Remaining useful life Prediction for lithium-ion battery based on CEEMDAN and SVR

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***Abstract*—Estimation of lithium-ion battery remaining useful life (RUL) is the key to lithium-ion battery health. Achieving accurate and reliable remaining useful life prediction of lithium-ion batteries is very vital for the normal operation of the battery system. This paper proposes a lithium-ion battery RUL prediction method based on the combination of complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and support vector machine regression (SVR) which is multiple input and single output. First, a measurable health factor is extracted during the discharge process, and the correlation between health factor and capacity is analyzed by Pearson and Spearman methods. Then, the health factor is decomposed by CEEMDAN to obtain a series of relatively stable components. Finally, the health factor decomposed by CEEMDAN is used as the input of SVR prediction model, and the capacity is used as the output, to realize lithium-ion RUL prediction. Based on the lithium-ion battery degradation data set provided by NASA PCoE, the effectiveness of the proposed RUL prediction model is verified.

Keywords—lithium-ion battery, remaining life, support vector machine, complete ensemble empirical mode decomposition with adaptive noise

I. Introduction

Lithium-ion batteries has the advantages of high energy density, long service life, low self-discharge rate, etc. It is widely used in transportation, communications, aerospace and other fields[1, 2]. However, complex physical and chemical changes occur in the lithium-ion batteries during using, and its performance will deteriorate or even fail, which may cause major safety accidents. Therefore, it is of great significance to study the remaining useful life (RUL) of lithium-ion battery[3, 4]. To solve the accuracy and reliability of the RUL of lithium-ion battery at present, typical research methods include model-based and data-driven methods.

The model-based method is mainly to realize the short term state of health (SOH) and long term RUL online prediction by analyzing the physical and chemical principles of lithium-ion batteries, and then establishing mathematical and physical models[5, 6], The existing model-based methods include equivalent circuit model, electrochemical model, Brownian motion model and particle filtering[7]. Although the model-based method has achieved good results, it is difficult to achieve accurate modeling of lithium-ion batteries because of the complexity of the internal changes inside the battery. and the influence of noise and environmental interference outside the battery. Compared with model-based method, the data-driven method is more convenient[8, 9], it only depends on the mining of historical data of lithium-ion batteries. Now more and more scholars use data-driven method to predict the RUL of lithium-ion batteries. Such as the autoregressive integrated moving average model[10], support vector machine model, neural networks model[11], etc. However, the capacity recovery of the lithium-ion battery degradation process will affect the performance of the prediction algorithm, it is difficult to make effective predictions in applications.

In addition, most of the current research for the RUL prediction of battery based on capacity, which is difficult to monitor online. In order to solve the problem of online monitoring, Zhou et al.[12] extracted a new health indicator (HI) which adopted the Box-Cox transformation from the operating parameters of lithium-ion batteries, Then, using relevance vector machine (RVM) to predict RUL based on the proposed HI. Chen et al.[13] selected the displacement entropy in the discharge voltage curve as a new HI to analyze the battery degradation. Zhao et al.[14]put forward two HIs, one is the time interval of equal charging voltage difference, the other is the time interval of equal discharging voltage difference, using a new method with feature vector selection and support vector regression (SVR) to simulate the relationship between these two HIs and capacity, it could predict SOH and RUL more accurately.

Because multiple HIs may cause information redundancy and lead to inaccurate predictions, the direct use of a single HI cannot effectively reflect the capacity recovery part, so this paper extracts the HI that have a high correlation with capacity and decomposes HI with complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) Decompose health factors to capture capacity recovery effectively to predict RUL. At the same time, in order to be able to effectively predict the fluctuation part of the capacity recovery, a precise prediction method of RUL for lithium-ion battery is proposed, which combines CEEMDAN and SVR.

II. RELATED ALGORITHMS

A. CEEMDAN

In order to improve the prediction accuracy of lithium- ion battery RUL, we use CEEMDAN to deal with the HI[15]. The specific process is as follows: the signal is decomposed into k inherent modal functions (IMF), each IMF is expressed by IMF_k. Define the operator as the first modal component of the given signal obtained by EMD calculation, assuming the original signal, this article takes the time when the discharge voltage reaches the lowest point, and CEEMDAN adds Gaussian white noise that meets the standard normal distribution to the following, perform the following step:

(1) Calculate IMF_1. The calculation process of IMF1 is the same as EEMD, the signal $s(n)+\varepsilon_0\omega_i(n)$ is decomposed times and the parameters ε control the signal-to-noise ratio between the additional noise and the original signal. The calculation method of IMF_1 is shown in (1):

$$IMF_1(n)=\frac{1}{I}\sum_{i=1}^{1} IMF_{i1}(n) \tag{1}$$

(2) Calculate the residual, the calculation method of the residual $r1(n)$ when k = 1 is shown in （2）:

$$r_1(n)=s(n)-IMF_1(n) \tag{2}$$

(3) Decompose $r_1(n)+\varepsilon_1 E_1(\omega_i(n))(i=1,2,\ldots I)$ to the first modal quantity, and define the second modal component as shown in （3）:

$$IMF_2(n)=\frac{1}{I}\sum_{i=1}^{I} E_1\left(r_1+\varepsilon_1 E_1\left(\omega^i(n)\right)\right) \tag{3}$$

(4) For k = 2, ..., K, calculate the k-th margin；

$$r_k(n)=r_{k-1}(n)-IMF_k(n) \tag{4}$$

(5) Decompose $r_k(n)+\varepsilon_k E_k(\omega_i(n))(i=1,2,\ldots,I)$ to the first modal quantity, and define the k+1-th modal component as:

$$IMF_{k+1}(n)=\frac{1}{I}\sum_{I}^{i=1} E_1\left(r_k(n)+\varepsilon_k E_k\left(\omega^i(n)\right)\right) \tag{5}$$

(6) Add 1 to k and repeat steps 4-6 until the residual is not suitable for decomposition, that is, the residual has at most an extreme value.

Finally, the original signal can be expressed as k IMFs and a $r(n)$,as shown in (5):

$$s(n)=\sum_{k=1}^{K} IMF_k + r(n) \tag{6}$$

B. SVR

The SVR model based on statistics can solve the regression problem of high-dimensional features[16]. It still has a good effect when the feature dimension is greater than the number of samples, and the generalization ability is strong.

Suppose a given sample set:

$$\begin{gathered} S=\{x_i,y_i\}_{i=1}^{n}, \\ \left(x_i\in X=R^n, y_i\in Y=R\right), \end{gathered} \tag{7}$$

x_i is the first input feature vector, y_i is the corresponding output, and n is the number of all samples. SVR transforms the data set into a high-dimensional feature space through the function ψ , which can be defined as:

$$f(x)=\omega\cdot\psi(x)+b \tag{8}$$

Where ω and b are the parameters to be determined, the relaxation variable is introduced, and the SVR problem can be formalized as:

$$\min_{w,b}\frac{1}{2}\|\omega\|^2+C\sum_{i}^{n}\left(\xi_i+\xi_i^*\right) \tag{9}$$

$$s.t.\begin{cases} y_i-\omega\cdot\psi(x)-b\le\varepsilon+\xi_i, \\ \omega\cdot\psi(x)+b-y_i\le\varepsilon+\xi_i^*, \\ \xi_i,\xi_i^*\ge 0. \end{cases} \tag{10}$$

Where C is the regularization constant, which $\varepsilon(\varepsilon>0)$ is the maximum error allowed for regression. The introduction of Lagrange multiplier and kernel function can be transformed into:

$$\begin{aligned} \max R\left(\alpha_i^*,\alpha_i\right) &= -\frac{1}{2}\sum_{i,j}^{n}\left(\alpha_i^*-\alpha_i\right)\left(\alpha_j^*-\alpha_j\right)\varphi(x_i)\varphi(x_j) \\ &\quad -\sum_{i}^{n}\alpha_i\left(y_i+\varepsilon\right)+\sum_{i}^{n}\alpha_i^*\left(y_i-\varepsilon\right) \end{aligned} \tag{11}$$

$$s.t.\begin{cases} \sum_{i}^{n}\left(a_i-a_i^*\right)=0, \\ 0\le a_i,a_i^*\le C, \quad i=1,2,\ldots n \end{cases} \tag{12}$$

a_i , a_i^* is the lagrangian multiplier. After minimizing the lagrangian function, the nonlinear SVR expression is:

$$f(x)=\sum_{i}^{n}\left(\alpha_i-\alpha_i^*\right)K(x_i,x)+b \qquad (13)$$

Where $K(x_i,x)$ is the kernel function, and the radial basis function is a commonly used kernel function in SVR, which is defined as:

$$K_{RBF}(x_i,x)=\exp\left(-\frac{1}{2\sigma^2}\|x_i-x\|^2\right) \qquad (14)$$

Among them σ are the parameters of the kernel function, which will affect the complexity of the SVR algorithm. This paper optimizes the parameters (C, g) by using Particle Swarm Optimization (PSO)[17], and the performance of prediction model is assessed using cross-validation.

C. PROPOSED METHOD

Fig. 1 is a flow chart of capacity and RUL prediction based on CEEMDAN and SVR models, mainly for the following six steps:

(1) By analyzing the degradation process of lithium-ion batteries, HI which can characterize the degradation of battery capacity is extracted;

(2) Through Pearson and Spearman correlation analysis, the correlation degree between HI and capacity determined;

(3) Using CEEMDAN to decompose HI (the result of CEEMDAN is shown in Fig. 4), so as to accurately capture the global degradation trend and the recovery part, and improve the prediction accuracy;

(4) The decomposed HI and capacity is divided into a training set and a test set respectively, the SVR model is established for the decomposed sequence and PSO is used to optimize the parameters of the model;

(5) Predicting capacity, then through the relationship between the capacity threshold and RUL, the predicted RUL result is obtained, and the proposed method is verified by analyzing the error between the predicted RUL and the real RUL.

According to the above analysis, the flowchart of the CEEMDAN-SVR method can be obtained in Fig. 1.

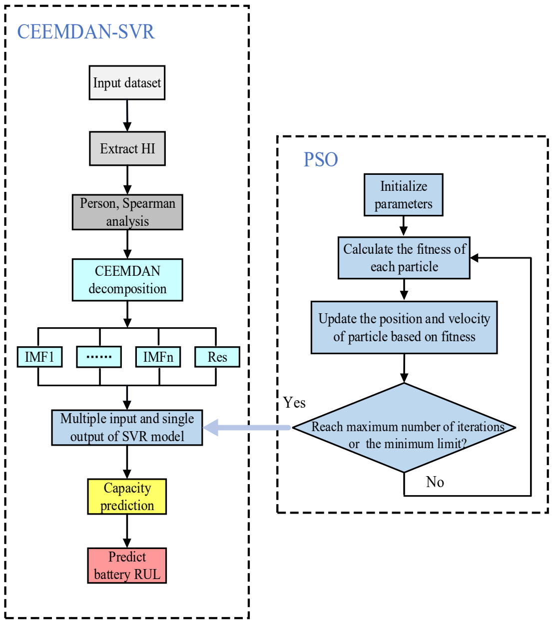

Fig.1. Flowchart of the proposed method

III. PROGNOSTIC EXPERIMENT

A. EXPERIMENTAL DATA

In order to prove the effectiveness and accuracy of CEEMDAN combined with SVR method, we adopted the public data set provided by NASA PCoE. These data were collected by charging and discharging and impedance testing of an 18650 lithium-ion battery with a rated capacity of 2Ah at room temperature(24℃). Charging in the constant current mode of 1.5 A until the battery voltage reaches 4.2 V, and then continue to charge in the constant voltage mode until the charging current drops to 20mA.Discharging in 2A constant current mode until the battery voltage drops to 2.7V, 2.5V and 2.5V respectively. Impedance: Impedance measurement is from 0.1Hz to 5kHz through the frequency sweep of electrochemical impedance spectroscopy (EIS). In this paper, lithium-ion batteries (Nos. 5,6 and18) are selected as the research object. Fig. 2 shows the capacity degradation curves of each battery.

B. EXTRACTION OF HI

The discharge voltage curves of different cycles during the degradation of No. 5 battery is showed in Fig. 3. It can be observed that the entire discharge process is divided into a discharge phase and a self-charging phase(after the battery is discharged, the battery discharge voltage tends to rise, called self-charging). In addition, Fig. 3 shows that as the charge and discharge cycle increases, the time for the voltage to reach the lowest point is decreasing. So this paper selects the time when the discharge voltage reaches the lowest point as HI.

In order to further clarify whether the extracted HI can effectively express the degradation trend of battery capacity, Pearson and Spearman are used to analyze the correlation between HI and battery capacity. Table I. shows the HI correlation analysis of batteries Nos. 5, 6 and 18. As can be seen from the analysis results, there is a high correlation between the change HI and the capacity, so the extracted HI can well describe the capacity degradation process of lithium-ion batteries.

C. PROGNOSTIC RESULT AND ANALYSIS

In order to verify the effectiveness of the CEEMDAN-SVR (named M1) lithium-ion battery capacity prediction model, we designed two comparison models M2 and M3. As shown in Table II. the M2 model utilizes SVR to directly establish the capacity prediction model without CEEMDAN . The model M3 utilizes RVM with CEEMDAN. Other steps are the same as model M1. M2 is utilized to analyze the role of CEEMDAN in the proposed M1 model, and M3 is utilized to explain the accuracy of the SVR prediction capacity. Experimental setting: the data from the first cycle to the 80th cycle is selected as the training sample, and the prediction starting point (SP) set as 81.

Fig. 5 shows the results of different prediction models. The results show that the prediction curve of the M1 model is closest to the actual capacity degradation curve. Compared with the M1 model, the prediction result of the M2 model increases with the number of cycles, and the error between the prediction result and the actual capacity becomes larger. Through comparison, it can be concluded that the use of CEEMDAN decomposition to build a prediction model can improve the prediction accuracy. At the same time, the M3 model uses CEEMDAN decomposition to predict, but the prediction curve of M3 deviates from the actual capacity curve, and the prediction effect is not stable.

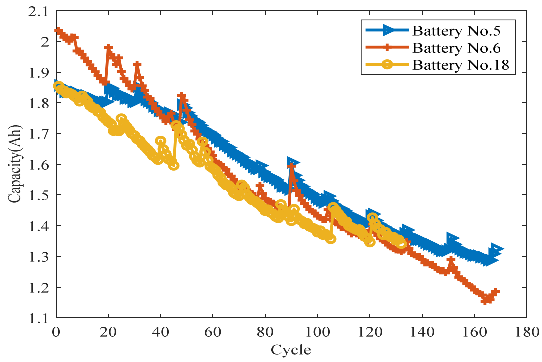

Fig.2. Capacity degradation curve

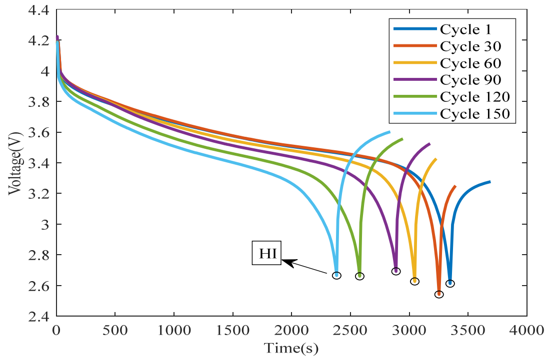

Fig.3. Discharging voltage curves of No. 5 with different cycles

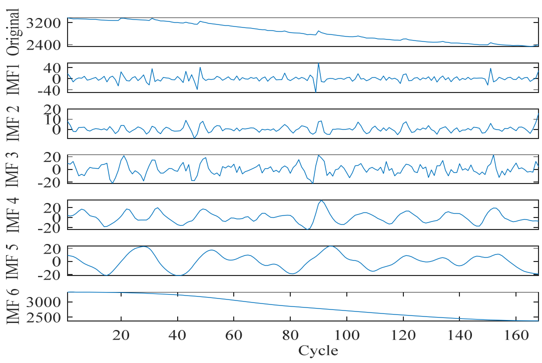

Fig.4. CEEMDAN decomposition HI

TABLE I. **Correlation analysis of HI and capacity**

Correlation analysis	Batteries No.		
	#5	#6	#18
Pearson	0.9998	0.9999	0.9994
Spearman	0.9995	0.9998	0.9989

Table II **The proposed three models (M1–M3).**

Model	Model Description
M1	CEEMDAN+SVR
M2	SVR
M3	CEEMDAN+RVM

D. *Evaluation criterion*

Two evaluation criteria are used to measure the performances of the proposed method.

RMSE: Root-mean-square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(y_k - \hat{y}_k\right)^2} \tag{15}$$

AE: absolute error

$$AE = \left|R_t - R_p\right| \tag{16}$$

In the above equations, y_k is the real capacity value and $\hat{y}_k$ is the predicted capacity value, R_t is the real RUL value, R_p is the predicted RUL value.

Table III. shows the comparison of the three sets of experimental evaluation indicators. It can be seen that the RMSE index of the method in this paper is the smallest, that is the error is the smallest, and the prediction accuracy is the highest. This means that there will be a very small error when predicting the next value which also lay a good foundation for predicting RUL.

Table III **Comparison of different prediction models.**

Models	RMSE		
	No. 5	No. 6	No. 18
M1	0.0031	0.0071	0.0104
M2	0.0144	0.0119	0.0175
M3	0.2848	0.056	0.0287

The NASA PCoE battery experiments takes the battery capacity degradation to 30% of the rated capacity as the end of life (EOL) standard. Among them, the battery capacity failure thresholds of Nos. 5, 6, and 18 are 1.38Ah, so the cycle period corresponding to the RUL value of each battery is 128, 112 and 100 respectively.

Table IV **Analysis of different SPs of different batteries in M1 model.**

Battery No.	SP	True RUL	Predicted RUL	AE of RUL	RMSE of capacity
	71	58	57	1	0.0049
#5	81	48	48	0	0.0031
	91	38	38	0	0.0026
	101	28	28	0	0.0021
#6	71	42	44	2	0.0138
	81	32	32	0	0.0071
	91	22	22	0	0.0070
	101	12	12	0	0.0035
#18	61	40	42	2	0.0104
	71	30	32	2	0.0073
	81	20	20	0	0.0061

Fig. 6 shows the prediction effect of the M1 model for four batteries(Nos. 5,6 and18) at different SPs. Overall, the prediction result at each SP is very close to the actual value, and different prediction SPs have no significant effect on the prediction result. This means that the M1 model proposed in this paper has high accuracy and stability.

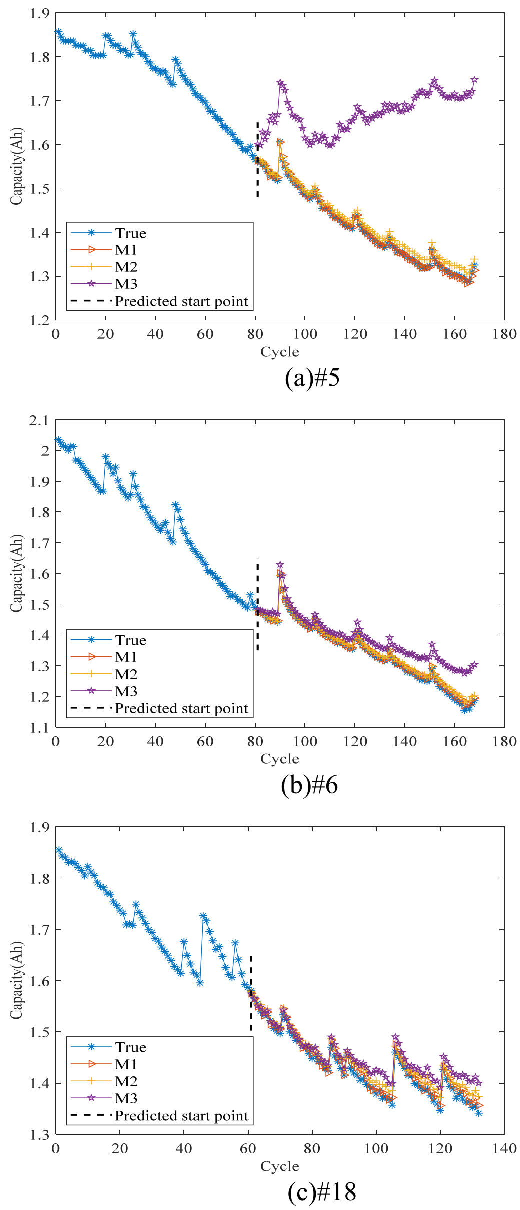

Fig.5. Results predicted by different models：(a) battery No. 5; (b) battery No. 6; (c) battery No. 18

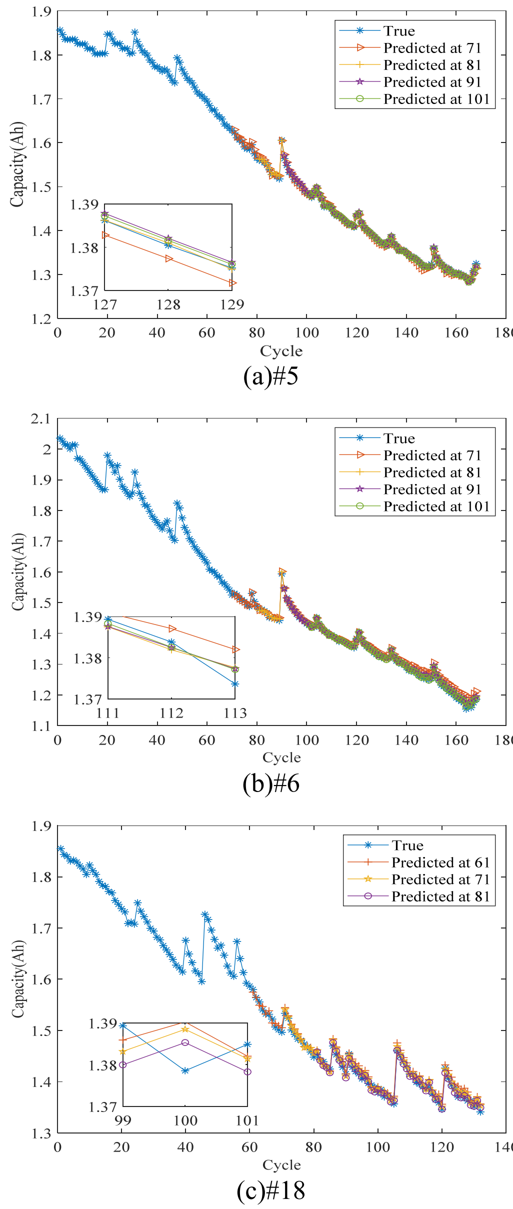

Fig.6. Results predicted by different models：(a) battery No. 5; (b) battery No. 6; (c) battery No. 18

Table IV gives the capacity and RUL prediction results of the M1 model at different SPs of batteries Nos. 5, 6, 7 and 18. From Table IV, we can see that the model M1 is relatively less affected by the SPs of prediction and the prediction performance is relatively stable. Compared with the existing methods, the decomposition of health factors improves the prediction accuracy and verifies the effectiveness of the method.

To compare with the proposed model in Ref.[18](named IHIs-GPR), we set the same SP and the AE values are calculated for comparison. The results are shown in Table V. it can be concluded that the AE of the CEEMDAN-SVR method are lower than or equal to IHIs-GPR with the same SP. In addition, we have better performance with more training data. For different SPs, the performance of CEEMDAN-SVR method is more stable and accurate than IHIs-GPR. The comparison shows that CEEMDAN-SVR method performs well in RUL prediction.

IV. CONCLUSION

Prediction of RUL of lithium-ion battery is a key component of battery health management. Accurate prediction of RUL of lithium-ion battery can ensure the safety and stability of system operation. Therefore, this paper proposes a method based on CEEMDAN and SVR which is multiple input and single output to predict the RUL of lithium-ion batteries. In addition, a set of NASA battery data is used to simulate the experimental data to verify the RUL prediction performance of the method. Compared with the method using only SVR and CEEMDAN combined with RVM, the results show that the method proposed in this paper can improve the prediction accuracy of RUL of lithium-ion batteries.

Table V **Comparison results of different methods for RUL prediction**

Battery	**SP**	**AE of different Model**	
		CEEMDAN-SVR	**IHIs-GPR**
No.5	70	1	9
	80	0	6
	90	0	4
No.6	70	1	1
	80	0	2
	90	0	3
No.18	60	1	2
	70	1	1
	80	0	2

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