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An Online Estimation Method of State of Health for Lithium-Ion Batteries Based on Constant Current Charging Curve

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Accurate estimation of state of health (SOH) is of great significance for the safety and reliability of lithium-ion batteries. In this paper, a novel method to estimate SOH online based on constant current charging curve is presented. In order to incorporate the factor of rates, a simple two-step data transformation process is carried out to make the method suitable for SOH estimation at different charging rates. Then polynomial is used to fit the transformed curve, and the coefficient sets of analytic expression obtained by fitting are taken as the battery aging feature variables. Finally, linear regression algorithm, the simplest machine learning algorithm, is employed to construct the mapping between feature variables and SOH, thus accomplishing the SOH estimation. When estimating SOH, only the charging curve of the whole constant current charging process is needed, regardless of the charging process at whatever rates. This method takes low computational cost, making it suitable for online estimation. The verification results on battery test data show that the method is of high accuracy and effectiveness.
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Lithium-ion batteries have been used extensively in electronic equipment, electric vehicles and other energy storage systems by virtue of a series of advantages such as long cycle life, high energy density, low self-discharge and fast charging and discharging speed.[1–5] However, as time goes on, the battery performance will inevitably decrease,[6,7] leading to degradation of capacity and power, which is called battery aging. In order to ensure the safety and reliability of batteries during the aging process, it is necessary to exactly estimate the current state of health (SOH) of batteries.[8–10] SOH can be defined in terms of capacity or internal resistance. In this study, SOH is defined by capacity, that is,

$$\mathrm{SOH} = Q/Q_0,$$

where Q is the current maximum charging and discharging capacity of the battery, and Q_0 represents the initial maximum charging and discharging capacity.[11] It is generally believed that the end of life (EOL) occurs when the usable capacity is lower than 80% of the initial capacity or the internal resistance increases to twice of the initial internal resistance.[12] As a result, SOH can provide valuable reference for battery health status.

However, it is a challenging task to accurately estimate SOH, especially online estimation, because battery aging involves many complex electrochemical reactions, which means that there are many influence factors.[13] At present, a lot of studies have reported many effective SOH estimation methods. In general, these methods can be divided into three categories: experimental methods, adaptive estimation methods and data-driven methods.

Experimental methods are to directly measure the capacity or internal resistance of the battery through a designed experiment, and then calculate the battery SOH according to the definition of SOH. This method is simple, direct and easy to understand, but it takes a long time to test and need to be implemented with the corresponding experimental equipment. Therefore, it is suitable for use in the laboratory and cannot meet the requirements of practical application scenarios.

Adaptive estimation methods are self-updating methods that can better fit new data samples, which can minimize the test workload required to develop accurate aging model.[14] Liu et al.[15] improved the particle learning framework, enabling it to adaptively adjust the number of particles in each iteration, thus reducing the running time of the algorithm and making it more suitable for online application. Feng et al.[16] applied five terminal sliding mode observers (TSMOs) to estimate the battery SOC and SOH, which is of high accuracy and fast response. Zou et al.[17] adopted two kinds of extended Kalman filtering with different time scales to estimate SOC and SOH jointly. In addition, some other adaptive SOH estimation methods have been reported, such as autoregressive integrated moving average (ARIMA),[18] unscented particle filter (UPF),[19] regularized auxiliary particle filter (RAPF),[20] multiscale dual H infinity filter (HIF).[21] Adaptive estimation methods have been widely used because of its high accuracy, simple implementation and easy to industrialize, but they are often not suitable for online estimation because of its high computational cost and noise susceptibility.

For the past few years, due to the advantages of flexibility and being model-free, data-driven method has gradually become one of the important methods for battery SOH estimation.[22] It treats the battery as a "black box" and does not need to analyze the complex aging decay mechanism inside the battery.[23] To estimate SOH by data-driven method, it is often necessary to preprocess the measured data first, and then extract the representative health feature variables, finally use a certain machine learning algorithm to find the hidden relationship between the feature variables and SOH. Patil et al.[24] proposed a method integrating classification and regression for real-time remaining useful life (RUL) estimation. Firstly, the classification model was used to estimated RUL roughly. If the battery was close to EOL, then the accurate RUL was predicted by the regression model. Yang et al.[25] extracted four features from the charging curve and established Gaussian process regression (GPR) model to estimate SOH. With the same GPR model, Li et al.[26] extracted health feature variables from the incremental capacity curve to estimate SOH. GPR was a relatively common used algorithm in SOH estimation, which was also exploited in many other studies.[27,28] Since most SOH estimation methods tended to take advantages of the features of voltage and current and ignored temperature changing, Tian et al.[29] developed a SOH estimation method based on battery surface temperature. However, Tan et al.[30] proposed a SOH prediction method based on transfer learning. Compared with the traditional data-driven method, only the first 25% of the data set was needed for transfer training, which greatly improved the practicability of the model. To guarantee the superior performance, Meng et al.[31] proposed an ensemble learning framework to estimate SOH, boosting the performance by integrating the

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weak learners. In addition, feed forward neural network (FFNN),[32] artificial neural network (ANN),[33] long short-term memory network (LSTM),[34] relevance vector machine (RVM),[35–37] support vector machine (SVM),[38,39] elastic net,[40] extreme learning machine (ELM)[41] and other algorithms have been used for SOH estimation.

Although the existing studies can get bright estimation results, they are often not applicable to SOH estimation when the charging rates are different. However, in the actual use of batteries, the charging rates are not always the same as the training data in many cases. In order to solve this problem, we developed a two-step data transformation method for constant current charging data, then fitted the curves after data transformation with polynomials, and took the coefficient sets of analytic expression as feature variables, and finally employed linear regression algorithm to construct the mapping between feature variables and SOH, thus accomplishing the SOH estimation. The model obtained by this method based on battery charging data at a certain rate can be applied to the SOH estimation at other different rates. The evaluation results on the battery test data sets show that this method is of high accuracy, stability and robustness. Due to the use of the linear regression algorithm, the method takes up low computational cost, so it is suitable for online estimation.

The rest of this paper is structured as follows: The second section briefly introduces the curve fitting method and the basic principle of linear regression. The third section introduces the battery testing process and gives a detailed description of the extracted features. In the fourth section, the experimental results are given and the necessity of two-step data transformation is verified. The fifth section summarizes the main conclusions of this paper.

Methodology

Although the linear regression algorithm is simple, it often shows a very good effect on the premise that there is a linear relationship between the label value and the feature variables. Moreover, linear regression is one of the few machine learning algorithms that can be interpreted. In addition, linear regression's another advantage is that it takes up very low computational cost. As a result, despite huge number of machine learning algorithms out there, there is still room for linear regression.

The purpose of this study is to estimate battery SOH based on constant current charging curves. First, it is necessary to use polynomials to fit the curves to get the coefficient sets of analytic expressions, and the task of linear regression is to establish the mapping function between the coefficient sets and the battery SOH. Therefore, the curve fitting method and the basic principles of linear regression are briefly elaborated in this section.

Curve fitting.—The "polyfit" function in the "numpy" library of Python is used to fit curves, which can fit curves easily with polynomials. If the abscissa of the data scatter to be fitted is $X = (x_1, x_2, \ldots, x_n)$ and the ordinate is $Y = (y_1, y_2, \ldots, y_n)$, then only X, Y and the order of polynomial are needed to input the function, and the best fitting curve is obtained by the least square method. The least square method is introduced in detail in the next part. The return result of this function is the coefficient set of analytic expression, which is arranged according to the power from high to low, that is, the feature variables.

Linear regression.—Linear regression is usually recognized as the simplest machine learning algorithm with low computational cost, which is suitable for online estimation of SOH. When it comes to linear regression, it generally refers to multiple linear regression, in which every sample has multiple features. For a dataset with m samples and n features per sample, the regression results of linear regression can be written as the following equation (Eq. 1),

$$\hat{\boldsymbol{y}} = \omega_0 + \omega_1 \boldsymbol{x_1} + \omega_2 \boldsymbol{x_2} + \ldots + \omega_n \boldsymbol{x_n} \tag{1}$$

where $\hat{\boldsymbol{y}}$ is the column vector containing the regression prediction results of m samples, $\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_n}$ is the column vector of n features of m samples, and ω is collectively called the parameter of the model, in which ω_0 is called intercept and ω_1–ω_n are called regression coefficient. The equation can be expressed in terms of matrix as follows (Eq. 2),

$$\hat{\boldsymbol{y}} = X\boldsymbol{\omega} \tag{2}$$

where $\hat{\boldsymbol{y}} = \begin{bmatrix}\hat{y_1} & \hat{y_2} & \cdots & \hat{y_n}\end{bmatrix}^{\mathrm{T}}$, $\boldsymbol{\omega} = [\omega_0\ \omega_1\ \cdots\ \omega_n]^{\mathrm{T}}$, $\boldsymbol{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1n} \\ 1 & x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$.

The task of linear regression is to construct a prediction function to map the linear relationship between the input feature matrix $\boldsymbol{X}$ and the label value $\boldsymbol{y}$. The essence of this prediction function is the model we need to construct. The core of constructing the prediction function is to find out the parameter vector $\boldsymbol{\omega}$ of the model. To do this, the loss function is constructed as below (Eq. 3),

$$\sum_{i=1}^{m} (y_i - \hat{y_i})^2 = \sum_{i=1}^{m} (y_i - \boldsymbol{X_i\omega})^2 \tag{3}$$

where y_i is the real label corresponding to sample i, $\hat{y_i}$, that is $\boldsymbol{X_i\omega}$, is the prediction result of sample i under a set of parameters $\boldsymbol{\omega}$. This loss function actually calculates the distance between real labels and predicted values, so the loss function measures the difference between the predicted results of the constructed model and the real labels. Obviously, the smaller the difference, the better the prediction effect is. Thus, the goal of the solution can be transformed into Eq. 4,

$$\min_{\omega} \sum_{i=1}^{m} (y_i - \boldsymbol{X_i\omega})^2 = \min_{\omega} \|\boldsymbol{y} - X\boldsymbol{\omega}\|_2^2 \tag{4}$$

This formula is often referred to as residual sum of squares (RSS). So, the problem becomes to solve the parameter vector ω which minimizes the RSS. This method of solving the parameters by minimizing the RSS between real values and predicted values is called the least square method. The first step of solving the extreme value is to take the first derivative and let the first derivative equal to 0, and the ω value of the first derivative equal to 0 is the optimal solution of the parameter. Therefore, we can solve for Eq. 5, as follows,

$$\boldsymbol{\omega} = (\boldsymbol{X^T X})^{-1}\boldsymbol{X^T y} \tag{5}$$

In this way, the optimal ω value is obtained, and an optimal prediction function is constructed.

Estimation of SOH Based on Constant Current Charging Curve

In this section, the details of battery aging experiments conducted in our laboratory are introduced first, then the extraction process of feature variables is elaborated, finally the overall framework of SOH estimation method is presented and the function of curve preprocessing process is analyzed.

Battery aging experiment.—The charge and discharge cycles of two types of 18650 batteries were tested by Neware battery testing system at 25 °C. The detailed parameters of the batteries are shown in Table I. As can be seen from the table, the cathode materials of the two types of batteries are different, one is NCM811 cathode material, the other is lithium cobalt oxide cathode material. The parameters measured by the battery testing system included voltage, current, time, capacity and so on. Each battery went through the process of constant current charging, constant voltage charging and constant current discharging. First, constant current charging was carried out until the voltage rose to the maximum charging voltage

Table I. Battery detailed parameters.

Parameters	Model Ⅰ	Model Ⅱ
Rated Capacity	2900 mAh	2200 mAh
Rated Voltage	3.7 V	
Upper Cut-off Voltage	4.2 V	
Low Cut-off Voltage	2.75 V	
Positive Electrode	NCM 811	LCO
Negative Electrode	graphite	

of 4.2 V, then constant voltage charging until the current dropped to the cut-off current of 0.01C, and finally constant current discharging until the voltage dropped to the cut-off voltage of 2.75 V, forming a complete charge-discharge cycle. As shown in Table II, three batteries of each type were tested. The three batteries went through the constant current charging process of 0.75C, 1C and 1.25C respectively, and the discharge currents were all 1C. The batteries are numbered as Ⅰ−1, Ⅰ−2, Ⅰ−3, Ⅱ−1, Ⅱ−2, Ⅱ−3 respectively. The changes of current and voltage during test are shown in Fig. 1.

Features extraction.—In order to estimate battery SOH accurately and quickly, first of all, it is necessary to find the feature variables related to the aging of batteries. On the one hand, the feature variables should be as correlated as possible with SOH, and they should also be of certain universality. On the other hand, they would better be relatively easy to obtain. In general, voltage, current and temperature are easier to measure. Because the aging of batteries involves many complex and coupled physical and chemical reactions, it is hard to find the feature variables related to it from these easily measured quantities.

In the actual use of batteries, there are two status: charging and discharging. The discharging process is subject to the change of actual use demand, and the discharge current changes rapidly, almost without any law to follow. While the charging process of batteries often goes through in a fixed mode,[32] which commonly consists two subprocesses, constant current-constant voltage charging. Therefore, it is far more convenient to extract the relevant feature variables from the charging process than the discharge process, as has been done in many related studies.[42–44]

The constant current charging curves of battery Ⅰ−1 in different cycles are showed in Fig. 2. It can be seen clearly that as cycles go on, that is, as the battery ages, the curves change slightly, which means that the curves themselves can be used to characterize SOH of the battery.[45] If polynomials of the same order are used to fit the curves, analytical expressions of the same form can be obtained for the charging curves of each cycle. Since there is one-to-one correspondence between fitted analytic expressions and curves, that is, there is one-to-one correspondence between the coefficient sets of analytic expressions and curves. Therefore, the coefficient sets of analytic expressions obtained by fitting curves with polynomials can be used as aging features variables.

However, as shown in Fig. 3a, when charging at different rates, charging curves are different greatly due to different charging current. Therefore, if charging curves are used to characterize SOH, namely, the coefficient sets of analytic expressions obtained by fitting charging curves with polynomials are taken as feature variables, then the feature variables can only be applied to a certain rate. If the charging rate is changed, the feature variables will be no longer applicable, which means the universality is low. If some data transformation is performed on charging data to integrate the factor of charging rate into it, so that the charging curves at different charging rates are in similar shapes, then the coefficient sets obtained by curve fitting will become highly universal feature variables applicable to different rates.

After many attempts, we finally find a data transformation method that meets the requirements. The method is divided into two steps. The first step is "rate processing," which means that all recorded times of a constant current charging curve are multiplied by the charging rate, C*t, and then the second step is "logarithmic processing," that is taking the natural logarithm of the data after "rate processing." It should be noted that since the charging time is recorded from 0, and 0 has no logarithm, thus one is added before

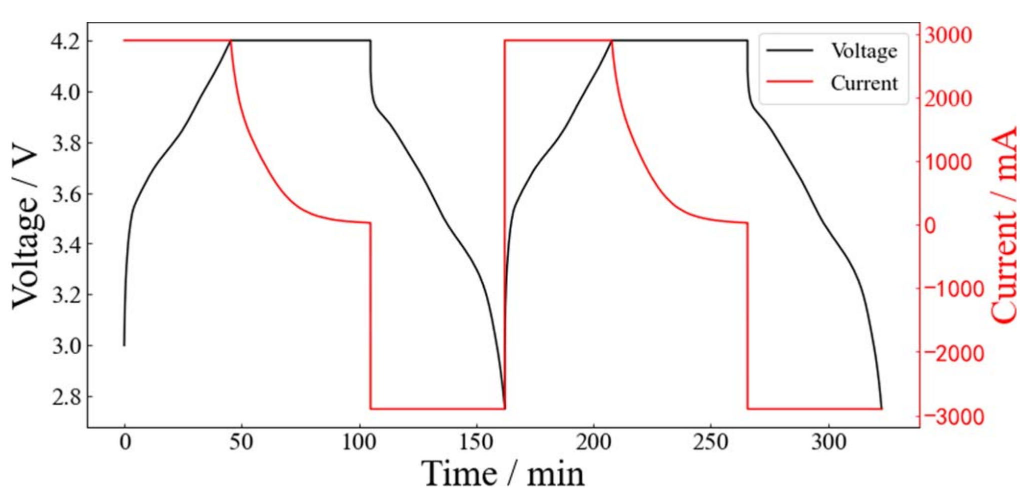

Figure 1. Changes of current and voltage during battery test.

Table II. Detailed parameters of battery cycle test.

Num.	Charging current	Charging cut-off current	Discharge current
Ⅰ−1	2175 mA (0.75C)		
Ⅰ−2	2900 mA (1C)	29 mA (0.01C)	2900 mA (1C)
Ⅰ−3	3625 mA (1.25C)		
Ⅱ−1	1650 mA (0.75C)		
Ⅱ−2	2200 mA (1C)	22 mA (0.01C)	2200 mA (1C)
Ⅱ−3	2750 mA (1.25C)		

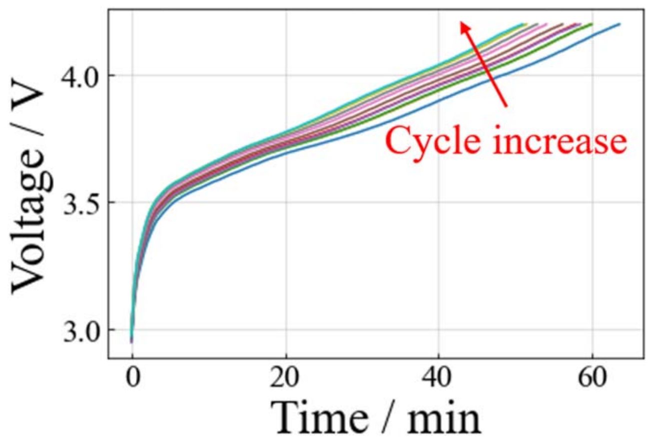

Figure 2. Charging curves during the constant current charging process.

"logarithmic processing" to avoid taking logarithm of 0, that is $\ln(C \times t + 1)$. "Rate processing" is inspired by Zhang et al.,[46] while "logarithmic processing" is a data transformation method commonly used in statistics. The charging curves after two-step data transformation are named as logarithmic charging curves. As shown in Fig. 3b, logarithmic charging curves at different charging rates show a relatively similar shape. Therefore, it is speculated that if the logarithmic charging curves are used to characterize SOH, the coefficient sets of analytic expressions obtained by fitting logarithmic charging curves with polynomials can be used as the feature variables, which can be applied to the charging process at different rates.

Let $x = \ln(C \times t + 1)$, then an analytical expression of order n can be obtained by fitting a logarithmic charging curve with an n-order polynomial, as shown in Eq. 6,

$$U = A_m^1 x^n + A_m^2 x^{n-1} + \ldots + A_m^{n-1} x^2 + A_m^n x + A_m^{n+1} \quad [6]$$

where, U represents the ordinate voltage, A_m^1–A_m^n represents coefficients obtained by fitting, A_m^{n+1} represents an intercept, and the subscript m represents the cycle number. Since the intercept A_m^{n+1} does not affect the shape of the curve, it is not regarded as a feature variable, that is, the coefficient set obtained is $[A_m^1,\ A_m^2,\ldots,A_m^{n-1},\ A_m^n]$.

SOH estimation framework.—The overall framework of the SOH estimation method proposed in this study is shown in Fig. 4. This method can be divided into two parts: offline model training and online estimation. In the offline stage, the original data of all cycles of a battery at a certain charging rate should be collected at first, and then the curve preprocessing process should be carried out to get the coefficient set of analytic expression of each curve, which can be used as training data to train a model. When the training is complete, the offline stage is complete. Here, the data transformation process and the polynomial fitting logarithmic charging curve are combined and collectively referred to as the curve preprocessing process. What's more, the coefficient set obtained by curve preprocessing process is selected for its predictive ability, not its physical meaning. When estimating SOH online, it is only needed to obtain the data of a complete constant current charging process of a battery to be tested through sensors, and then carry out the same curve preprocessing process as the offline stage to get the fitting coefficient set, and then input it into the trained SOH estimation model, and the model can output the SOH estimation results.

It is easy to find that whether offline or online, the curve preprocessing process is an essential part and plays a crucial role. The curve preprocessing process plays the following roles in this method. First, due to various reasons such as inconsistent data recording frequencies and battery aging, the number of data points recorded in different constant current charging processes is almost impossible to be completely identical, while the inputs must be the same dimension for most machine learning algorithms. For this reason, the same order polynomial is utilized to fit the scattered points of recorded data in the curve preprocessing process, and then the coefficient set obtained by fitting is taken as the input. In this way, the dimensions of data before input can be guaranteed to be the same, which meets the requirements of the algorithms for input dimensions. Second, by fitting the whole curve to obtain an analytical expression, all recorded data can be made full use of. Most importantly, the common influence factor of charging rate is skillfully integrated, so that the SOH estimation method can be applied to estimate SOH at different charging rates.

Experimental Results and Discussion

In this part, the SOH estimation model based on linear regression algorithm is analyzed and discussed. Firstly, the polynomial order of curve fitting is determined, and then the proposed method is evaluated and validated by the battery test data. Finally, the necessity of the two-step data transformation step is verified.

Determine the order of the fitted polynomial.—To fit a curve with a polynomial, the first thing to do is to determine the order of the polynomial. Generally, the higher the order is, the better the fitting effect will be. However, if the order is too high, the analytical expressions obtained by fitting will be susceptible to noise. What's more, the higher the order is, the more terms of the polynomial and the more coefficients are, which means that the dimension of feature variables is increased, adding the computational cost of subsequent machine learning algorithm. On the contrary, if the order is too low, it is impossible to fit the curve well. Therefore, it is necessary to find an optimal fitting order, which is as low as possible but can fit the curve well. Since all logarithmic charging curves are almost exactly

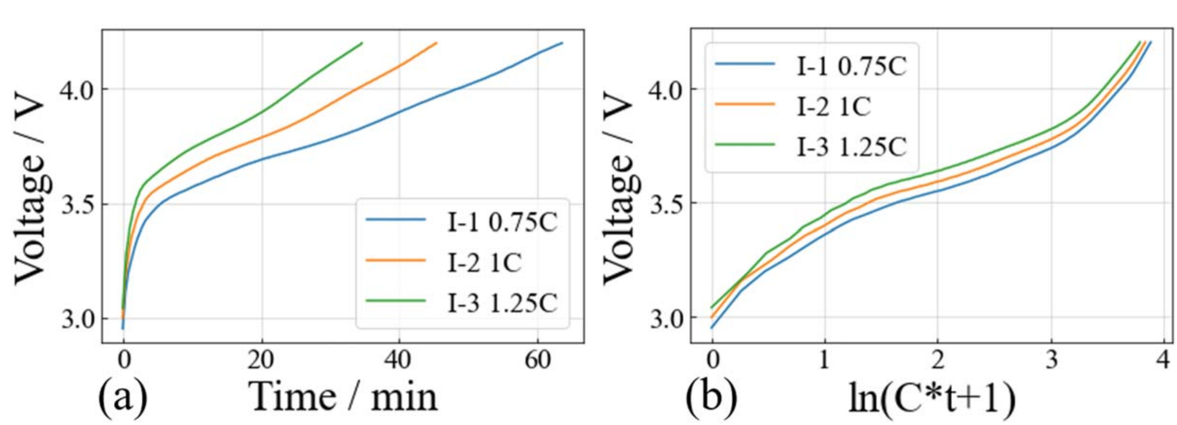

Figure 3. (a) Constant current charging curves of battery model Ⅰ at different rates. (b) Logarithmic charging curves of battery model Ⅰ at different charging rates.

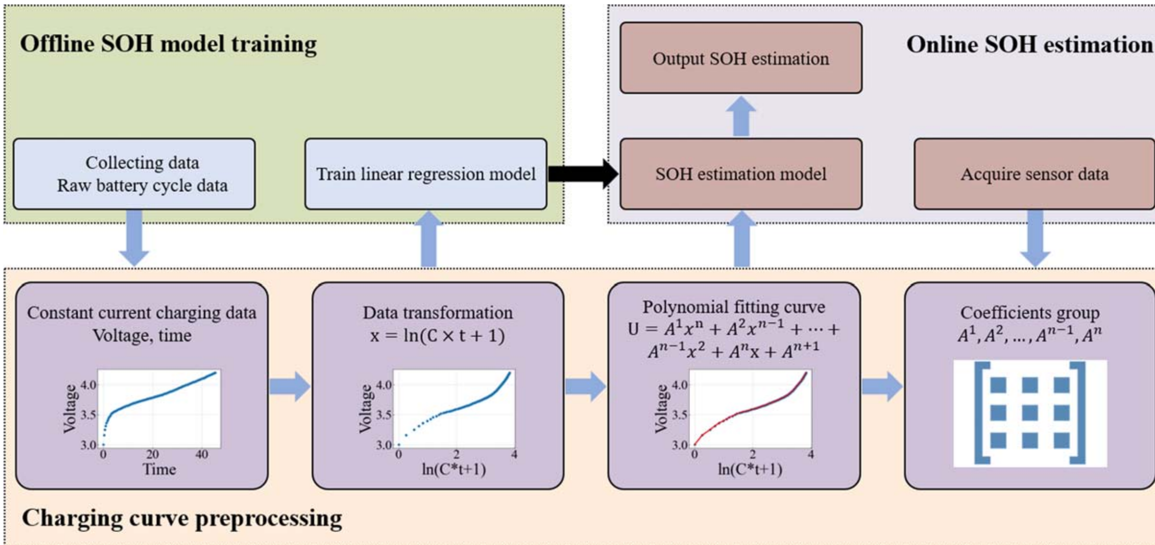

Figure 4. The flow chart of the proposed SOH estimation method.

in the same shape, it is sufficient to focus on the fitting effect of only one curve to determine the optimal fitting order. In order to evaluate the fitting effect more directly, two indexes, determination coefficient (R^2) and mean absolute error (MAE), are introduced. R^2 refers to the fitting degree of the regression curve to the real value, whose maximum value is 1. The closer it is to 1, the better the fitting effect is. MAE is the average number of the absolute error between estimated values and true values. Obviously, the smaller it is, the better the fitting effect is. The calculation formulas for them are as follows (Eqs. 7 and 8).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad [7]$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad [8]$$

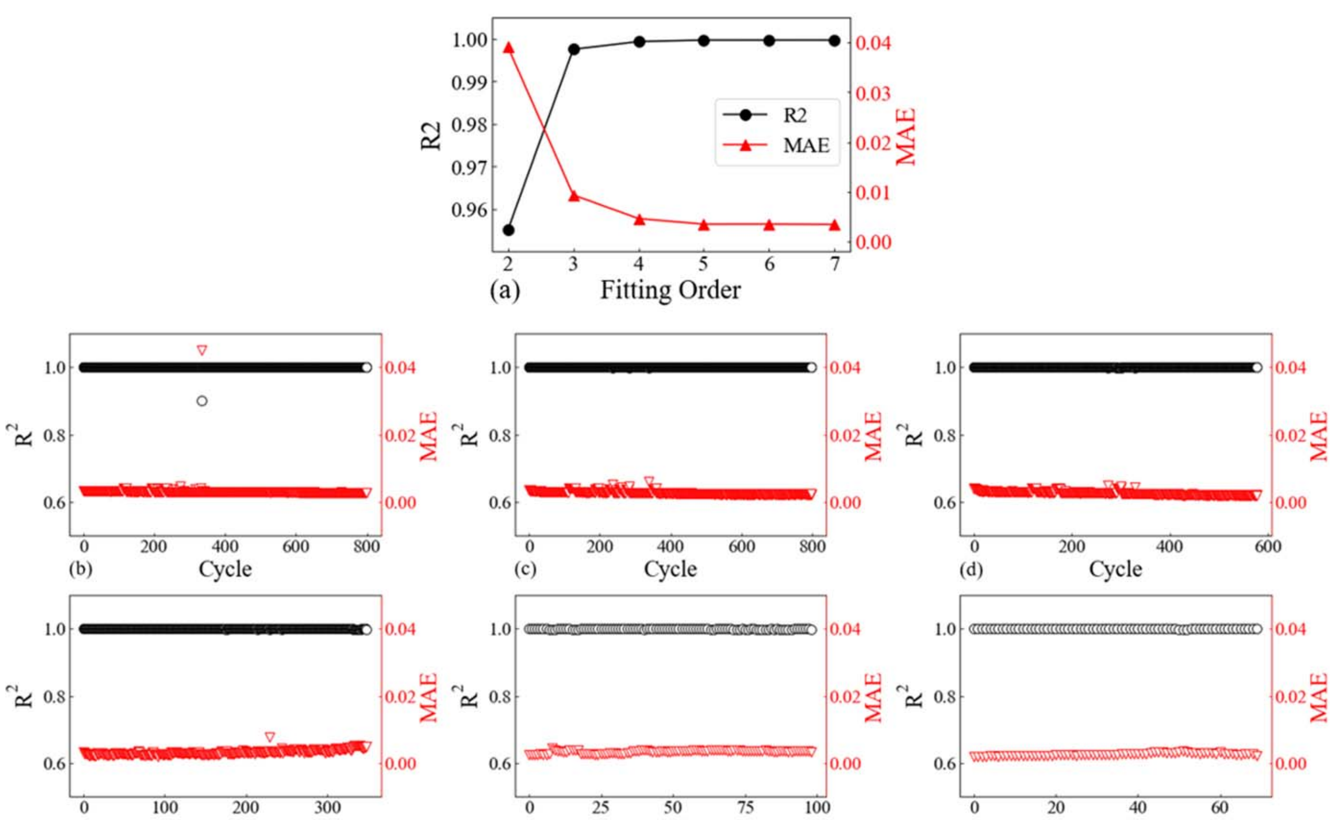

Figure 5. (a), The variation of R^2 and MAE values along with the order. The diagrams of R^2 and MAE when fitting the logarithmic charging curves of all six batteries with 5-order polynomials, (b)–(g) correspond to battery Ⅰ−1, Ⅰ−2, Ⅰ−3, Ⅱ−1, Ⅱ−2, Ⅱ−3 respectively.

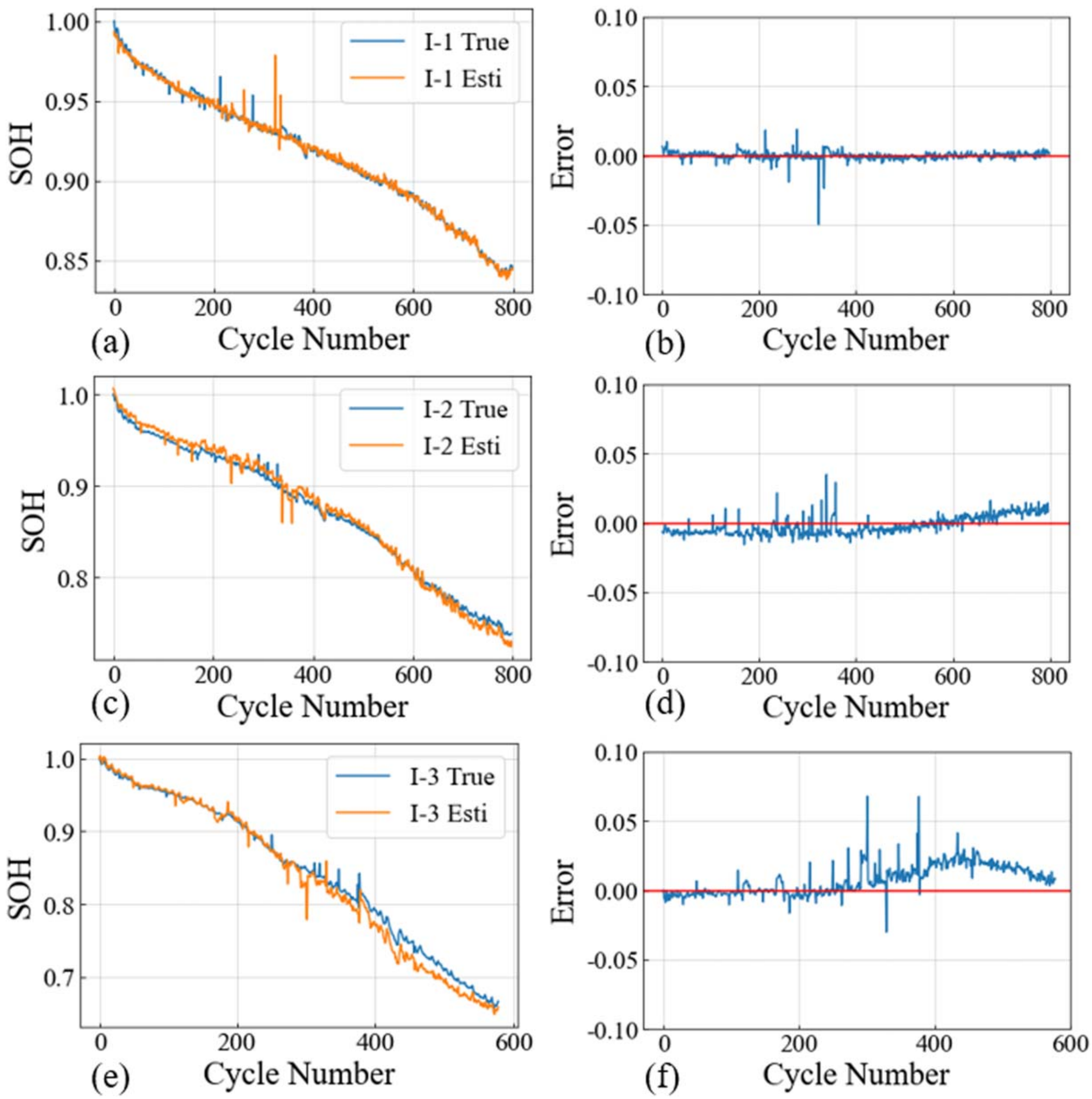

Figure 6 . SOH estimation results for battery model Ⅰ. (a), (c), (e) are the SOH estimation results of battery Ⅰ−1, Ⅰ−2, Ⅰ−3, respectively. (b), (d), (f) are estimation error of battery Ⅰ−1, Ⅰ−2, Ⅰ−3, respectively.

where y_i is the true value of the ith sample point, $\hat{y}_i$ is the corresponding fitting value, $\bar{y}$ is the mean of all true values, and n is the number of sample points.

Therefore, a randomly selected logarithmic charging curve is fitted by using polynomials of 2–7 order, and the values of the two evaluation indexes are compared to select the optimal order. Figure 5a shows the variation of R^2 and MAE values along with the order. It can be seen that, with the increase of order, R^2 values gradually increase and MAE values gradually decrease, indicating that the fitting effect is getting better and better. By synthesizing these two lines, it can be found that when the order reaches 4-order, the fitting degree is already relatively high, and when it is increased to 5-order, the fitting effect still increases, but in a limited range. And the evaluation index values of 5–7 order polynomials are almost the same, indicating that it is of little significance to set the order to more than 5 order. In order to keep the order as low as possible, it is understandable to set the order as 4. However, since this is only the result of fitting a random curve, in order to ensure good fitting effects for all curves, it is necessary to set the order slightly higher here. Therefore, a polynomial of 5-order may be a better choice. Figure S1 (available online at stacks.iop.org/JES/169/050514/mmedia) is a schematic diagram of fitting data scatter points of a logarithmic charging curve with polynomials of 2–7 order. It can also be seen that 5-order polynomial is the best choice, which further confirms the above conclusion.

To prove that 5-order polynomials can fit all curves perfectly, the logarithmic charging curves of all cycles of six batteries were fitted with 5-order polynomials, and the corresponding R^2 and MAE values were recorded, as shown in Figs. 5b–5g. It can be seen that almost all R^2 is close to 1 and MAE is close to 0, which means 5-order polynomials can fit almost all logarithmic charging curves well. In battery Ⅰ−1 shown in Fig. 5b, there was a pair of R^2 and MAE deviating from the normal values significantly, which may be caused by the large fluctuations in the data records due to the interference of man-made external factors during the battery testing. The fitting results of all the other curves are in the normal range, and the small fluctuations may be caused by accidental errors or slight noise in the data records, but the errors are still maintained in a small range, and this will not impact much on the final SOH estimation. The results of fitting logarithmic charging curves of battery Ⅰ−2 at

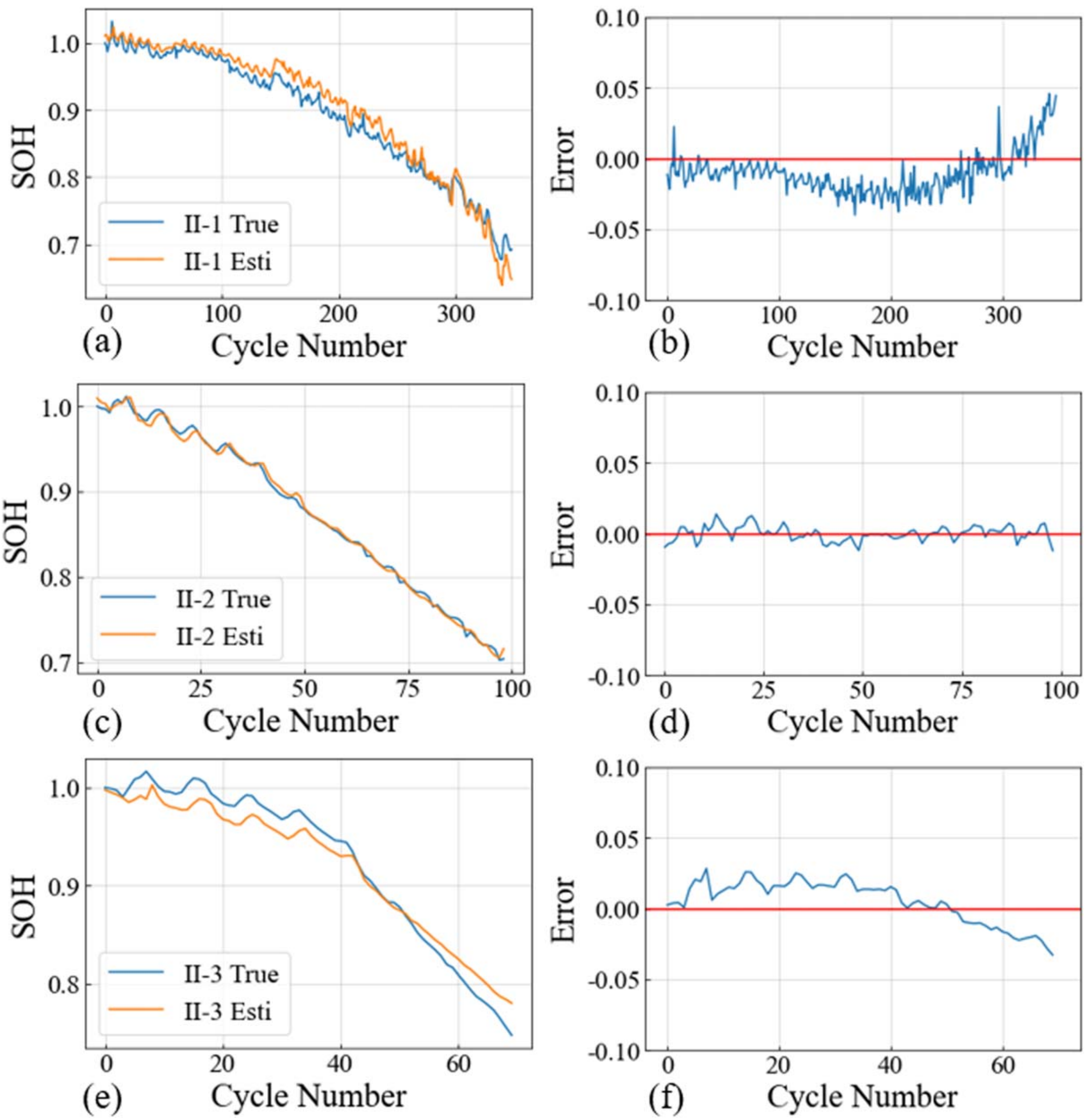

Figure 7. SOH estimation results for battery model II. (a), (c), (e) are the SOH estimation results of battery II−1, II−2, II−3, respectively. (b), (d), (f) are estimation error of battery II−1, II−2, II−3, respectively.

different cycles are shown in Fig. S2. In addition, the analytical expressions obtained by fitting are given in Table SI.

SOH estimation method evaluation.—In order to reveal the feasibility of the proposed SOH estimation method, the test data of two types of batteries are used to evaluate and validate it. The coefficient sets obtained by fitting logarithmic charging curves are taken as the input variables of the model, and the SOH corresponding to the curves are taken as the output. Linear regression algorithm, the simplest machine learning algorithm, is employed to construct the mapping between input and output. Three commonly used evaluation indexes in regression model, namely mean absolute error (MAE), mean square error (MSE) and R^2, were used to evaluate the effect of the model. The meaning and calculation formula of R^2 and MAE have been given above, while MSE is the average number of the square error between estimated values and true values. MSE is calculated by Eq. 9,

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad [9]$$

where, y_i denotes the true value of the ith sample point, $\hat{y}_i$ denotes the corresponding estimated value, and n is the number of sample points.

As for battery model I, data of battery I−1, which was charged with rate of 0.75C, was selected to train a model, and then the model was tested with data of I−2 and I−3. The estimation results and errors of the model are shown in Fig. 6, in which Figs. 6a, 6c and 6e are the estimation results of the model for batteries I−1, I−2 and I−3, respectively. The blue lines in the figure are the SOH actually measured by the battery testing system, while the orange lines are the SOH estimation results of the model. Figures 6b, 6d and 6f show the absolute error between actual values and estimated values, with the red line representing error of 0. Since SOH in this study is defined as the percentage between the current maximum capacity and the initial maximum capacity, the initial SOH of all batteries is strictly equal to 1. It can be seen from Figs. 6c–6f that the developed method can also estimate SOH accurately for battery I-2 and I-3 with different charging rates. Note that there is relatively large SOH estimation error in several cycles for each battery, which may be due to some deviation in the data recording during the battery test. Even

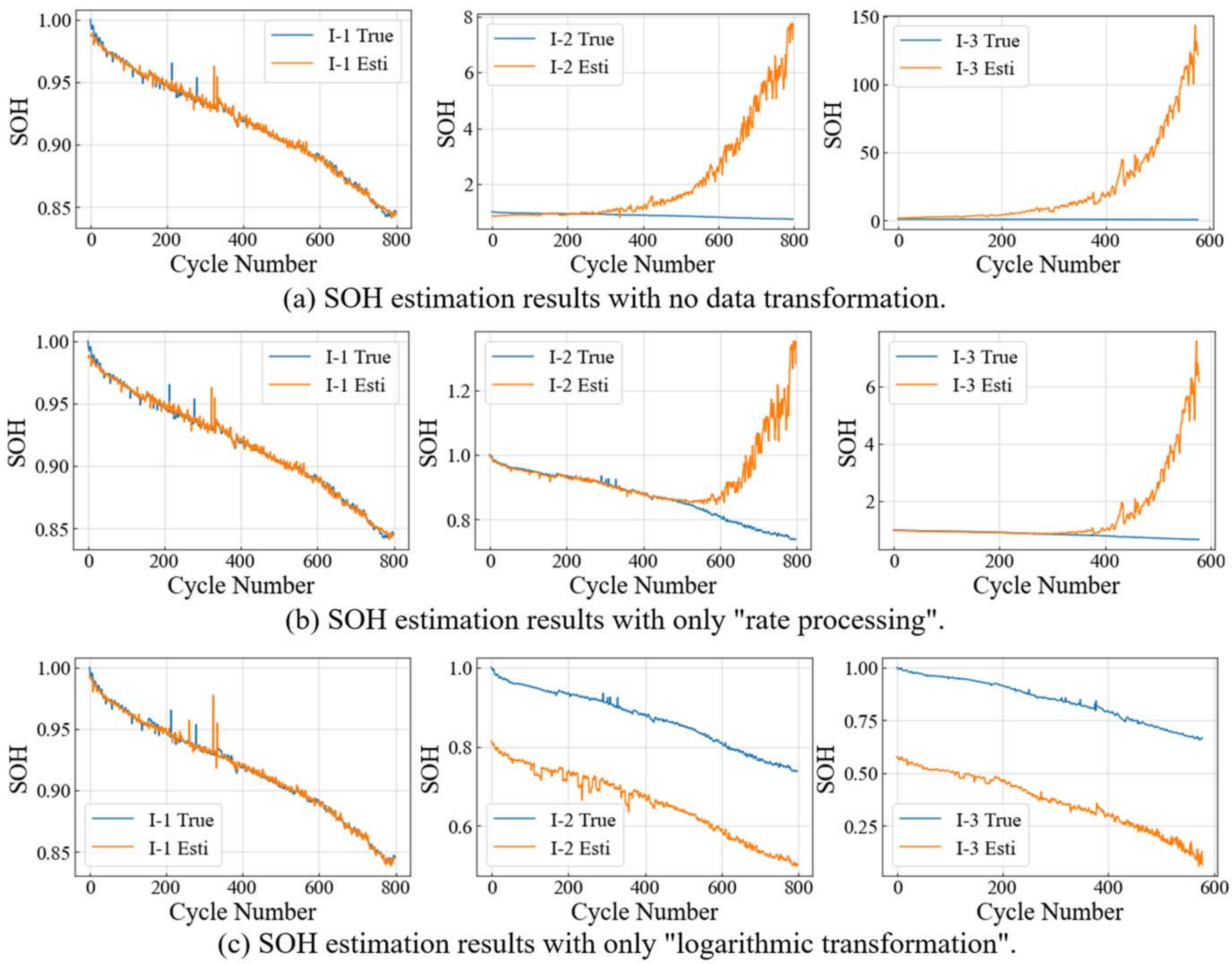

Figure 8. SOH estimation results after the three data transformation methods.

so, the MAE of this method is only 0.0018 for Ⅰ−1, 0.0061 for Ⅰ-2, and 0.0095 for Ⅰ-3, as listed in Table III.

Similarly, as shown in Fig. 7, for the battery model Ⅱ, the method can also provide accurate SOH estimation results. However, it should be noted that the data from battery Ⅱ−2 was used as train data, and the data of Ⅱ−1 and Ⅱ-3 was used to validate the model. As can be seen from Fig. 7, we can further draw the conclusion that the developed method can be used to estimate SOH at different charging rates, and it is not significantly affected by the charging rate of training battery.

In addition, the values of three evaluation indexes for SOH estimation of each battery are listed in Table III. It can also be observed from these values of each index that the overall estimation performance of the method proposed in this study is high. What's more, we find that the proposed method performed relatively better for the SOH estimation of battery model Ⅰ. Combining the raw battery test data, it can be found that the batteries of model Ⅱ aged very soon. The lifespan of battery Ⅱ−2 and Ⅱ−3 was even less than 80 cycles. This may be the main reason that the SOH estimation performance of battery model Ⅱ is worse in terms of the statistical evaluation indexes.

Verify the necessity of data transformation.**—**As mentioned above, the data transformation proposed in this study is divided into two steps. The first step is "rate processing" and the second step is "logarithmic processing." The necessity of these two steps was verified in this section by comparison. The three data transformation methods of no data transformation, only "rate processing" (C*t) and only "logarithmic processing" (ln(t+1)) were compared with the two-step data transformation method mentioned above. The data of battery model Ⅰ was used for verification. In order to make the results more convincing, similarly, the linear regression model was trained with data of battery Ⅰ−1, and tested with data of battery Ⅰ−2 and Ⅰ−3, and the 5-order polynomial was used in curve fitting.

Table III. Statistical results of SOH estimation.

Battery number	R^2	MAE	MSE
Ⅰ−1	0.9933	0.0018	9.9661e-6
Ⅰ−2	0.9907	0.0061	4.7524e-5
Ⅰ−3	0.9828	0.0095	1.6845e-4
Ⅱ-1	0.9611	0.0153	3.2246e-4
Ⅱ−2	0.9970	0.0040	2.6459e-5
Ⅱ−3	0.9604	0.0141	2.5787e-4

Figures 8a–8c show the SOH estimation results when no data transformation, only "rate processing" (C*t) and only "logarithmic transformation" (ln(t+1)) are carried out respectively. As can be seen from the figure, after these three data transformation methods, the model provided very large error when estimate battery SOH at

different charging rates, which can only be applied to estimate SOH at the same rate as the training data. Thus, we can conclude that the two-step data transformation method of "rate processing" and "logarithmic processing" are crucial for estimating SOH of batteries at different rates. No matter which step is missing, the model cannot estimate SOH accurately at different charging rates.

Conclusions

In this study, a new method is proposed to estimate SOH of lithium-ion batteries online based on charging curves of constant current process. Firstly, logarithmic charging curves are obtained by two-step data transformation of the constant current charging data, and then analytical coefficient sets obtained by fitting the logarithmic charging curves with polynomials are taken as the feature variables. Finally, the estimation of battery SOH is enabled by employing linear regression algorithm. In practical application, the battery SOH can be estimated only by obtaining a complete constant current charge curve. The performance of the proposed method was evaluated and verified by the test cycle data of two types of batteries in three charging rates. Experimental results show that the proposed method is of high accuracy and robustness. In the meantime, this method is very suitable for online estimation because of low computational cost.

To the best of the authors' knowledge, this is the first attempt to estimate battery SOH at different charging rates. The method proposed in this paper skillfully integrates the common factor of rates into SOH estimation, and takes low computational cost, so it has a certain potential for practical application.

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