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A Health Estimation Method for Lithium-ion Battery Based on Charging Voltage Characteristics

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Abstract: In order to effectively predict and evaluate the health status of lithium-ion battery, this paper analyze NASA Ames PcoE battery samples and put forward a method based on the characteristics of charging voltage to extract health indicator to predict the state of health. In the process of lithium-ion battery's constant current charge, respectively extract the selection of terminal voltage rise rate, time interval of constant voltage range as health indicator, using the least squares polynomial regression, it can realize accurate estimation of battery state of health. The results show that the estimation error of the method converges to about 2%, can achieve precise estimates of lithium battery state of health.

Keywords: Lithium-ion Battery, Health Indicator, Regression Prediction, Status of Health.

1. Introduction

Lithium-ion battery has become the first choice of electric vehicle power battery with the advantages of short charging time, long available cycles, mild memorial effects, high energy density. However, in the process of continuous use, the capacity of lithium-ion battery is declining and the internal resistance is rising, the energy density and power density of lithium-ion battery is declining , so it is necessary to exactly estimate the Status of Health (SOH) for lithium-ion batteries.

General estimation methods of SOH can be classified as constant current discharge, model, data-driven[1], etc. The method of constant current discharge used to evaluate other SOH algorithm accuracy in laboratory conditions, it is hard to match the requirement of online estimate in working vehicle. Models include electrochemical model [2,3], equivalent circuit model [4] and experience model [5], etc. The accuracy of algorithm based on the performance of model: the sampling accuracy of the sensor is required to be high, and the adaptability of the model is poor, so it is difficult to cope with various complex working conditions. The data-driven based on the data of the aging battery samples, using the theory of machine learning [6] or the method of neural network [7] to train the estimation models offline. At last, the prediction algorithm of Status of Health which can be applied online for lithium-ion battery is obtained.

Data-driven, in addition to study algorithms and optimization models, there are a lot of research focused on the method of extracting lithium-ion battery health indicator. Health indicator (HI) as characteristic parameters to characterize the health status of lithium battery, can be divided into two categories, as follows: 1, the direct health indicator: mainly the internal parameters of lithium-ion batteries, such as capacity and resistance; 2, indirect health indicator: refers to have strong correlation with battery capacity or resistance and the ability to characterize the other parameters of the lithium battery state of health. The direct health indicator belongs to the internal parameter of battery, which is only suitable for offline measurement of SOH under laboratory conditions. It is difficult to measure and obtain it under real vehicle conditions And the research for extracting indirect health indicator, mainly focus on battery discharge process.For examples, the discharge voltage sample entropy characteristic [8] searched by Achmad Widodo et al ,the time-interval discharge voltage difference [9] extracted by Liu et al, and the average voltage attenuation [10] selected by Zhou et al. These methods share the disadvantage of high precision of sensor, many restrictions on health indicator, weak anti-interference ability and fault tolerance of algorithm. Compared with the discharging process, the charging process of the lithium -ion battery is controlled by the vehicle charger, which is less affected by the driving environment and complex working conditions. Therefore, in the process of constant current charging of lithium-ion battery, this paper extract terminal voltage rise rate and time interval of constant voltage range as the health indicator, and then the polynomial linear regression equation of health indicator is fitted to realize the accurate estimation of health for lithium-ion battery.

2. Lithium-ion Battery Aging Experiment

2.1 Aging Experimental Design

This paper choose the No.B0005 (hereinafter referred to as the B5 batteries) battery data sample [11] in NASA Ames PcoE (Prognostics Data Repository on NASA Ames) battery database. The research center repeatedly charge and discharge the 18650 lithium ion battery with capacity of 2Ah, under the condition of the environment temperature which is 24 °C.

A single charge and discharge cycle experiment steps are as follows:

1. charging test: firstly, charge the battery with A constant current of 1.5a until the terminal voltage of the battery reaches 4.2V; Then, continue charging at a constant voltage until the charging current is reduced to 20mA, ending the charging.
2. impedance test: after charging, the electrochemical impedance spectrum of the battery was scanned at a frequency range of 0.1hz ~ 5kHz.
3. discharge test: discharge at a constant current of 2a until the battery reaches the cut-off voltage of 2.7v.
4. impedance test. The test method is the same as step 2.

The main characteristics of health in lithium-ion batteries are attenuation of capacity and increase of resistance. Thus, the total electric quantity released in the discharge test of a charge-discharge cycle aging experiment is selected in this paper as the characterization of SOH of lithium-ion batteries, and the calculation formula is as follows:

$$SOH = \frac{Q_i}{Q_{rated}} \times 100\% \tag{1}$$

In the formula, Q_i Is the total charge released by the battery in the discharge test of a charge-discharge cycle experiment, Q_{rated} Is the factory rated capacity of the battery, both in Ah.

If the total power released by the battery in a discharge test drops to about 70% of the rated capacity, the battery's life is considered to be terminated and the battery aging experiment is stopped. Otherwise, the battery will continue to undergo the next round of charging and discharging cycle aging experiment.

2.2 Analysis of Experimental Results

As shown in Fig . 1, with the rise of charge-discharge cycles, lithium-ion battery discharge capacity of the whole present a declining trend. Considering the possible irregularities in experiments, the precision of sensor in measurement, the impact of impedance spectrum test to battery capacity, equipment electromagnetic interference or other reasons bring about the charge and discharge loop, causing discharge capacity and swiftly growing again and again.

From the empirical data analysis, repeated charging and discharging cycle will lead to the accelerated ageing of the battery, battery capacity should be with the rise of cycles of continuous decline. In order to more comprehensively and objectively analyse the degradation of battery capacity to turly reflect the degradation of health state, it is necessary to filter and preprocess the original data.

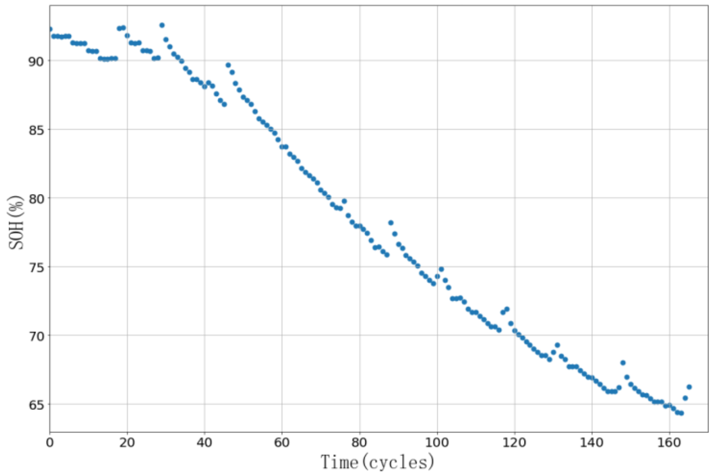


Fig . 1 Relationship between battery cycle and capacity

In the first nineteen time charge and discharge cycles of B5 battery, no impedance test was added after the charge test and discharge test. Considering the consistency of experimental test operation, the first nineteen time cycles should not be adopted as the sample set of research algorithm and training model.

Again considering before and after the 29th, 46th, 88th, 100th et al, cycle discharge capacity and swiftly growing again, in order to be more truly reflect the battery capacity characterizing the health state of degradation process, filter abnormal points in the training data should be executed before the training algorithm. Abnormal detection algorithm description is as follows:

1. Beginning conditions: if the discharge quantity measured in the discharge test increases in a certain cycle experiment compared with the last cycle experiment, and the increase is greater than 0.01Ah, the abnormal point detection will begin.

2. Detection Algorithm: if a loop experiment compared with the last cycle experiment and the next cycle experiment, the absolute value of discharge capacity difference is greater than 0.01 Ah, is that the cycle of data samples exist larger fluctuation, is the abnormal points. And start to check whether the data sample of the next cycle for the abnormal points, until she reached the end condition.

3. End conditions: if no abnormal point is detected in the three consecutive cycles of experimental data, the data is considered to be stable and the abnormal point detection algorithm is withdrawn.

Finally, the cyclic data samples after the 19th cyclic cycle and with relatively stable fluctuation range of discharge capacity are taken as the final training samples and data sets of the evaluation algorithm in this paper, as shown in Fig . 2.

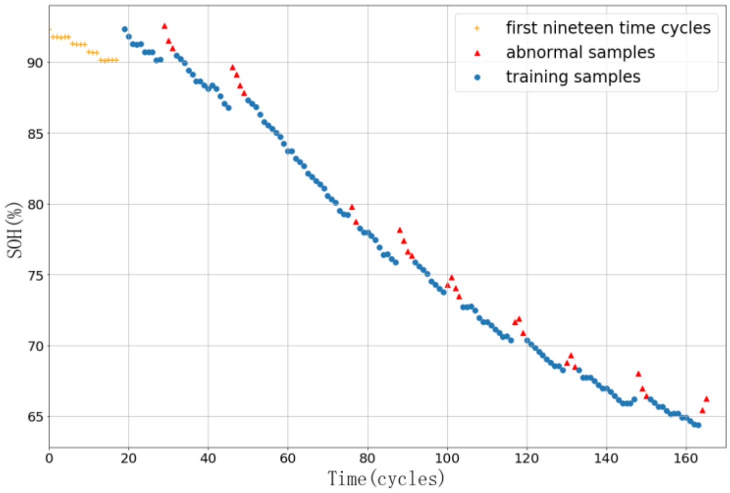


Fig . 2 Data distribution point

3. Correlation analysis and model evaluation methods

3.1 Correlation Analysis

Pearson correlation coefficient , also known as product difference correlation (or product moment correlation) coefficient, is used to quantitatively reflect the linear relationship between two sets of data sequences. Two sets of variables are assumed $X=(x_1,x_2 \ldots,x_n)$, $Y=(y_1,y_2 \ldots,y_n)$, then the calculation method of Pearson correlation coefficient between the two groups of data is shown in formula (2) :

$$r=\frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2}\sqrt{\sum(y_i-\bar{y})^2}} \tag{2}$$

Pearson correlation coefficient values between 1 and 1, the value of 1 or 1, can be said by the straight line equation to describe the relationship between the two groups of data sequence. The coefficient value of 0 means no linear relationship between two sets of variables. Pearson correlation coefficient of the absolute value of the closer to zero, shows that the linearity between the two sets of data, the worse; On the contrary, if the absolute value is closer to 1, it indicates that the linearity of the two data sequences is better. After a reasonable mathematical transformation, the relationship between them can be described by linear equations approximately.

Spearman correlation coefficient, also called Spearman rank correlation coefficient or rank difference method, is a rank characteristic research method of correlation between two variables. Similar to Pearson correlation coefficient, which reflects the close degree of association between two sets of data sequences, value range between 1 and 1. But and Pearson correlation coefficient of the difference is that coefficient of Spearman rank is based on the difference between the two levels of each peer in pairs series for calculation, as shown in formula (3) :

$$r_s = \frac{\sum(R_i - \overline{R})(Q_i - \overline{Q})}{\sqrt{\sum(R_i - \overline{R})^2}\sqrt{\sum(Q_i - \overline{Q})^2}} \tag{3}$$

In formula, R_i means x_i in X The rank of, Q_i means y_i in Y, where the rank order represents the ordinal number of the original data after the values of the variables are arranged in order from large to small. Conversely, if the monotone correlation degree of the two sets of data sequences is lower, the spearman correlation coefficient is closer to 0.

Spearman rank coefficient to evaluate two groups of statistical variables of monotonic correlation, but the spearman rank correlation of data conditions without product-moment correlation coefficient, strict, as long as the two groups of data of observation is pairs of rating data, or by continuous variable observation data into the level of data, regardless of two groups of data of population distribution pattern, the size of the sample size, spearman rank correlation can be used to study.

3.2 R^2 and RMSE

R^2, also known as r-square, fitness coefficient or determination coefficient, describes how well the model fits the data and reflects the percentage of variance that can be explained by the regression equation in the variance of the dependent variable. Its definition is as follows:

$$R^2 = 1 - \frac{\sum(y_i - f(x_i))^2}{\sum(y_i - \bar{y})^2} \tag{4}$$

In formula, $f(x_i)$ is is the model input pair, and x_i means the predicted value.When R^2 is approximately close to 1, indicating that the better the model fits the data, if the model always returns the expected value y_i, at this time R^2 return 0. And when the model fitting effect is very poor, R^2 might return negative.

RMSE(Root Mean Square Error), also known as Root Mean Square Error, reflects the Error between the predicted value of the model and the real value, and is a common method to measure and evaluate the predicted result of the regression model. The calculation method is shown in formula (5).

$$RMSE = \sqrt{\frac{1}{m}\sum(y_i - f(x_i))^2} \tag{5}$$

In formula, $f(x_i)$ is the model input pair x_i Given that rmse is the square root of the mean square error, and the effect of each error on rmse is proportional to the size of the error, rmse is sensitive to outliers.

3.3 Normalization

Normalization is a common method of dimensionless data processing in machine learning. During data preprocessing or feature extraction, data normalization is often used to scale features to a specific range, avoiding that the target value of the training set sample points will be dominated by individual feature values after feature digitalization. The calculation method is as follows:

$$x_{scale} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

4. Health indicator extraction and SOH prediction estimation

As shown in Fig . 3, with the increase of cell cycle, the initial battery terminal voltage rise gradually, less time to charge cut-off voltage used. Considering the factors such as user operation habit, battery charging process in actual application scenario may be difficult to reach full charge state, so the selection of lithium ion battery of the constant current charging process rather than a battery of the constant current constant voltage charging process for the extraction of health indicator and SOH prediction.

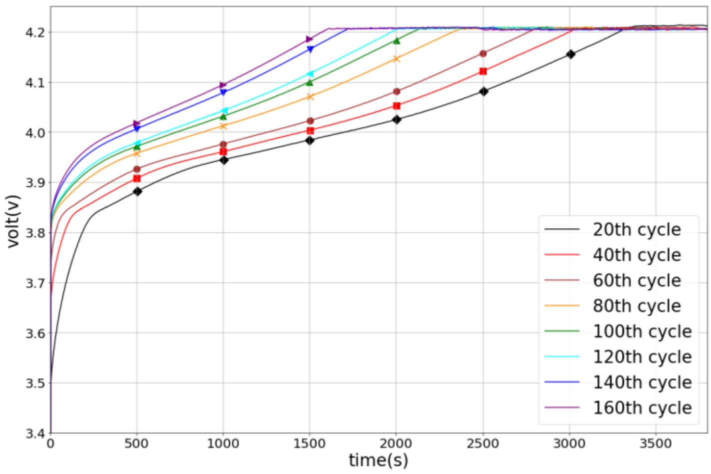


Fig . 3 Charging voltage variation curves of different cycles

4.1 Extract the Voltage Rise Rate as the Health Indicator

The results of the analysis on the charging voltage variation curves of different cycles show that during the 20th cycle of charging, with the increase of charging time, the slope of the terminal voltage of lithium ion batteries increases first, then decreases, then flattens, and finally rises again. In the charging process of the 120th, 140th and 160th cycles, the change trend of the voltage slope at the battery terminal is not obvious after 250 seconds of charging: the battery terminal voltage rises in a nearly straight line until the cut-off voltage of charging is reached.

In order to better explore different health status of lithium ion battery, this pager selects 3.9V, 4.0V and 4.1V voltage characteristic points as research. The study found, as shown in Fig . 4, the terminal voltage at 3.9V in the process of charging voltage rise speed, and battery state of health SOH has the very good relevance: with the continuous attenuation of battery capacity, battery voltage at 3.9V rise rate is gradually increased; And the increased rate of 4.0V, 4.1V voltage and battery SOH correlation is obvious not equal to 3.9V. In order to further analysis and verification that the increased rate of voltage and health indicator linear correlation and monotonic correlation, respectively based on Pearson correlation coefficient and szpilman correlation coefficient, the calculation of 3.9V, 4.0V and 4.1V voltage rise rate and health indicator, the relationship between the results as shown in Table 1.

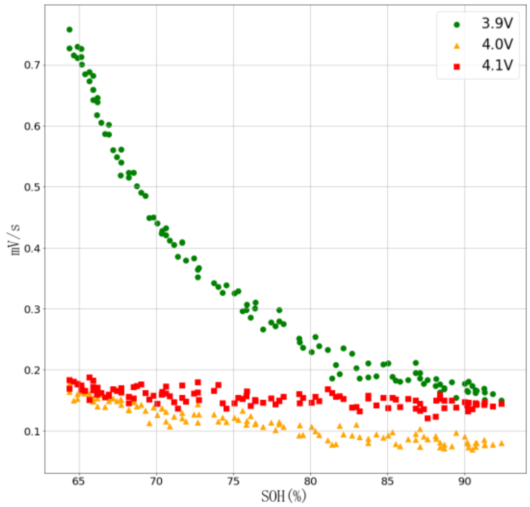


Fig . 4 Relationship between SOH and soltage rise rate at different voltage characteristic points

Table 1 Correlation Coefficients between Different Voltage Characteristic Points and SOH

Voltage Characteristic Point	Pearson correlation coefficient	Spearman correlation coefficient
3.9V	-0.933	-0.992
4.0V	-0.940	-0.950
4.1V	-0.704	-0.724

Comprehensive Fig .4 and Table 1, find different aging degree of lithium battery in the range of the increased rate of voltage change in the 3.9V is larger, and SOH has good linearity relationship. After by reasonable mathematical transformation, can use linear equation to describe approximately 3.9V voltage rise rate and the relationship between the battery state of health. This article selects the battery terminal voltage up to 3.9V before and after the fourth sample point voltage differential pressure, divided by the interval between two sampling points, for the increased rate of terminal voltage of 3.9V, to estimate the battery SOH health indicator, computation formula is as follows:

$$x_i = \frac{v_{it_2} - v_{it_1}}{t_{i2} - t_1} \tag{7}$$

In formula, x_i For the sample i Health indicator, v_{it_2} , t_{i2} For the sample i The voltage and sampling time of the battery's circuit end obtained at the 4th sampling after the voltage of the circuit end rose to 3.9V, v_{it_1} , t_{i1} For the sample i The battery terminal voltage and sampling time measured at the fourth penultimate sampling point before the voltage rises to 3.9V.

After obtaining the health indicator for estimating the battery, the health indicator needs to be evaluated x_i After feature normalization treatment with SOH, the least square polynomial regression fitting was carried out. Finally, the fitness coefficient R^2 and RMSE were used to evaluate the accuracy of the model. The fitting results corresponding to different fitting times are shown in Table 2.

Table 2 R^2 and RMSE of Different Fitting Times

Times of fitting	R^2	RMSE
2	0.970	0.0550
3	0.981	0.0431
5	0.983	0.0413

Considering the indicator such as simple calculation and avoid over fitting, when using only 3 times polynomial to 3.9V as to estimate the battery terminal voltage rising rate of SOH health indicator, which fit to the actual SOH under 75% and the lithium battery has very good prediction effect, and the actual SOH in more than 75% of the predicted effect of battery is a bit poor, SOH prediction effect a scatter diagram and the error is shown in Fig . 5.

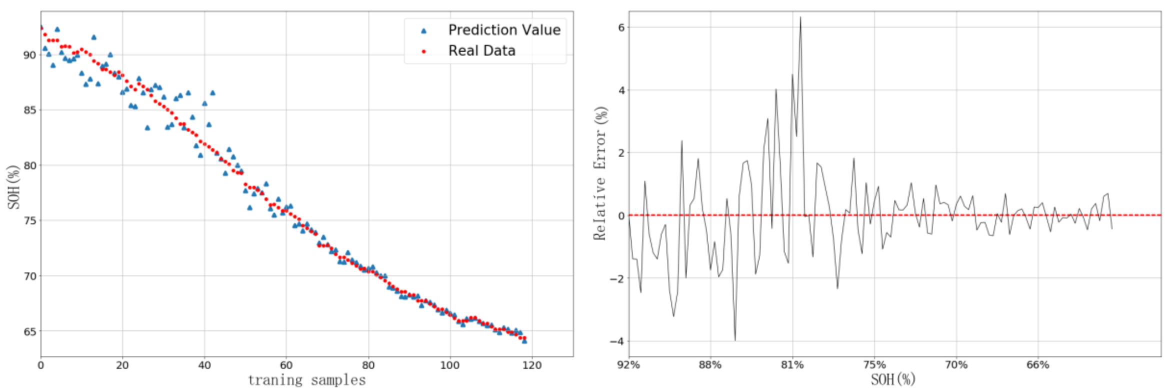


Fig . 5 Prediction Effect and Prediction Relative Error

4.2 Extract the Time Interval of the Constant Voltage Interval as the Health Indicator

With the rise of the cycles, battery aging degree of intensified, constant current battery charging time shorter, as shown in Fig . 3. Consider different health status of the battery in the process of constant current charging, analysis the battery terminal voltage from 3.9V to start, each rose 0.1V voltage, the relationship between the time and the battery SOH is shown in Fig . 6. It can be seen that with the decrease of the cell SOH, battery in the process of constant current charge, every time decrease gradually while 0.1V: increased from 3.9V to 4.0V time reduce the most severe, followed by the time 4.0V to 4.1V, 4.1V to The time variation trend of 4.2V is less obvious than that of the previous two. The Pearson correlation coefficient and spearman correlation coefficient of SOH in the three periods are shown in Table 3.

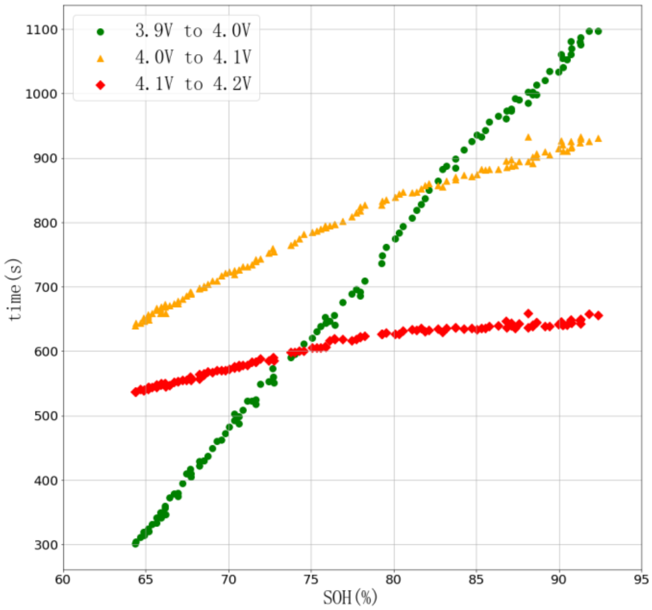


Fig . 6 Relationship between SOH and time used for each 0.1v rise in voltage

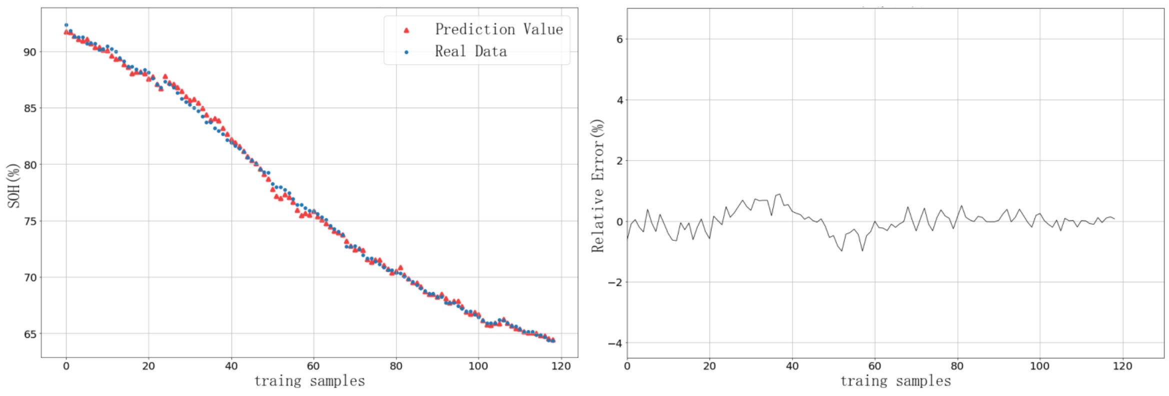
Table 3 Correlation Coefficients between SOH and Different Time Periods

Period of time	Pearson correlation coefficient	Spearman correlation coefficient
3.9V ~ 4.0V	0.999	0.999
4.0V ~ 4.1V	0.992	0.997
4.1V ~ 4.2V	0.966	0.990

Raise the terminal voltage from 3.9V to 4.0V and from 4.0V to 4.1V, respectively And increased from 4.1V to 4.2V of time interval, as calculated battery SOH health indicator, characteristics of the normalized least squares polynomial fitting after processing, will and results of fitting as shown in Table 4. Respectively to the battery terminal voltage from 3.9V to 4.0V is used in time, and the battery terminal voltage from 4.0V to 4.1V 2 times fitting SOH estimation of the time used and the error is shown in Fig . 7, as shown in Fig . 8, and for the battery terminal voltage from 4.1V to 4.2V 5 times fitting SOH estimation of the time used figure and the error is shown in Fig . 9. The fitting results show that different old The level battery at constant current charging stage, has risen from 3.9V to 4.0V used time and time increased from 4.0V to 4.1V is used, has a good degree of differentiation, in using only two items under the condition of fitting, most absolute error less than 2%, and the fluctuation range is smaller, the root mean square error control within 0.025 rmse, fitness coefficient r^2 were higher than 0.99. And the battery terminal voltage from 4.1V to 4.2V of the time used fitting effect is poorer, after using the polynomial fitting 5 times, is still difficult to get satisfactory result.

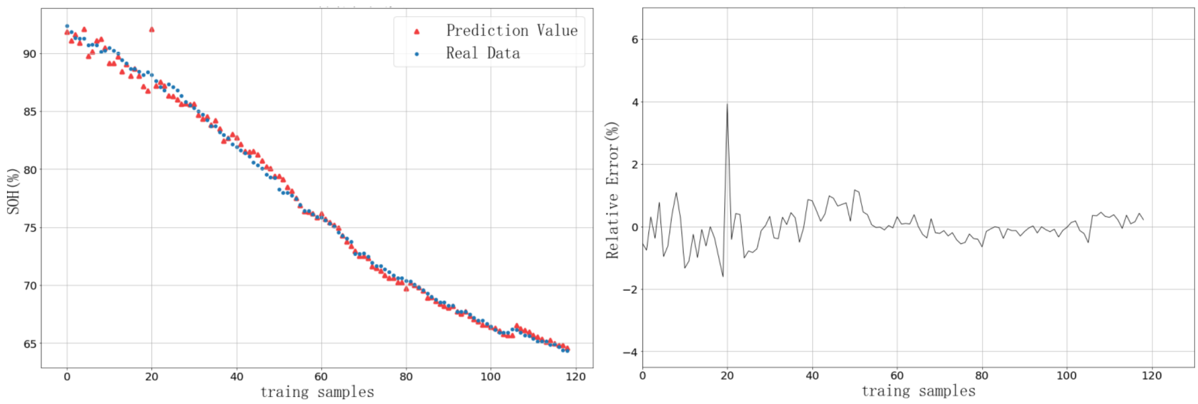
Table 4 Fitting Items in Different Time Periods and Fitting Results

Period of time	Number of fitting	R^2	RMSE
3.9V ~ 4.0V	2	0.998	0.013
	3	0.999	0.012
	5	0.999	0.011
4.0V ~ 4.1V	2	0.995	0.022
	3	0.995	0.022
	5	0.997	0.017
4.1V ~ 4.2V	2	0.964	0.060
	3	0.967	0.058
	5	0.980	0.045



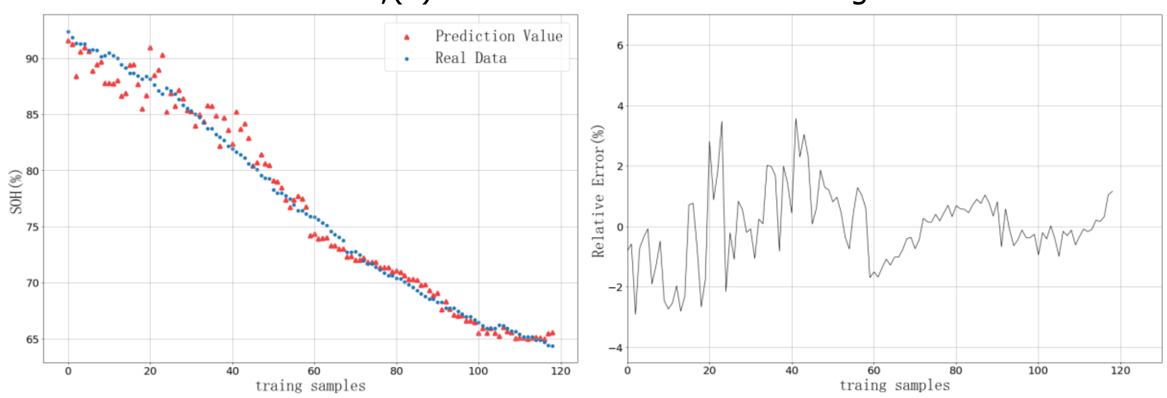
(a) (b)

Fig . 7 Prediction effect and prediction relative error :(a) the time it took for the battery terminal voltage to rise from 3.9V to 4.0V, and the prediction effect diagram was fitted twice;(b) relative error of 2 times fitting



(a) (b)

Fig . 8 Prediction effect and prediction relative error :(a) the time it took for the battery terminal voltage to rise from 4.0V to 4.1V, and the prediction effect diagram was fitted twice;(b) relative error of 2 times fitting



(a) (b)

Fig . 9 Prediction effect and prediction relative error:(a) the time it took for the battery terminal voltage to rise from 4.0V to 4.1V, and the prediction effect diagram was fitted for 5 times;(b) relative error of 5 times fitting

5. Conclusion

This article first explores the lithium ion battery capacity in the process of decay, in the constant current charging process of change rule. Then based on the data driven and statistical learning methods, extraction can characterize battery capacity attenuation characteristics of the health indicator, assessment of health indicator and correlation coefficient of SOH. At last, by polynomial regression fitting out SOH estimation model of lithium batteries, and use the R^2 and RMSE to evaluate precision of the model. The results show that in the process of lithium ion battery of constant current charging, battery terminal at 3.9V voltage rise rate and the battery terminal voltage at 3.9V The time interval between 3.9V~4.0V and 4.0V~4.1V is used as a health indicator for the estimation of battery health, and the estimation error converts to within 2%. This method is simple and adaptable, and can accurately estimate lithium battery health, which is conducive to the online prediction and application of residual life of lithium ion power batteries in electric vehicles.

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