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Remaining useful life of Lithium-ion batteries based on EMD-GSA-ELM

Zhao Qinfeng, Cai Yanping, Wang Xingjun
Rocket Force University of Engineering, XiAn, China
N13026478057ZQF@163.com, 2676802970@qq.com, 190432895@qq.com
Corresponding Author: Cai Yanping Email: 2676802970@qq.com,

Abstract*—The widespread popularity of new energy vehicles has a higher demand for accurately determining battery health and ensuring battery safety performance. Considering that the capacity regeneration phenomenon during using lithium batteries is difficult to track, the model is difficult to build, and the prediction accuracy is not high. In order to reduce the computational complexity and improve the efficiency of establishing a lithium-ion battery remaining life prediction model, a method of fusion of empirical mode decomposition and extreme learning machine based on gravity search algorithm is proposed to establish a lithium battery remaining life prediction model. First, introduce EMD to analyze the battery's early health factor and capacity data to obtain fluctuation and trend components. Second, obtain a battery capacity decay prediction model by learning and training on different components. Finally, use NASA's lithium-ion battery test data to verify the performance of the EMD-GSA-ELM model. The experimental results show that the proposed model can better track the capacity decline and has better accuracy.

Keywords—*Lithium-ion batteries; Empirical Modal Decomposition; Gravity search algorithm; Extreme Learning Machine; Capacity regeneration*

Introduction

Lithium-ion batteries are widely used in aerospace and new energy vehicles because of their advantages of high cycle times, high specific energy, stable discharge, and strong environmental adaptability [1][2], and in recent years, the country has vigorously promoted green energy, the rise of the new energy vehicle industry, and the emergence of a number of new energy vehicles with superior performance, such as BYD series of electric vehicles and BAIC new energy electric vehicles, etc. However, the Lithium-ion batteries are widely used at the same time there is also a greater risk, due to its high battery energy, and the battery will age with use, it is easy to cause a short circuit inside the battery, causing the battery to burst into flames and may even explode, endangering people's lives and property, so it is important to accurately determine the remaining service life of the battery.

Currently, there are mainly model-based and data-driven approaches for lithium-ion battery life prediction [3]. The model-based approach is modeled through an in-depth understanding of the internal working principle and materials of the battery, which can better reflect the decline trend of a specific battery, however, its modeling process is more complex and more influenced by the external working environment and its tiny processes in the battery production process, therefore, its applicability is not strong. Based on the data-driven approach, the current research hotspot is to establish the mapping model of health factor to capacity for battery RUL prediction using correlation vector machine, BP neural network or extreme learning machine algorithm for battery operation data, which does not require professional battery-related knowledge, and the battery remaining life prediction model can update the model parameters with the change of working environment and other conditions. This method does not require specialized battery-related knowledge, and the battery remaining life prediction model can update the model parameters as the operating environment and other conditions change. In recent years, data-driven methods have flourished, and Liu Jian et al. proposed a method for predicting the remaining life of lithium batteries based on isobaric discharge time and Gaussian process regression for the problem of difficult to predict the capacity regeneration of lithium batteries during operation [4]; Wang Yixuan et al. used an improved support vector machine method for predicting the remaining life of lithium batteries [5]; Jian Xianzhong et al. proposed the use of correlation vector machine for predicting the remaining life of lithium batteries in order to improve the prediction accuracy , proposed the use of correlation vector machine for the prediction of the remaining life of lithium batteries [6]. However, the above methods have large long-term prediction errors and cannot accurately track the trend of battery capacity degradation, so Yuanyuan Jiang et al. proposed the use of Extreme Learning Machine (ELM) method to establish the indirect prediction model of battery RUL for the problem of difficult and inaccurate prediction of remaining life of lithium batteries, but the standard ELM model is not accurate due to Therefore, Chen, Zewang, Liu, and others introduced a genetic algorithm to optimize the parameters of the ELM model and establish an indirect prediction model for the remaining service life of lithium batteries. Jia-Sen Miao, Yang-Zheng Ding et al. used particle swarm optimization of the input weights of the extreme learning machine to build a battery charge state estimation model. The above methods were able to predict the RUL of Li-ion batteries with high accuracy, however, the optimization method is more complex and reduces the real-time prediction performance of the model.

To address the above problems, this paper selects the equal voltage drop discharge time during the operation of lithium battery as the health factor, obtains the new lithium battery RUL prediction health factor through Empirical Modal Decomposition (EMD) analysis, uses the Gravity Search Algorithm (GSA) to optimize the ELM algorithm input weights, obtains the appropriate model parameters, and establishes the lithium battery RUL prediction model. Algorithm (GSA) to optimize the input weights of the ELM algorithm, obtain suitable model parameters, and establish the Li-ion battery RUL prediction model, and finally verify the validity and prediction accuracy of the EMD-GSA-ELM prediction model based on NASA's Li-ion battery test data B0006 and B0007.

I. INDIRECT HEALTH FACTOR CONSTRUCTION FOR LI-ION BATTERY RUL PREDICTION

In this section, NASA battery experimental data sets B0006~B0007 were selected for exploratory analysis. The battery model parameters are rated capacity 2Ah and rated voltage 4.2 V. The batteries were charged at room temperature in a constant current mode of 1.5A until the battery voltage reached 4.2 V. Then the charging was continued in a constant voltage mode until the charging current dropped to 20 mA and discharged in a constant current of 2A until the battery voltage dropped to 2.5V, 2.2V, respectively, and all three batteries were fully charged and discharged state.

Predicting the capacity change trend of Li-ion battery requires finding the battery parameters with high capacity correlation. curve. Table 1 shows the correlation analysis results of equal voltage drop discharge time and battery capacity.

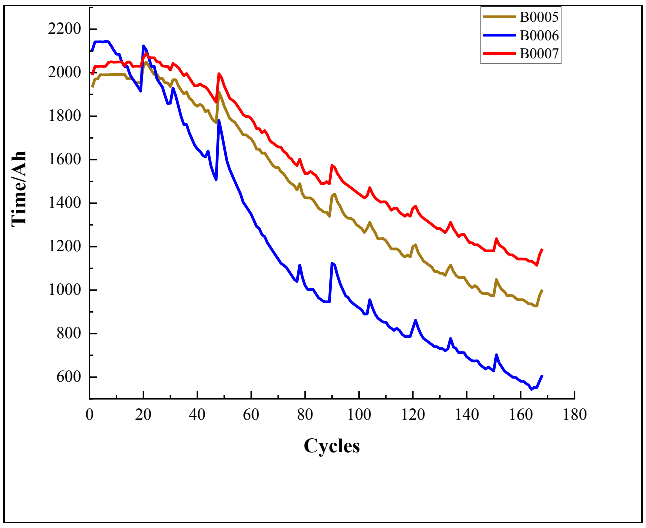


Fig. 1 Variation curve of equal voltage drop discharge time

TABLE 1 CAPACITY AND BATTERY ISOVOLTAGE DROP TIME BIAS CORRELATION ANALYSIS

Dataset	*Related analysis results*
B0006	*0.9945*
B0007	*0.9985*

From the correlation analysis results, it can be obtained that the isovoltage drop time is highly correlated with the battery capacity and can be used as a health factor for battery capacity prediction.

II. LITHIUM-ION BATTERY RUL PREDICTION MODEL CONSTRUCTION

A. Improved Extreme Learning Machine Algorithm

Extreme learning machine is a learning algorithm of single hidden layer feedforward neural network, which is widely used in the prediction of health status because of its simple model and strong learning ability [7], however, because its input weights and thresholds are given randomly during training and prediction, which leads to fluctuations in the output and unreliable prediction results, so, for this problem, it is proposed to optimize ELM using gravitational search algorithm to obtain more stable and reliable prediction results.

The structure of ELM algorithm consists of 3 layers, which are input layer, implicit layer and output layer, and its structure is shown in Figure 2.

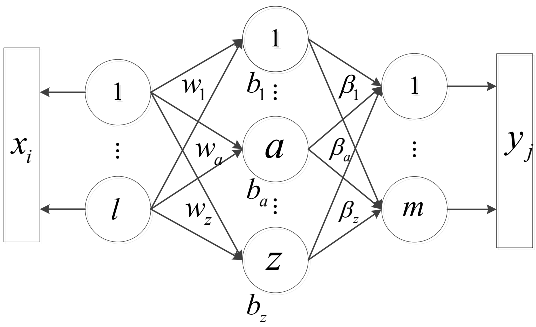


Fig. 2 Algorithm structure of extreme learning machine

According to the structure diagram, the ELM algorithm can be described as follows.

$$y_j = \sum_{i=1}^{N} \beta_i g(x_i) = \sum_{i=1}^{l} \beta_i g(w_i \cdot x_i + b_i) \quad j = 1,\dots,m \qquad (1)$$

Among them. $x_i = [x_{i1}, x_{i2}, \dots, x_{il}]^T \in R^l$, $y_j = [y_{j1}, y_{j2}, \dots, y_{jm}]^T \in R^m$, $w_i = [w_{i1}, w_{i1}, \dots, w_{il}]^T$, which are the weights from the input layer to the implied layer. $\beta_i = [\beta_{i1}, \beta_{i1}, \dots, \beta_{im}]^T$ is the weight of the implied layer to the output layer. $g(\cdot)$ is the implicit layer activation function, and b_i is the implicit layer bias. Then the output of the ELM network is.

$$Y = G \cdot \beta \qquad (2)$$

$$G(w_1,\dots w_z,b_1,\dots b_z,x_1,\dots x_l) = \begin{pmatrix} g(w_1\cdot x_1+b_1) & \dots & g(w_l\cdot x_1+b_z) \\ \vdots & \ddots & \vdots \\ g(w_1\cdot x_l+b_1) & \cdots & g(w_l\cdot x_l+b_z) \end{pmatrix} \quad (3)$$

By determining the input weights with the hidden layer bias and loading the training set, the output weights can be determined.

$$\hat{\beta}=G^{+}T \quad (4)$$

G^{+} is the Moore-Penrose generalized inverse matrix of the matrix. After getting β, the training of ELM was completed. The ELM model generated from the training set is then used to make predictions for the remaining samples.

Improving the jumpiness of ELM prediction results, the model is optimized by introducing GSA, which was proposed by Esmat Rashedi et al. in 2009 as a population optimization algorithm based on the law of gravity and Newton's second law, and compared to other optimization algorithms, such as genetic algorithms, simulated degeneracy, artificial immune system algorithms, and ant colony algorithms, the gravitational search algorithm can provide better performance than other algorithms [8]. The particles "communicate" with each other through gravity, with the more massive particles (corresponding to better solutions) moving slower than the lighter ones, and each particle contains four properties: position, inertial mass, active gravitational mass, and passive gravitational mass. The particle's position corresponds to the solution of the problem to be optimized, and as time goes on, each particle adjusts its gravitational and inertial masses to navigate according to the fitness, which will eventually present the optimal solution in the search space.

B. *Overview of empirical modal decomposition methods*

The EMD method is a new adaptive signal time-frequency processing method creatively proposed by N. E. Huang at NASA and others in 1998, which is particularly suitable for the analytical processing of nonlinear non-stationary signals, and can decompose different types of fluctuations and trends in the signal [9].EMD has a good adaptability to highlight the structure that may be neglected in the signal, and It also separates the noise and the effective signal into different eigenmode functions (IMFs) and residuals, with the IMF reflecting the characteristics of the oscillatory fluctuations of the original time series and the residuals reflecting the trend of the series [10].EMD is suitable for processing nonlinear and nonstationary data, and is suitable for processing battery capacity data to obtain the characteristics of complex nonlinear time series of battery capacity. The specific steps are as follows.

(1) Find all extreme value points of the time series.

(2) Formation of the envelope Emin(t) for very small value points and Emax(t) for very large values by interpolation.

(3) Calculate the mean value.

$$m(\mathrm{t}) = \frac{(\mathrm{Emin(t)}+\mathrm{Emax(t)})}{2} \quad (5)$$

(4) Extraction details.

$$d(\mathrm{t}) = \mathrm{x(t)} - \mathrm{m(t)} \quad (6)$$

(5) Repeat the above procedure for the residual items.

The capacity of Li-ion battery will be increased for a short period of time during the working process, which causes the fluctuation of capacity data, and this phenomenon is capacity regeneration phenomenon. From B0006 and B0007 capacity fluctuations, it can be found that there is similarity in fluctuations, and the fluctuation and trend components are obtained by decomposing the capacity and extracted health factors through EMD method.

C. *Lithium-ion battery RUL prediction model construction*

The fluctuation and trend components obtained using the EMD method are loaded into the improved extreme learning machine model for training, and the relevant parameters of the RUL prediction model are obtained. The first 80 sets of data are selected as the training data set, and the remaining data are the test set for prediction. The specific process is as follows.

(1) Collecting battery operation data: capacity.

(2) Loading data for EMD analysis.

(3) Integrating IMF components as fluctuation components and residuals as trend components.

(4) Load the trend component into the GSA-ELM model and train the model to obtain the correlation of trend decay.

(5) Load the fluctuation component into the GSA-ELM model and train the model to obtain the correlation of battery capacity regeneration.

(6) Predicting the fluctuating component and the trend component to obtain the trend of lithium battery capacity variation.

(7) Using the mean absolute error (MAE) and root-mean-square error (RMSE) as evaluation criteria.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(x_i - x_i^{'})^2} \quad (7)$$

$$MAE = \frac{1}{n}\sum_{i}^{n}|\,x \; - x^{'} \,| \quad (8)$$

in the formula, x_i is the true value, That is, the actual capacity of the lithium-ion battery. $x_i^{'}$ is the forecast capacity value. n is the number of cycles.

When the capacity of a Li-ion battery drops to the failure threshold, the error between the actual and predicted values of the number of cycles is defined as follows.

$$E_r = |P - R| \tag{9}$$

$$PE_r = \frac{|P - R|}{R} \times 100\% \tag{10}$$

where P is the predicted number of cycles and R is the actual number of cycles.

III. EXPERIMENTAL DEMONSTRATION

In this subsection, the proposed EMD-GSA-ELM battery RUL model is validated by NASA battery test data sets B0006 and B0007, the first 80 sets of run data are selected to train the model, and the residual health factor is loaded on the trained mature model to obtain the battery capacity variation trend in the later period. The capacity variation curves from B0005 to B0007 are shown in Figure 3.

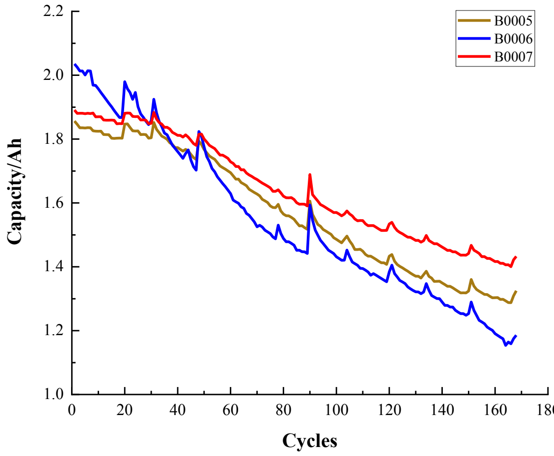
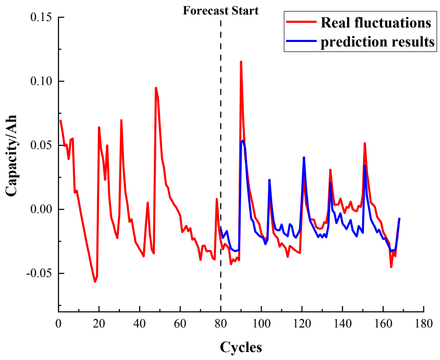
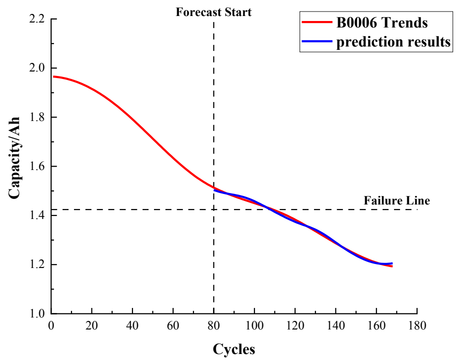


Fig. 3 B0005~B0007 capacity change curve

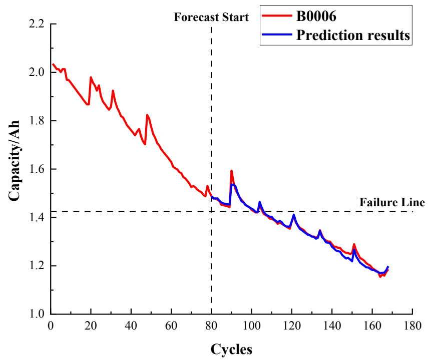
The three groups of battery capacity with equal voltage drop time are EMD processed to obtain the trend component and fluctuation component, and the first 80 groups of data are taken and loaded into the battery RUL prediction model for training respectively, and then the remaining battery data are loaded to predict the later capacity. The failure threshold is set to 70% of the initial capacity, and the prediction results are shown in Figure 4.



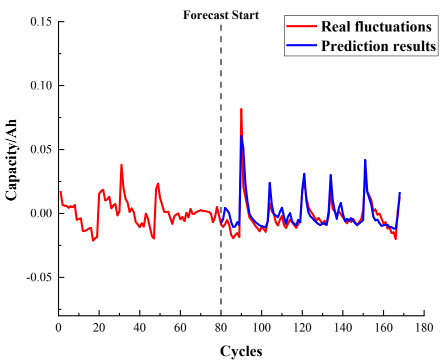
(a) B0006 fluctuation forecast



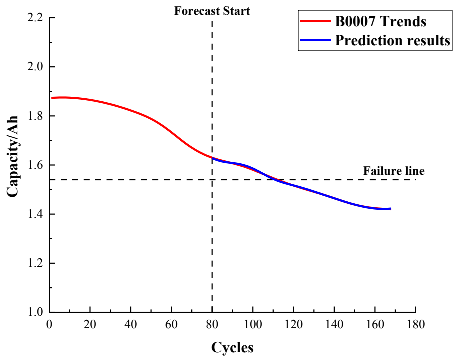
（b） B0006 trends forecast



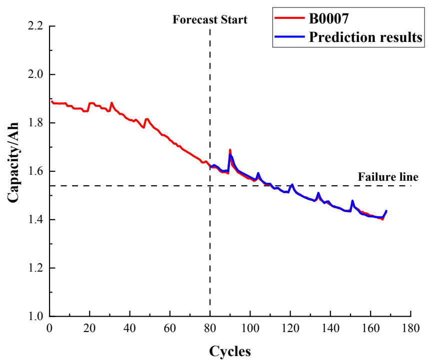
（c） B0006 results



（b） B0007 fluctuation forecast



（b） B0007 trends forecast



（c） B0007 results

Fig.4 Battery RUL prediction results based on EMD-GSA-ELM model

From the prediction result image observation, the proposed model is able to track the battery capacity change well whether in the fluctuation prediction or trend prediction of the battery, and further, the prediction results are evaluated, as Table 2 shows the evaluation results of the relevant indexes of the model.

TABLE 2 EVALUATION RESULTS OF BATTERY RUL PREDICTION BASED ON EMD-GSA-ELM MODEL

NO.	*Method*	*R*	*P*	*Er*	*PEr*	*MAE*	*RMSE*
B0006	*EMD-GSA-ELM*	*105*	*106*	*1*	*0.952%*	*0.0087*	*0.0124*
B0007	*EMD-GSA-ELM*	*110*	*106*	*4*	*3.636%*	*0.0049*	*0.0069*

From the evaluation result index, the RUL prediction model of Li-ion battery based on EMD-GSA-ELM model has high accuracy regardless of the prediction of the number of remaining cycles, and the tracking of the capacity curve also has less error, and in summary, the proposed model is effective.

IV. CONCLUSION

This paper proposes a method based on EMD-GSA-ELM to construct a RUL prediction model for Li-ion batteries, which can track the trend of battery capacity change well, and can track the capacity regeneration phenomenon well. The validity of the EMD-GSA-ELM based method is demonstrated. The specific conclusions are as follows.

(1) Based on the decomposition of the trend and fluctuation quantities contained in the capacity and health factors of lithium-ion batteries by the EMD method, smooth capacity decay trend components can be obtained to avoid the phenomenon of capacity regeneration during battery operation caused by the degradation of model applicability due to fluctuation of mixed data.

(2) The introduction of GSA algorithm to optimize the filtering of ELM input weights can obtain a more stable battery RUL prediction model, while the proposed EMD-GSA-ELM method based on lithium battery RUL prediction can also track battery capacity changes well in the middle and late stages, indicating that the proposed method has good apply.

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