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An AdaBoost-Support Vector Regression Method for Remaining Useful Life Prediction of Lithium-ion Batteries

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ABSTRACT

For the remaining useful life prediction of lithium-ion batteries, the reliability of the features and the validity of the regression algorithm used to construct the prediction model are very important to the prediction results. For this reason, this paper proposes a prediction method based on AdaBoost-support vector regression. First, 9 features are extracted from the battery aging data, and the correlation between features and RUL is verified. Then, the random forest is used to select the extracted features to improve the reliability of the features. Finally, based on the selected features, the prediction model of RUL is established by using AdaBoost to optimize the support vector regression model. The validity of the proposed method is verified in NASA lithium battery data set.

Keywords: Lithium-ion Battery, Remaining Useful Life, Random Forest, AdaBoost, Support Vector Regression

1. INTRODUCTION

Lithium-ion battery has been promoted worldwide due to its high energy density, cleanliness, long service life and other advantages [1]. The remaining useful life (RUL) is an important parameter to measure the performance and safety of the battery [2]. Therefore, it is of great significance to predict the RUL of the battery.

Data-driven method is a popular RUL prediction method in recent years. Because it doesn't take into account the working mechanism of the battery, it can be applied to different types of batteries [3].

However, the reliability of features can directly affect the prediction result of the data-driven method [4]. When the selected features are not highly correlated with RUL, the prediction accuracy of the model will be reduced [5]. Therefore, in order to ensure the reliability of features, it is necessary to extract features that can reflect the aging state from the historical data of batteries. In practical applications, the sources of aging data are very limited. For example, the battery management system for electric vehicle provides only voltage, current, temperature, and time intervals [6]. Fortunately, battery aging is also affected by these factors, and the degree of aging is also reflected in these features [7]. Therefore, we can extract these features from the battery charging or discharging stage. However, battery aging is a complex nonlinear process, which leads to the fact that the relationship between extracted features and RUL is generally not linear. There is a problem: the same features for different batteries, its correlation with RUL will change, making the prediction accuracy decrease.

In addition, the validity of regression algorithm also affects the quality of prediction model. Support vector regression (SVR) is widely used in RUL prediction because nonlinear data can be linearized by kernel function. Wei [8] extracted the features from the charging stage, and then established the capacity aging model with SVR to complete the prediction of RUL. However, the performance of SVR is also affected by the parameters of kernel function. Therefore, some scholars have tried to optimize the parameters of the SVR kernel function with Genetic Algorithm [9].

The contribution of this paper is to propose an AdaBoost-SVR method to predict RUL. Firstly, in order to ensure the reliability of features, the correlation between extracted features and RUL is calculated. Then, through random forest, each feature is ranked according to the importance of RUL prediction, and features with high importance are selected as the input. Finally,

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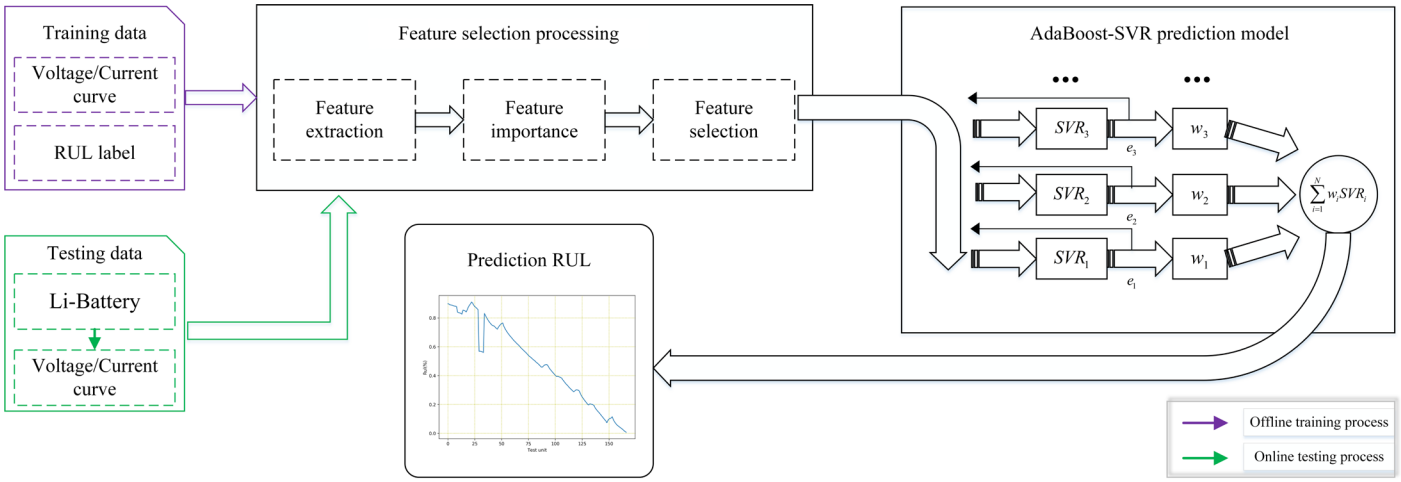


Fig 1 The proposed method for RUL prediction of lithium-ion battery

AdaBoost-SVR is used to establish a RUL prediction model. SVR is regarded as a "weak learner" and iterative optimized by AdaBoost.

2. PROPOSED RUL PREDICTION METHOD

This part mainly introduces the RUL prediction method proposed in this paper. Its system block diagram is shown in Fig 1.

2.1 Feature extraction and correlation analysis

From NASA's data set, it can be found that voltage, current and temperature curves will change as the battery ages. Therefore, features are extracted from these curves to predict battery RUL [10]. For the charging phase, the duration of constant current charging stage and constant voltage charging stage are chosen as features, because the former can reflect the polarization of the battery, while the latter can reflect the difficulty level of lithium-ion intercalation process [11]. For the discharge phase, the time corresponding to the minimum voltage and the time corresponding to the maximum temperature are chosen. Considering that it is not rigorous enough to describe battery aging only from the perspective of time, this paper also added signal energy (E) as a supplement, and the calculation formula is as follows:

$$E = \int_{-\infty}^{\infty} |x(t)|^2 \, dt \tag{1}$$

where $x(t)$ is the signal and t is time [10].

According to the above analysis, 9 features can be extracted from the battery aging process:

F1: Constant current charging time;
F2: Constant voltage charging time;
F3: The time required to discharge to minimum voltage;
F4: The time required to discharge to maximum voltage;
F5: The time required to discharge to the lowest temperature;
F6: The time required to discharge to the highest temperature;
F7: Signal energy of discharge voltage curve;
F8: Signal energy of discharge temperature curve;
F9: Discharge capacity.

In order to verify the correlation between the raw features and RUL, the correlation coefficient can be used to measure,

$$\gamma(X,Y) = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{2}$$

where x_i is the feature value of the i th observation sample, and y_i is the RUL value of the i th observation sample. $\bar{x}$ and $\bar{y}$ are the corresponding averages. n is the number of samples. If the coefficient is closer to 1 or -1, then the correlation is stronger.

2.2 Assess the importance of features by random forest

For machine learning methods, the more input features, the better the accuracy of the prediction model. But as the number of features increases, so does the difficulty of machine learning tasks. The accuracy of model prediction is also affected by some irrelevant features. Therefore, we should select the features according to their importance for the extracted features.

It is convenient to use random forest (RF) to achieve feature importance ranking, because the idea is to take the average value according to the contribution degree of each feature in each tree in random forest, and finally compare the contribution degree between features. In this paper, out of bag data (OOB data) error rate is used as the evaluation index to measure the contribution

degree. Assuming that there are K decision trees in RF, the importance of feature a can be obtained from Algorithm 1:

Algorithm 1 Random forest

Step 1. Let k = 1, use boot-strap resampling to generate training set and OOB data, and build decision tree on the training set.

Step 2. OOB data are predicted and classified based on tree, and the number of samples with correct classification is counted, denoted as R_k .

Step 3. The value of feature a in OOB is perturbed to obtain a new OOB sample set. Then tree is used to classify and predict the new OOB sample set. The number of correctly classified samples is counted and denoted as R'_k .

Step 4. Let k = 2, 3, ..., K , repeat step 1 to 3.

Step 5. The importance of feature a can be calculated from the following formula:

$$Importance(a) = \frac{1}{K}\sum_{k=1}^{K}(R_k - R'_k)$$

2.3 AdaBoost-SVR prediction model

SVR is the most common application form of SVM. The main objective of SVR is to estimate a relationship between input and output random variables. RUL prediction model established through the SVR is as follows:

$$\hat{y}_i = f(x) = \sum_{i=1}^{M}\beta_i k(x, x_i) \quad (3)$$

where x is a feature vector, $\hat{y}_i$ is the predictive value of RUL, M is the number of sample points, β_i is support vector, $k(.)$ is the function kernel.

However, due to the nonlinear characteristics of battery aging, general SVR is not a good predictor of RUL. As an integrated algorithm, AdaBoost can combine several weak learners into a strong learner. AdaBoost adopts the idea of iteration. Each iteration only trains one weak learner, and the trained weak learner will participate in the use of the next iteration. Follow Algorithm 2 to build the AdaBoost-SVR prediction model.

Algorithm 2 AdaBoost-SVR prediction method

Step 1. Select s groups of data as training samples, and the initial weights are assigned to each group of samples $D(i) = 1/s$.

Step 2. Select the appropriate kernel parameters and use SVR as the weak learner for training to get the j th weak learner $h(j)$.

Step 3. Calculate prediction error ε_j between the output value of $h(j)$ and the actual value, accumulate the corresponding sample weight value $D_j(i)$ exceeding the error limit.

Step 4. Calculate the weight α_j of $h(j)$,

$\alpha_j = \frac{1}{2}\ln(\frac{1-\varepsilon_j}{\varepsilon_j})$.

Step 5. Adjust test data weights.

$$D_{j+1}(i) = \frac{D_j(i)}{sum(D)} \times e^{q\cdot\alpha}\begin{cases} q = -1, \varepsilon_j < \delta_j \\ q = 1, \varepsilon_j \geq \delta_j \end{cases}$$

Step 6. Strong learner $H(x)$ obtained by training J times:

$$H(x) = \sum_{j=1}^{J}\alpha_j h_j(x)$$

3. EXPERIMENT AND RESULTS ANALYSIS

The proposed RUL method is validated by the battery data set from NASA Prognostics Center of Excellence [12]. The data set is based from NASA's battery test-bed and is collected on several 18650 lithium-ion batteries. Specifically, our method is implemented on 4 batteries (B0007, B0033, B0034, B0036). Table 1 shows their operation parameters.

Table 1
Batteries partial operation parameters

	Discharge current(A)	End voltage(V)	End-of-life capacity	Cycle
B0007	2	2.2	30% fade	168
B0033	4	2.0	20% fade	197
B0034	4	2.2	20% fade	197
B0036	2	2.7	20% fade	197

3.1 Evaluation index

The RUL of i th cycle is defined as the following percentage form:

$$RUL_i = \frac{N_{EOL} - N_i}{N_{EOL}} \times 100\% \quad (4)$$

where N_{EOL} is the number of cycles to the aging threshold, N_i is the number of i th cycle.

The root mean squared error (RMSE) is used as evaluation index to evaluate the prediction result, it is given as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (5)$$

where y_i is the actual RUL value of i th cycle, $\hat{y}_i$ is the prediction RUL value of i th cycle, N is the number of test units.

3.2 Features selection

The correlation coefficient between the 9 features and RUL is calculated, as shown in Table 2. Through observation, it can be found that the same feature for different batteries, its correlation with RUL is changing. Sometimes this change is even huge. For example, feature F2 has a strong correlation with RUL for B0007. For B0036, there is a weak correlation between this feature and RUL. This is because battery aging is a highly nonlinear process, and it is unreasonable to reflect this aging trend by relying on a single feature. Therefore, the features should be selected before they are used as input to the RUL prediction model.

Table 2
The coefficient between features and RUL

	B0007	B0033	B0034	B0036
F1	-0.6320	-0.5128	-0.8303	-0.9018
F2	0.6970	0.2834	0.2051	0.1837
F3	-0.9886	-0.4391	-0.7797	-0.7056
F4	-0.1750	-0.1419	-0.0958	-0.0130
F5	-0.2682	-0.0219	-0.0104	-0.2216
F6	-0.9895	-0.4428	-0.7716	0.3321
F7	-0.9886	-0.3352	-0.6751	-0.6490
F8	-0.8327	-0.1306	-0.1211	0.1457
F9	-0.9893	-0.4381	-0.7781	-0.7147

By using the random forest method to calculate the importance of the features of 4 batteries(B0007, B0033, B0034, B0036), it can be found that the calculated results can be roughly divided into two cases, as shown in Fig 2: (1) there exists a single feature with very prominent importance, so that the importance of other features can be approximately ignored (e.g. B0034); (2) there are several significant and relatively average features (e.g. B0036). Considering that if a fixed threshold (e.g., importance=0.15) is used as the basis for feature selection, for case (1) only one feature, F7, can be used as the input to the prediction model, this obviously wastes the information carried out by many other features. If the threshold is further lowered (e.g., importance =0.01), and for case (2) most of the features meet the requirements, then there is no need for feature selection. Therefore, it is obviously unreasonable to take a fixed threshold as the standard of feature selection.

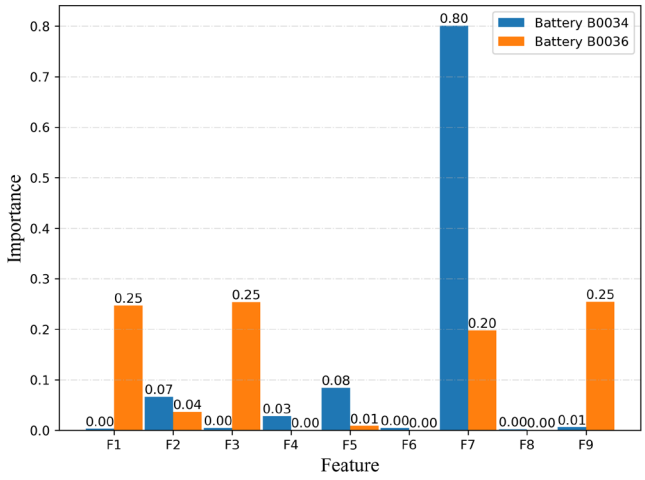


Fig 2 The importance of each feature to RUL prediction

3.3 Results analysis

3.3.1 Case1：verification experiment of single lithium-ion battery

Since a fixed threshold cannot be used as the criteria for feature selection, a fixed number of features should be considered as the criteria for feature selection. To verify the feasibility of this method, a verification experiment was set up on a single battery. The features are ranked in order of importance and the number of features is increased as input to the prediction model. Use 70% battery data as a training set and 30% as a testing set to predict RUL.

Fig 3 shows the RUL prediction error obtained by the feature with the highest current importance value of 4 cells in successive increments. As can be seen from the figure, although there are fluctuations in the process of

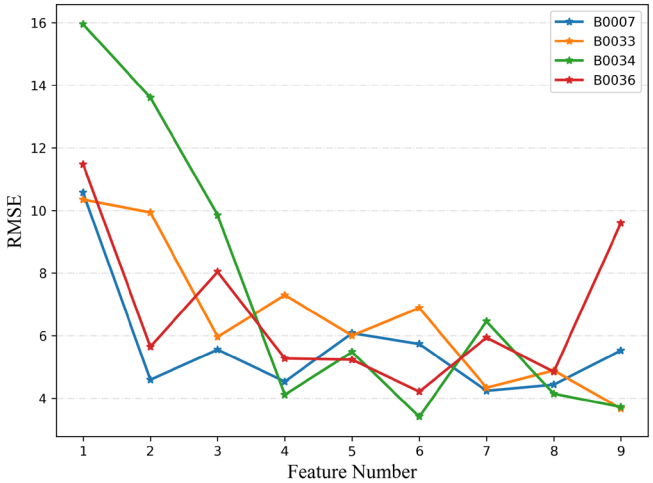
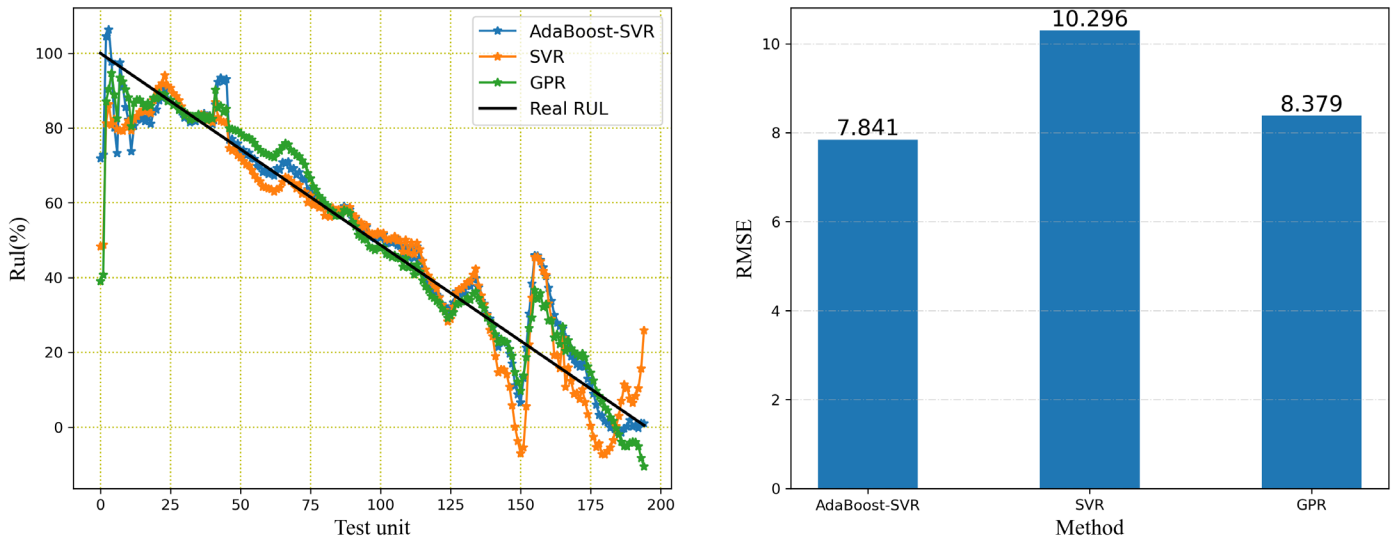


Fig 3 The RUL prediction error (RMSE) with different feature number of model input



(a) (b)

Fig 4 The RUL prediction results of B0033 when B0034 is used as training set: (a) The RUL prediction using different methods (b) The RMSE of prediction using different method

increasing the number of features as input to the model, the RMSE prediction error of the 4 cells generally decreases with the increase in the number of features. Besides, with the increase of the number of features, the decline in amplitude of RMSE prediction error decreases. In other words, the use of partial features can achieve a similar predictive effect to the use of all features, which is also the purpose of feature selection. In the end, we decided to use the first 5 features in the order of importance from large to small as inputs to the prediction model.

3.3.2 Case2： RUL prediction of untrained battery

To verify the prediction effect of the AdaBoost-SVR prediction method for the unknown battery, the data of battery B0034 is used as the training set to predict the RUL of battery B0033. As can be seen from Table 1, the discharge terminal voltage of B0034 is 2.2V, while that of B0033 is 2.0V. So, it can assume that the battery predicted is unknown.

According to the conclusion drawn in the previous section, we choose the 5 features with the highest importance as the input of the prediction model. Meanwhile, in order to compare the prediction result of proposed method with other machine learning methods, SVR and Gaussian process regression (GPR) are used for RUL prediction under the same conditions. It can be seen from Fig 4(b) that the AdaBoost-SVR method has the smallest prediction error of 6.399. This is because SVR itself is superior to GPR in processing non-linear data. In addition, AdaBoost eliminates the influence of some kernel functions on SVR through multiple iterative optimizations.

4. CONCLUSIONS

In response to the reliability of battery aging features and the validity of regression algorithm used to build prediction model, an AdaBoost-SVR method is proposed. The method has been validated in the NASA data set. The experimental results show that this method has smaller prediction error than the single SVR or GPR method. This is because SVR alone is used for sample learning, and the model performance depends on the selected kernel function and parameters. Using SVR as AdaBoost's weak learner can reduce the influence of kernel function and parameter selection. In addition, in the stage of feature selection, it is confirmed that the prediction accuracy of a certain number of features with higher selection importance as model inputs is similar to that of all features as model inputs, and sometimes even better.

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