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Research on Life Prediction of Lithium-ion Battery based on WEMD-ARIMA Model

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Abstract: With the development of AGV and AMR, lithium-ion battery, as the main energy source of mobile robot, has also received extensive attention. In view of the low accuracy of the current prediction methods for the remaining cycle life of lithium-ion batteries, a new prediction model for the remaining cycle life of lithium-ion batteries is proposed in this paper. The cycle life degradation data of lithium-ion battery is regarded as a set of random time series. Firstly, the time series are decomposed by WEMD; They are decomposed into several IMF subsequences. The WEMD model proposed in this paper is improvement by adding white noise to the sequence on the basis of EMD. It makes the decomposed IMF sequence without modal mixing. Then, use the ARIMA prediction to predict each IMF subsequence; Finally, the prediction results of IMFs are superimposed to obtain the final prediction results. In this paper, experiments are carried out using NASA open cycle life degradation data of lithium-ion battery. The experimental results show that the model has better accuracy. The MAE and MAPE of B0005 and B0006 batteries are almost less than 0.01 and 1.

Key Words: Lithium-on battery, Life Prediction, Time Series, AGV, AMR

1 INTRODUCTION

In recent years, with the continuous development of manufacturing industry, AGV(automated guided vehicle) and AMR(autonomous mobile robot) industry, which can replace human beings for industrial production and manufacturing, have also developed rapidly. For some mobile robots, the main power source is rechargeable lithium-ion batteries. So how to ensure the safe and reliable operation of lithium-ion battery, timely predict the remaining cycle life of lithium-ion battery, so as to replace the battery in time and prevent the failure of AGV robot and AMR robot in the process of industrial production have become problems that scientists all over the world need to study.

With the application of lithium-ion battery in more and more fields, the prediction of lithium-ion battery life has attracted more and more attention. Since lithium-ion batteries are used in many important devices, if we can not find out whether the battery energy is about to run out in time, so as to replace the battery, it is likely to have a huge hidden danger. The cycle residual capacity data of lithium-ion battery can be used as a set of time series, so we can make good use of the time series prediction analysis method to predict the residual life (RUL) of lithium-ion battery.

Aiming at the characteristic that the data of lithium-ion battery cycle residual capacity is a time series, this paper explores the feasibility of time series prediction. The experimental data used in this paper is the NASA open source of lithium-ion residual cycle life data set. This group of time series contains many complex components. Firstly, we need to decompose the sequence into several subsequences. This paper designs an EMD model with white noise——WEMD, which can obtain several IMF sequences with different signal scales. Then ARIMA model (Auto Regressive Integrated Moving Average model) is used to predict all subsequences. Finally, the prediction results of all subsequences are superimposed to obtain the final prediction results. Comparing the results of WEMD-ARIMA prediction with those of ARIMA prediction directly, it is found that the prediction effect of this method is better. It provides some experience and reference ideas for the remaining life prediction of lithium-ion battery at this stage.

2 RESEARCH METHOD

2.1 Empirical Mode Decomposition

EMD (empirical mode decomposition) was proposed by American Chinese scientist Norden E. Huang in 1998[1]. This method is an adaptive time-frequency local analysis method. Its core is to decompose the signal into a group of single component signals by Hilbert transform. Different from the traditional Fourier decomposition and wavelet decomposition, EMD can be applied to any type of signal decomposition. So it can be widely used to deal with nonlinear and non-stationary sequences. The mode decomposition method can decompose complex signals into multiple intrinsic mode functions (IMF). The decomposed

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IMF contains different local characteristic information of the original signal. The EMD method has many advantages. It is adaptive and can generate the basis function automatically. The multi-resolution and filtering characteristics are also adaptive. EMD signal decomposition is complete, and the superposition of decomposed IMF will regain the properties of the original signal.

In the EMD algorithm, firstly we find the local maximum and limit value of $x(t)$, and then use the cubic spline difference method to construct the upper envelope $h(t)$ and the lower envelope $l(t)$. The mean $m(t)$ of the upper and lower envelopes is:

$$m(t)=\frac{h(t)+l(t)}{2} \quad (1)$$

Judge whether $r(t)$ is monotonous. $r(t)$ is the difference between the original signal $x(t)$ and $m(t)$. If monotonous, an IMF sequence can be decomposed. EMD decomposes a series of IMF signals, and the formula is as follows:

$$x(t)=\sum_{i=1}^{n} imf_i(t)+r_n(t) \quad (2)$$

Where $imf_i(t)$ is the ith IMF obtained by EMD decomposition; $r_n(t)$ is the signal residual component after decomposition of N IMFs.

The flow chart of EMD algorithm is shown in Figure 1.

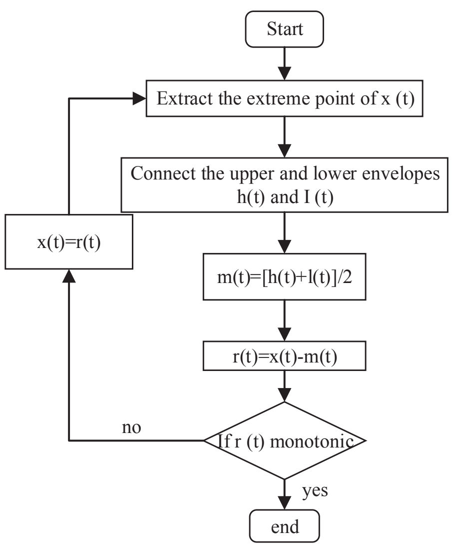

Fig 1. EMD flow chart

2.2 White Noise Empirical Mode Decomposition

The EMD method has many advantages. It is adaptive and can automatically generate basis function, filtering characteristics and multi-resolution. The decomposition of EMD is completed, and the superposition of decomposed IMFs will regain the properties of the original signal. However, EMD also has problems and deficiencies. The biggest problem is the existence of modal mixing in IMF. There are two main forms of modal mixing: one is that there are different signals with a wide range of scales in the same IMF component. Second, there are signals with similar scales in different IMF components. Therefore, this paper proposes a new solution: WEMD(white noise empirical mode decomposition). In this algorithm, the white noise with normal distribution is added to the original signal, so that the time series is divided into different time-frequency scales. Adding normal white noise for many times can make the signal scales of different IMF sequences different, and there are no signals with different scales in the same IMF. And because the white noise with normal distribution is added, it does not affect the final decomposition of the original signal.

WEMD algorithm steps are as follows:

(1) The white noise with normal distribution is added to the original signal

(2) Taking the signal with white noise as a whole, EMD decomposition is carried out to obtain each IMF component;

(3) Repeating steps (1) and (2) for many times, adding white noise with normal distribution each time;

(4) The IMF obtained by multiple decomposition is integrated and averaged as the final result.

The flow chart of WEMD algorithm is shown in Figure 2.

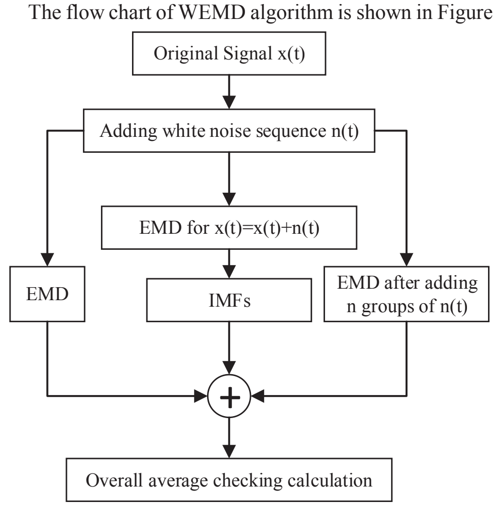

Fig 2. WEMD flow chart

2.3 Auto Regressive Integrated Moving Average

ARMA model (auto regressive moving average model) is one of the prediction and analysis methods of time series[2]. The basic idea of time series prediction method based on ARMA model is to treat the data series formed by battery residual capacity with time as a random time series. ARMA model considers that the observation value at the nth time in the sequence is not only dependents on the first (n-1) observation value, but also dependents on the disturbance entering the system at the first (n-1) time. Therefore, a prediction model is established to predict the future value. It is applicable to the high and stable correlation of the data itself.

The prediction method of ARMA model is to superimpose or combine the past and present errors with the previous series. The model expression is:

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3}$$

Formula 3 is recorded as ARMA (p, q). In this formula p is the autoregressive order and q is the moving average order; c is a constant term; X_t is the time series value at time t; φ_i is the autocorrelation coefficient; θ_i is the moving average coefficient; ε_t is the white noise at time t.

With the passage of time, the data of most time series can not keep stable all the time, so it is not feasible to use ARMA model directly. Therefore, the data needs to be differentiated first. The ARMA model after differential operation is called Auto Regressive Integrated Moving Average model (ARIMA model). The model expression is:

$$\Delta X_t = c + \sum_{i=1}^{p} \phi_i \Delta X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4}$$

Formula 4 is recorded as ARIMA (p, d, q). In this formula p is the autoregressive order and q is the moving average order; X_t is the time series value after difference at time t, φ_i is the autocorrelation coefficient; θ_i is the moving average coefficient, ε_t is the white noise at time t.

The flow chart of ARIMA model is shown in Figure 3.

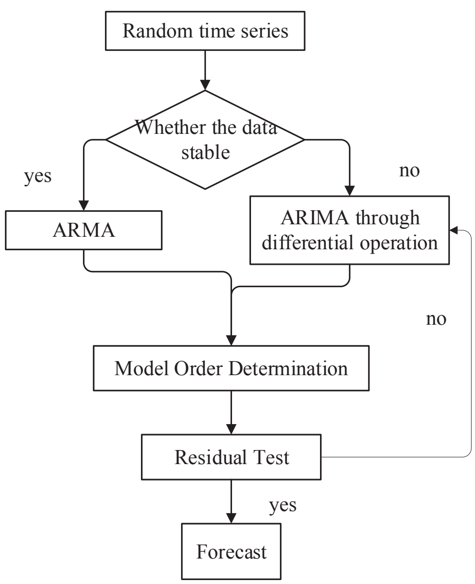

Fig 3. ARIMA flow chart

2.4 WEMD-ARIMA Model

The overall process of lithium-ion battery life prediction based on WEMD-ARIMA is shown in figure 4, which is mainly divided into two modules: original data processing module and sub sequence prediction module. Specific tracking process:

(1) Obtain NASA open cycle life degradation data of lithium-ion battery $x(t)$（t=1,2,…）;

(2) Using WEMD algorithm to decompose $x(t)$ into several single component signals $imf_i(t)$ and a residual signal $r_0(t)$;

(3) The ARIMA model is established to predict every $imf_i(t)$ and residual signal $r_0(t)$, and the prediction results are input.

(4) Through WEMD reconstruction, all single component prediction results are integrated to obtain the total prediction value of lithium-ion battery

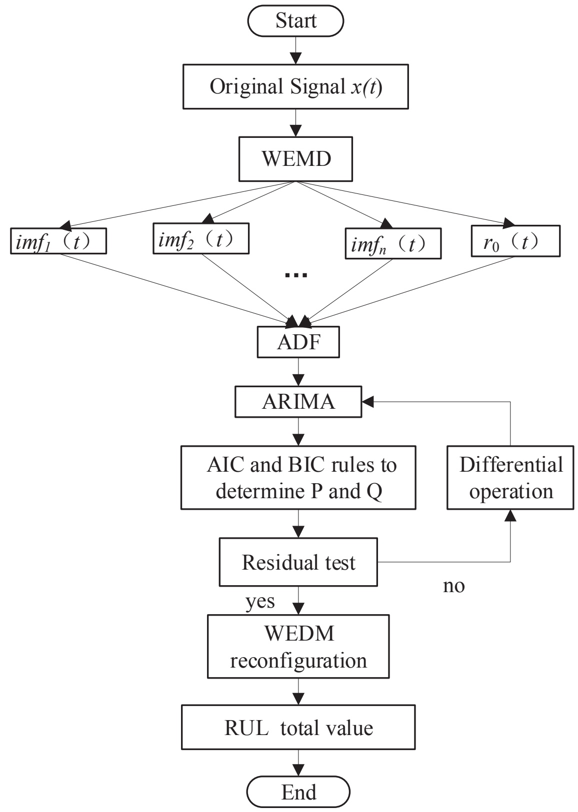

Fig 4. WEMD-ARIMA flow chart

3 Experimental process

3.1 Data selection

The data used in this project is the open source lithium-ion lifetime experimental data set provided by NASA Ames Research Center[3]. 18650 lithium battery with rated capacity of 2Ah was used in the experiment. 18650 battery is a standard lithium-ion battery model set produced by Sony Company. It has been widely used because of its large capacity, long service life, high safety performance, high voltage, no memory effect, small resistance, series or parallel 18650 battery pack and many other advantages. Therefore, taking the life data of 18650 battery as the experimental sample has practical reference value. There are six groups of lithium-ion lifetime experimental data sets downloaded from NASA Ames experimental center, and the main experimental conditions are as follows.

The first set of experimental batteries are numbered B0005, B0006, B0007 and B0018. The charge discharge mechanism and the experimental temperature conditions are as follows:

(1) Temperature: 24 ℃ room temperature.

(2) Charge: charge in the constant current (CC) mode of 1.5A until the battery voltage reaches 4.2V, and then continue charging in the constant voltage (CV) mode until the charging current drops to 20mA.

(3) Discharge: discharge at the constant current (CC) mode of 2A until the battery voltage of B0005, B0006, B0007 and B0018 drops to 2.7V, 2.5V, 2.2V and 2.5V respectively.

(4) Impedance: the impedance is measured by electrochemical impedance spectroscopy (EIS) frequency, and the frequency scanning range is 0.1Hz-5kHz.

The second to sixth groups of experiments mainly study the accelerated degradation of lithium-ion batteries. The degradation is accelerated by increasing the discharge current or temperature. From the first to sixth groups of experimental conditions, the first group of conventional degradation test experimental data is selected. The data structures of lithium-ion open source data set include: cycle (top-level structure array including charge, discharge and impedance operation), type (charge, discharge or impedance), time (date and time of cycle start, using MATLAB date vector format), data (data structure including measured values). This experiment mainly uses the capacity in the discharge field of data as the main prediction basis. Extract the remaining circulating capacity data and draw it, as shown in Figure 5. The effective data extracted from B0005, B0006, B0007 and B0018 lithium ion batteries are 167, 167, 168 and 132 groups respectively.

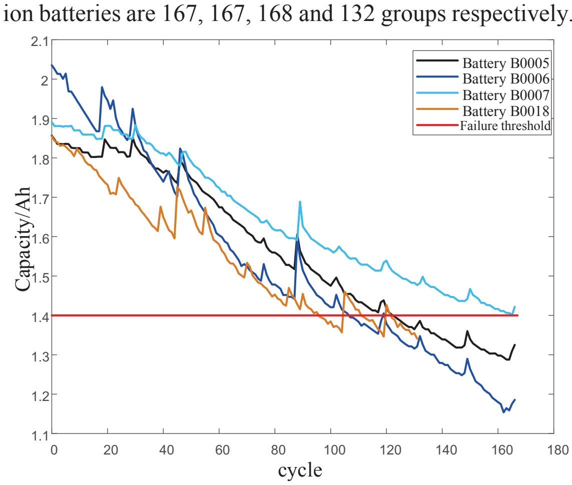

Fig 5. the remaining circulating capacity data

It can be seen from figure 5 that the capacity of single lithium-ion battery shows a degradation trend with the increase of charge and discharge times, and the degenerate trajectory is nonlinear and random. For lithium-ion batteries, 70% of the rated capacity is usually regarded as the threshold of battery aging. That is, after reaching 70% of the rated capacity, it is considered that the battery fails and the service life is over. The red line in Figure 5 is the set failure threshold of 1.4Ah.

It can be seen from the figure that the experiment was stopped before the battery B0007 fell to the failure threshold. Battery B0018 has a small amount of data. Therefore, this paper selects the remaining cycle capacity data of B0005 and B0006 lithium-ion batteries to study the prediction model.

3.2 Experimental verification index

In order to better evaluate the performance index of the whole model, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used as evaluation criteria. The calculation formulas of MAE and RMSE are shown in formula (5)、(6).

$$MAE = \frac{1}{m}\sum_{k=1}^{m}\left|\tilde{SOH}_k - SOH_k\right| \quad (5)$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{\tilde{SOH}_k - SOH_k}{SOH_k}\right| \quad (6)$$

$\tilde{SOH}_k$ and SOH_k are the estimated value and real value of lithium battery *SOH* in the *k* charging cycle respectively; *m* is the length of time series.

Lithium-ion battery health status(*SOH*) is shown as formula (7):

$$SOH(t) = \frac{Q_t}{Q_o} \quad (7)$$

Q_t is the battery capacity at time *t*, and Q_0 is the initial battery capacity.

The smaller the MAE and MAPE are, the smaller the deviation between the estimated value and the real value, and the higher the prediction accuracy. The MAE and MAPE predicted by using the research scheme of this subject, ARIMA model alone and WEMD-ARIMA are calculated respectively.

3.3 Analysis of experimental results

The residual cycle capacity of B0005 and B0006 lithium-ion batteries were decomposed into six IMF functions and a residual sequence by WEMD. The decomposition of B0005 and B0006 batteries are shown in Figure 6 and 7 respectively.

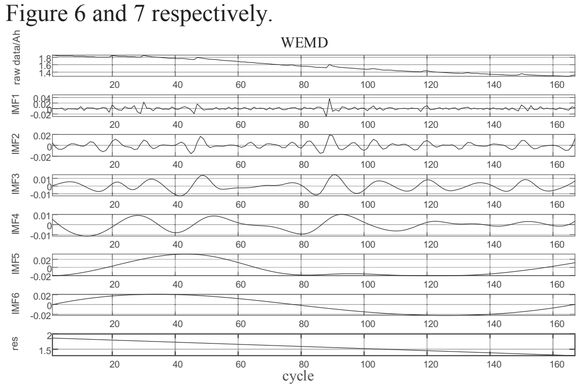

Fig 6. WEMD of B0005

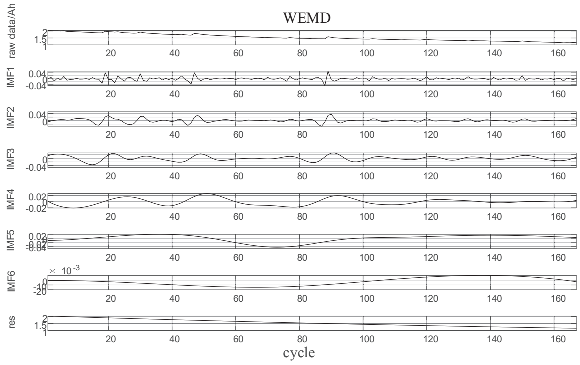

Fig 7. WEMD of B0006

Figure 8 shows the final results of the prediction of the previous 60 sets of data for the training set of B0005 lithium-ion battery. The black curve represents the real residual cycle capacity of B0005 battery, the dark blue curve represents the prediction result of directly using ARIMA model, the green curve represents the prediction result of using WEMD-ARIMA model, and the red straight line represents the failure threshold of 1.4Ah. It can be seen from the figure that the residual life predicted by WEMD-ARIMA is closer to the real value than that predicted by ARIMA model directly.

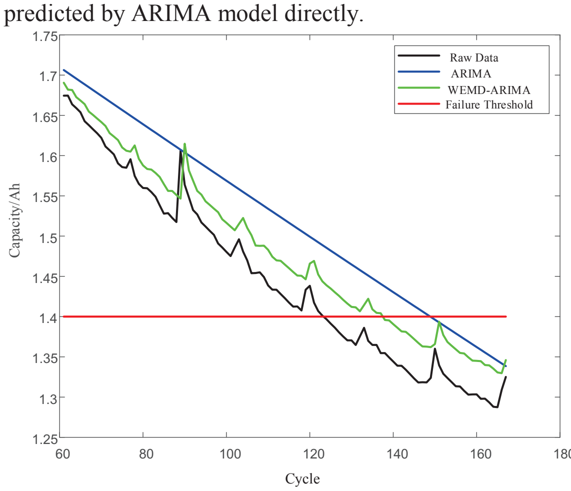

Fig 8. Prediction results of WEMD-ARIMA based on the first 60 groups of data of B0005 battery

Figure 9 and Figure 10 show the prediction results of the previous 80 and 100 sets of data of B0005 lithium-ion battery as the training set. It can be seen from the figure that the prediction effect of WEMD-ARIMA is better than that of ARIMA alone. And with the increase of training set data, the prediction effect is getting better and better.

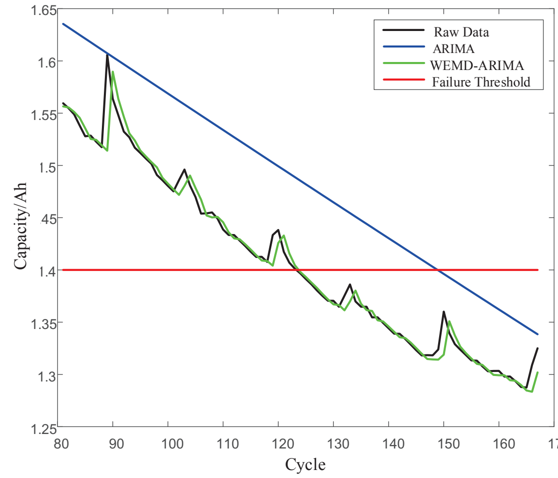

Fig 9. Prediction results of WEMD-ARIMA based on the first 80 groups of data of B0005 battery

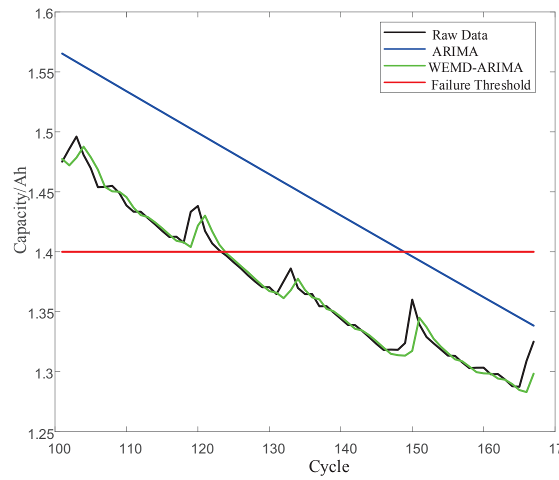

Fig 10. Prediction results of WEMD-ARIMA based on the first 100 groups of data of B0005 battery

Figures 11-13 show the comparison of prediction results of the previous 60, 80 and 100 sets of data of B0006 lithium-ion battery. The final accuracy of WEMD-ARIMA prediction method in Figure 11 is not as good as that predicted directly by ARIMA model. The reason should be that the number of data sets is not enough and the prediction accuracy is not accurate enough. The prediction results using the first 80 and 100 groups of data are better than those using ARIMA directly.

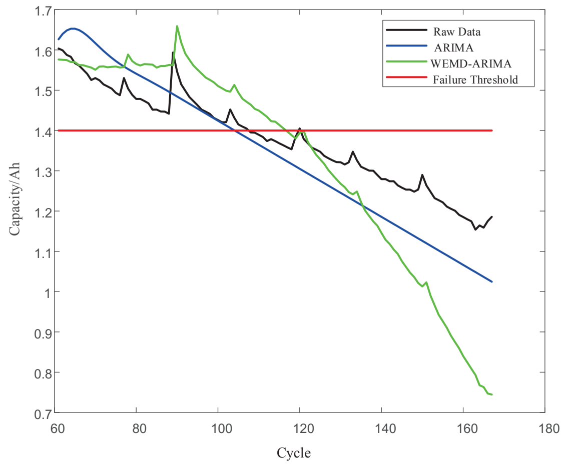

Fig 11. Prediction results of WEMD-ARIMA based on the first 60 groups of data of B0006 battery

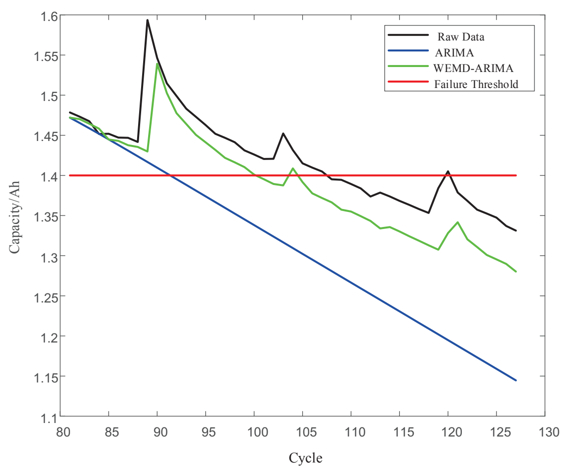

Fig 12. Prediction results of WEMD-ARIMA based on the first 80 groups of data of B0006 battery

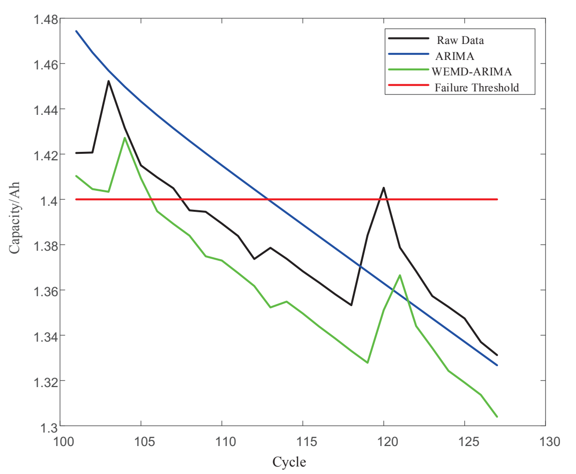

Fig 13. Prediction results of WEMD-ARIMA based on the first 100 groups of data of B0006 battery

In order to see the results of each model method more conveniently and intuitively, the tables of MAE and MAPE are listed. Table 1 shows MAE table of six groups of experimental data, and Table 2 shows MAPE. It can be seen intuitively from the data that the evaluation index values of the WEMD-ARIMA algorithm proposed in this paper are very small. Mae values are almost less than 0.01 and MAPE values are less than 1. Therefore, the estimation of battery capacity is closer to the real value. It shows the rationality and superiority of the model in this paper.

Table1. MAE comparison of different models

Battery	Start Point	ARIMA	WEMD-ARIMA
B0005	60	0.0341	0.0024
	80	0.0357	0.0019
	100	0.0472	0.0032
B0006	60	0.0101	0.0135
	80	0.0520	0.0023
	100	0.0231	0.0030

Table2. MAPE comparison of different models

Battery	Start Point	ARIMA	WEMD-ARIMA
B0005	60	4.3345	0.3221
	80	5.1380	0.2841
	100	4.8642	0.4230
B0006	60	0.7742	0.9956
	80	8.5640	0.6752
	100	7.5563	0.2842

4 SUMMARY

A prediction model of lithium-ion residual cycle life based on WEMD-ARIMA is proposed in this paper. The remaining cycle life of lithium-ion is regarded as a group of time series, which is decomposed into several IMF subsequences by WEMD. Then ARIMA model is made for IMF series, and finally the prediction is superimposed to obtain the final result. Comparing the model designed in this paper with the ARIMA model directly, it is proved that the accuracy of the model proposed in this paper is higher. It has certain application value in the field of AGV and AMR.

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