a polynomial regression model to predict the remaining useful performance of lithium-ion batteries. Yan et al. [16] introduced a LS-FDP framework for prognosis. Lebesgue sampling (LS) are applied for “execution only when necessary”. Hu et al. [17] proposed an online estimation based on sparse Bayesian learning framework. Charge voltage and current are utilized as the input data samples to estimate the battery capacity. Some other data-driven method, such as naïve Bayes (NB) model [18], Markov Chain Mote Carlo approach [19], Support vector machine (SVM) [20–22], particle filter (PF) [23–26], Gaussian Process Regression (GPR) [27,28], Relevance Vector Machine (RVM) [29,30] etc. are widely used to estimate battery RUL. Data-driven methods predict the future system states relying on the similar past pattern of degradation. The inner relationship among each physical procession is ignored at same time. The accuracy of data-driven methods depend both on the quantity of modeling data samples and prior knowledge contained in monitoring data. Besides, the data-driven methods always generate implicit equations to present the model, and the prognostic process is opaque consistently. These two disadvantages obstruct the application of data-driven methods.

To address the stagnation of model-based approaches and data-driven methods, the fusion prognostics became a research hotspot to improve the RUL prediction performance. Liu et al. [31] utilized Artificial Neural Networks (ANN), the network weights are adaptively optimized using the recursive Levenberg-Marquardt (RLM) method to predict RUL. Liu et al. [32] fused the particle filter with data-driven method to improve the long-term prediction performance. He et al. [33] proposed a hybrid framework based on Dempster-Shafer theory and Bayesian Monte Carlo method. Saha et al. [34] integrated the RVM with Bayesian regression to monitor battery health. The PF is used to identification the parameters in RVM model. As The lithium-ion battery performance degradation is a kind of stochastic process, some classical data-driven methods such as autoregressive (AR) model and autoregressive moving average (ARMA) model, etc. have been used in lithium-ion battery prognostics. Long et al. [35] optimized the AR model by particle swarm algorithm and realized the prognostics of lithium-ion battery. Zhou et al. [36] combined autoregressive integrated moving average (ARIMA) model with empirical mode decomposition to diagnosis for lithium-ion battery. Kozlowski et al. [37] combined three predictors – ARMA model, NN and fuzzy – to establish a fusion framework. But the frameworks mentioned above ignore the nonlinear degradation of lithium-ion battery at the last phase of cycle life. Liu et al. [38] optimized the AR model by adding a nonlinear degradation function to estimate the battery RUL. The result shows high prediction accuracy especially at the last phase of life. And PF method is also utilized to gain the ability of uncertainty management. In summary, fusion framework with model-based approach and data-driven method are widely researched and utilized in prognosis and diagnosis of lithium-ion battery. Especially for AR model and other extended method are applied diffusely in this domain. Many attempts have been conducted to improve the estimation performance.

However, AR model is a linear regression model but lithium-ion battery is a nonlinear degradation process. This difference will make the model under-fitting especially for the long term prediction. Besides, the parameters remain the same during the whole prediction process once the AR model is trained. This will further impact the accuracy of the model. On the other hand, it is rather difficult to build the measurement function for almost all statistical filter method when predicting the RUL. To address these issues, this paper proposed a hybrid lithium-ion battery RUL prediction framework. A nonlinear degradation factor and an iterative updating approach are utilized to improve the long term prediction performance of the basic AR model. The improved model in this paper is named as “IND-AR” model. Moreover, the measurement function for long term prediction is hard to given in PF algorithm. In this paper, the capacity predicted by IND-AR model is set as the measurement function. With the process function from empirical capacity degradation function, PF can optimize the capacity prediction results of each cycle and present their uncertainty. The contribution of this paper can be summarized as follows. Firstly, to improve the prediction accuracy of, an iterative updating strategy is utilized in ND-AR model. The single step prognosis is conducted once the model trained. The prediction result will update the training data set and retrain the model to avoid the mismatch. Secondly, in the RPF model, it's difficult to establish the dynamic state system (DSS) model, especially the observation equation. Therefore, we set the output of the IND-AR model as the measurement value in DSS model. By this configuration, not only the DSS model can be established, but also the prognosis result can be intermingled with the model-based approach. This integration will optimize the prediction result. Furthermore, when the training data set is updated by the optimized value, the trained model will be more suitable for the lithium-ion battery failure pattern.

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