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Parameter Identification of 3R-C Equivalent Circuit Model Based on Full Life Cycle Database

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Abstract – The energy density, power density and ohm resistance of battery change significantly as results of battery aging, which lead to decrease in the accuracy of the equivalent model. A parameter identification method of the equivale6nt circuit model with 3 R-C branches based on the test database of battery life cycle is proposed in this paper. This database is built on the basis of experiments such as updating of available capacity, charging and discharging tests at different rates and relaxation characteristics tests. It can realize regular update and calibration of key parameters like SOH, so as to ensure the reliability of parameters identified. Taking SOH, SOC and T as independent variables, lookup table method is adopted to set initial value for the parameter matrix. Meanwhile, in order to ensure the validity of the model, the least square method based on variable forgetting factor is adopted for optimizing to complete the identification of equivalent model parameters. By comparing the simulation data with measured data for charging and discharging experiments of Li-ion battery, the effectiveness of the full life cycle database and the model are verified.

Keywords: Li-ion battery, Battery management system, Equivalent circuit model, State of health, Available capacity, State of charge

1. Introduction

Energy shortage and environmental pollution have grown up to be a hot issue that the whole world is facing and should be solved urgently. As the core of energy storage system and electric vehicles, batteries have drawn wide attentions and been widely used. [1-2]. Reliable, efficient and safe operation of Li-ion batteries largely is dependent on monitoring and management of battery management system (BMS). One of core functions of BMS is to accurately calculate state of charge (SOC) and state of health (SOH) of batteries, which is totally dependent on equivalent model of batteries [1-3].

An accurate model of batteries could be used not only to provide technical support for BMS, but also to predict battery performance, and to design battery pack and battery control system [3]. However, with a complicate electrochemical reaction process, li-ion battery shows intense nonlinear and time-varying characteristics, thus it's very difficult to build an accurate model. In addition, the difference of materials for anode and cathode, application environment, rate of charging and discharge, even batteries aging status will also seriously affect the accuracy of a model [1-4].

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Today, two commonly used models of li-ion batteries are electrochemical model and equivalent circuit model [3]. The electrochemical models reflect the chemical reaction characteristics inside the batteries with electrical components or mathematical models. As the chemical reactions in batteries are uncontrollable, with strong uncertainty, and with complex nonlinear relations, the electrochemical model and its calculation process are complex and difficult to realize. Moreover, since the dynamic characteristics of batteries are neglected in electrochemical models, the accuracy in predicting dynamic voltage is also worse. Even with certain achievements, the simplified electrochemical models proposed in [3] and [5] are still not suitable for embedding into actual BMS systems, due to their complex calculation process. The equivalent circuit models simulate dynamic characteristics of batteries using linear varying parameter. Although the accuracy is lower than electrochemical models, they are widely used in real-time system for SOC estimation on account of their clear principle, simple structure and simple calculation [1-4].

Commonly used equivalent circuit models of Li-ion batteries include Rint model [6], PNGV model, Randles model, RC model, and so on [3]. The first two models are single in circuit structures, poor in flexibility and limited in accuracy. By contrast, Randles model and RC model are flexible and extensible, and can be selected according to practical application. But the establishment of Randles model depends on experimental data by electrochemical impedance spectroscopy (EIS). Consisting of several resistor and capacitor (RC) pairs in series, the RC models are more versatility. The more the number of RC pairs in series is, the higher the order n is, and the higher accuracy is. At the same time, the complexity and computational cost are correspondingly increased [1, 3]. In this paper, a 3R-C equivalent circuit model is adopted to balance the model accuracy and complexity requirements.

The SOH represents the extent of a battery's aging, usually refers to the attenuation of the rated capacity of a battery. When 80% of the rated capacity is reduced to, the battery is considered to have reached its end of life [7, 8]. The aging of batteries will lead to changes in the parameters such as energy density, power density, and internal resistance, so as to affect the model accuracy [7]. These effects will be more pronounced with the increase of service years of batteries. It needs a multi time scale and data to measure SOH for which changes slowly as compared with SOC. Consequently, in a long-term use of power batteries, the coupling relationship between SOC and SOH is often neglected [7-9]. The accurate on-line estimation of available capacity of batteries is a key technical problem that needs to be solved urgently. Analysis of the relationship between available capacity and SOC of a battery, accurately modeling according to its degradation properties, precisely predicting its performance and estimating SOC are the guarantee of safe and reliable operation of batteries, and also hot topics of current research [1-10].

Ryan Ahmed et al. [8] proposed an aging test method for Li-ion batteries, establishing automobile model, simulating user's behaviors, testing batteries charging and discharging recycle performance, and building an aging feature database. Although many achievements have been made, the laboratory environment for these tests was different from the actual condition and working environment of batteries. Avnish Narula et al. [9] proposed testing and modeling the aging feature of $LiFePO_4$//Graphite cells at low temperature using a simple charge-discharge cycle with constant current rate spanning multiple C-rates (1C, 2C and 4C) and temperatures (0℃, -10℃ and -15℃). At present, study on aging characteristics of batteries mainly concentrated in the laboratory stage, lacking persuasiveness of practical application. The problem of online accurate estimation of battery available capacity is still not really solved. In this paper, it is proposed to establish a life cycle database for Li-ion batteries based on the real-time updating of aging status (available capacity).

Accurate parameter identification is the key factor of precise modeling. The commonly used methods of parameter identification include Extended Kalman Filter (EKF) [10], Least Square method [11], look-up table method based on experimental database [8], and parameter identification based on electrochemical characteristics [12]. The traditional Extended Kalman Filter method is suitable for state estimation of linear dynamic system [10]. But Li-ion battery has nonlinear characteristics. At the same time, with the increase of the size of identified parameters, both the dimension of the system and the amount of calculation increase, which is not conducive to engineering implementation. The Least Square algorithm can be used for identification, off-line or on-line, and is easy to realize. And the identified system is characterized with un-biasedness, consistency and convergence. However, as the amount of system operation data increases, the least square method will encounter data saturation, which will lead to the parameters cannot be accurately tracked for the time-varying system. In this paper, the Least Squares algorithm with forgetting factor driven by online data is proposed to determine parameters of the equivalent circuit model with 3 R-C branches.

In short, to establish accurate Li-ion battery model, we must start from the battery equivalent circuit model, the available capacity updates and online parameter identification considering the available capacity updates of SOH and SOC. At present, the online identification method based on the extended Kalman filter algorithm can achieve the accurate simulation of the dynamic terminal voltage variation of Li-ion power battery, but it ignores the battery temperature change of a single sampling time [14]. As for the battery model, more flexibility can be increased by setting additional R-C in the equivalent circuit, but this also makes the parameter estimation more complex [15].

To accurately represent the influence of aging state on parameters of battery model, a parameter identification method of 3R-C equivalent circuit model based on the test database of battery life cycle is proposed. First, the 3R-C equivalent circuit model is constructed, and variables of identification parameters and input data are identified. Secondly, the full life cycle test database of Li-ion batteries is established, based on experiments such as updating of available capacity, charging and discharge tests at different rates and relaxation characteristics tests. Then, the method is proposed for parameter identification of the equivalent circuit model with 3 R-C branches, which combines Lookup table and the Least Squares algorithm based on forgetting factor, driven by online data such as voltage, current and temperature. Finally, the validity of this method was verified by comparing data of test and simulation.

2. Equivalent Circuit Model with 3 R-C Branches

To accurately describe external characteristics of batteries and design a reliable SOC estimation model, BMS based on battery model has attracted extensive attention from electric vehicle manufacturers and the academic circles [1]. The BMS structure based on battery model is shown in Fig. 1. The processing unit can realize functions such as estimating SOC, real-time updating of available capacity, on-line estimation of internal resistance, calculation of OCV-SOC curve, data test and calculation on relationships between temperature and capacity.

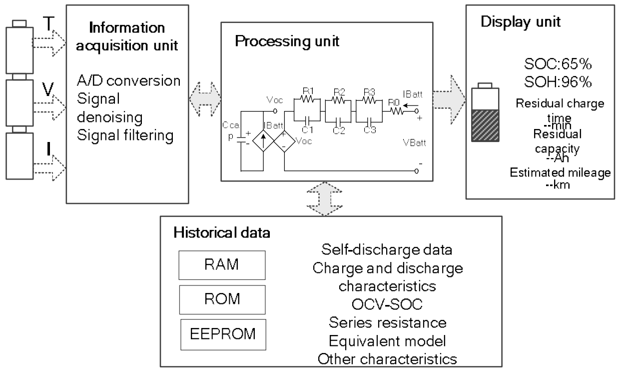


Fig. 1. BMS structure based on battery model

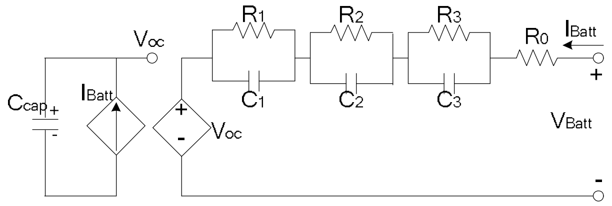


Fig. 2. Equivalent circuit model with 3 R-C branches of batteries

With the degradation of the state of health (ageing), the internal resistance of batteries increases and available capacity attenuates, which lead to significant biases in the model parameters [7-9]. A more accurate model is needed to ensure the effectiveness of simulation. The 3R-C equivalent model of batteries can balance the accuracy and computational complexity requirements, and its working principle is shown in Fig. 2. In Fig. 2, V_{Batt} is the terminal voltage of Li-ion battery; V_{OC} is the battery open circuit voltage, which is a nonlinear function of SOC and is represented by a controllable source; I_{Batt} is the charging current of Li-ion battery, and it's negative when discharge; C_{cap} is available capacity; R0 represents ohm resistance, and R_n and C_n are the polarization resistance and polarization capacitance of Li-ion battery.

The mathematical relation between output voltage and input current can be obtained by Kirchhoff's law and Laplace transform.

$$V_{Batt}(s) = V_{oc}(s) + I_{Batt}(s)(R_0 + \frac{R_1}{1+R_1C_1s} + \frac{R_2}{1+R_2C_2s} + \frac{R_3}{1+R_3C_3s}) \tag{1}$$

The transfer function of this model is

$$\begin{aligned} G(s) &= \frac{V_{Batt}(s) - V_{oc}(s)}{I_{Batt}(s)} \\ &= -(R_0 + \frac{R_1}{1+R_1C_1s} + \frac{R_2}{1+R_2C_2s} + \frac{R_3}{1+R_3C_3s}) \end{aligned} \tag{2}$$

Associated with aging occurs, unknown parameters of the equivalent circuit model with 3 R-C branches such as R0, R2, R3, C1, R1, C2 and C3, will change significantly. A comprehensive battery life cycle test database is of great importance for accurate modeling. Map Eq. (2) from S plane to Z plane using bilinear transformation

$$s = \frac{2}{\Delta t}\frac{1-Z^{-1}}{1+Z^{-1}} \tag{3}$$

Where △t is the system sampling interval time. The equations on Z plane obtainedare.

$$G(z^{-1}) = \frac{a_5 + a_6Z^{-1} + a_7Z^{-2} + a_8Z^{-3}}{a_1 - a_2Z^{-1} - a_3Z^{-2} - a_4Z^{-3}} \tag{4}$$

$$\begin{cases} a_1 = -t^3 - 2\gamma_1 t^2 - 4\gamma_2 t - 8\gamma_3 \\ a_2 = -3t^3 - 2\gamma_1 t^2 + 4\gamma_2 t + 24\gamma_3 \\ a_3 = -3t^3 + 2\gamma_1 t^2 + 4\gamma_2 t - 24\gamma_3 \\ a_4 = -t^3 + 2\gamma_1 t^2 - 4\gamma_2 t + 8\gamma_3 \\ a_5 = -\gamma_4 t^3 - 2\gamma_1 t^2 - 4\gamma_2 R_0 t - 4\gamma_6 t - 8\gamma_3 R_0 \\ a_6 = -3\gamma_4 t^3 - 2\gamma_1 t^2 + 4\gamma_2 R_0 t + 4\gamma_6 t + 24\gamma_3 R_0 \\ a_7 = -3\gamma_4 t^3 + 2\gamma_1 t^2 + 4\gamma_2 R_0 t + 4\gamma_6 t - 24\gamma_3 R_0 \\ a_8 = -\gamma_4 t^3 + 2\gamma_1 t^2 - 4\gamma_2 R_0 t - 4\gamma_6 t + 8\gamma_3 R_0 \end{cases} \tag{5}$$

$$\begin{cases} \gamma_1 = C_1R_1 + C_2R_2 + C_3R_3 \\ \gamma_2 = C_1R_1C_2R_2 + C_2R_2C_3R_3 + C_1R_1C_3R_3 \\ \gamma_3 = C_1R_1C_2R_2C_3R_3 \\ \gamma_4 = R_0 + R_1 + R_2 + R_3 \\ \gamma_5 = C_1R_1(R_0 + R_2 + R_3) + C_2R_2(R_0 + R_1 + R_3) \\ \qquad + C_3R_3(R_0 + R_2 + R_1) \\ \gamma_6 = C_1R_1C_2R_2R_3 + C_2R_2C_3R_3R_1 + C_1R_1C_3R_3R_2 \end{cases} \tag{6}$$

The final equations are obtained by

$$\begin{aligned} V_{t,k} = \frac{1}{a_1}\Big[& (1 - \sum_2^8 a_i)V_{oc,k} + a_2V_{t,k-1} + a_3V_{t,k-2} + a_4V_{t,k-3} \\ & + a_5I_{Batt,k} + a_6I_{Batt,k-1} + a_7I_{Batt,k-2} + a_8I_{Batt,k-3} \Big] \end{aligned} \tag{7}$$

Where a_i (i=1, 2…8) is the identification coefficients, $V_{t,k}$ is the terminal voltage., $V_{oc,k}$ is the open circuit voltage , and $I_{Batt,k}$ is the value of current I_{Batt} at time k respectively. To sum up, input data matrix and parameter matrix of 3RC equivalent circuit model are given by.

$$\begin{cases} \mathbf{\Phi}_k = \begin{bmatrix} 1 & V_{t,k-1} & V_{t,k-2} & V_{t,k-3} & I_{Batt,k} & I_{Batt,k-1} & I_{Batt,k-2} & I_{Batt,k-3} \end{bmatrix} \\ \mathbf{\theta}_k = \frac{1}{a_1}\begin{bmatrix} (1 - \sum_2^8 a_i)V_{oc,k} & a_2 & a_3 & a_4 & a_5 & a_6 & a_7 & a_8 \end{bmatrix}^T \\ y_k = V_{t,k} \end{cases} \tag{8}$$

The system equations can be simplified as

$$y_k = \mathbf{\Phi}_k \mathbf{\theta}_k \tag{9}$$

Where y_k is the output variable, $\mathbf{\Phi}_k$ is the input data variables matrix and $\mathbf{\theta}_k$ is the parameter variable matrix of the system.

3. Establishment of Life Cycle Test Database

The development of key algorithms in BMS depends on the quality of test data. An accurate and systematic test data of battery life cycle will help the BMS optimization.

The flow chart of the life cycle test database establishment of Li-ion battery is shown in Fig. 3. The independent variables are determined by collecting the battery temperature, updating the battery SOH and SOC. The dependent variables, including R_0, R_1, C_1, R_2, C_2, R_3, C_3, and V_{oc}, are measured by DC internal resistance tests and relaxation characteristics tests to form a complete database. The database also contains key parameters and experimental data, such as self-discharge data, charge and discharge characteristic data, and OCV-SOC relation characteristic data.

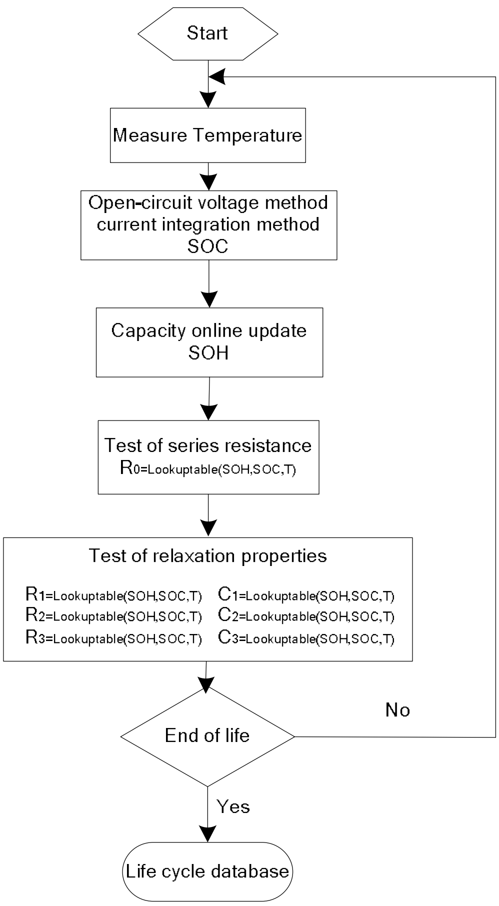


Fig. 3. Flow chart of life cycle database establishment

3.1 online Capacity updating

Because of its influence on 3R-C equivalent model parameters, aging status (residual capacity) online updating is crucial for improving model accuracy. During the service course of Li-ion batteries, there are three states: static, charging and discharge [16]. Online updating of residual capacity is classified into updating in charging state and updating in static state. The flow chart of capacity online updating is shown in Fig. 4.

The open circuit voltage in static equilibrium was recorded using the clock function of the BMS, when the battery is in static state, like the P1 and P2 points shown in Fig. 5. The current maximum capacity available is

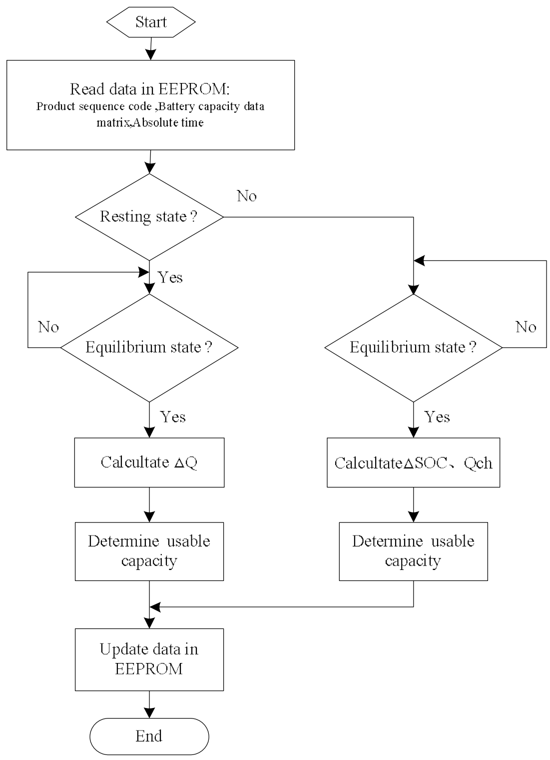


Fig. 4. Flow chart of capacity updating online

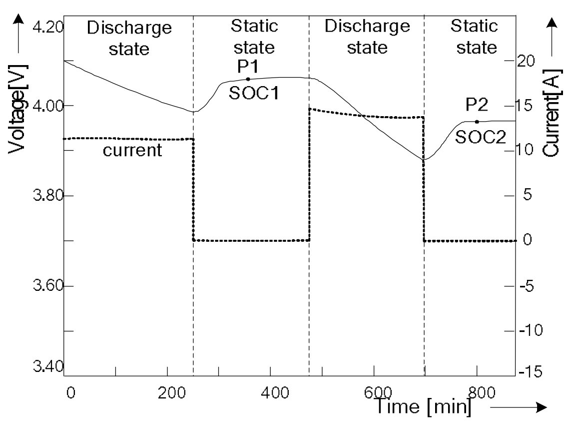


Fig. 5. Capacity updating in static state

calculated from the capacity integral and V_{OC} after a stationary period, and the capacity variation ΔQ between P1 and P2 is recorded at the same time. Thus,

$$SOC(t) = (\frac{Q_n - \int_0^t i(t)dt}{Q_n}) \times 100\% \tag{10}$$

$$Q_{\max} = \frac{\Delta Q}{SOC_{p1} - SOC_{p2}} \times 100 \tag{11}$$

Where Q_n and Q_{max} respectively represents the rated capacity and the residual capacity of li-ion battery, and $i(t)$ is the discharge current.

When the li-ion battery is in hibernation or shutdown mode, i.e. in a static state, it does not need to increase self-discharge correction model, as an accurate corresponding relation between the open circuit voltage V_{OC} and SOC exists, and V_{OC} reflects the influence of self-discharge on SOC. In addition, the SOC estimation of a battery in the static state can provide an accurate initial value for the current integration method in charging state. Once batteries operate into the charging mode, current integration method plays a major role, updating SOC regularly.

When the battery aging, the released capacity during the process from P1 to P2 is calculated and capacity data are updated between these two points by recording the voltage V_{OC1} and V_{OC2} in a static state for points P1 and P2 respectively. In this way, capacity data in the entire EEPROM of BMS are updated.

Terminal voltage V_{Batt} (t) is affected by aging of battery with loads as a result of capacity degradation and V-I characteristics change affecting by the aging of battery.

With the aggravation of aging process, the V_{Batt} (t) increases irregularly during charging and discharging, as shown in Fig. 6, and battery will approach the charging and discharging threshold voltage more quickly.

The chemistry performance of li-ion batteries is stable in constant current constant voltage (CCCV) charging process, and BMS can record the time when meeting equilibrium before and after the battery charging.

During the charging process of an aged battery, SOC is specified as 100% when the charge cut-off voltage is reached after constant voltage charging, and SOC is

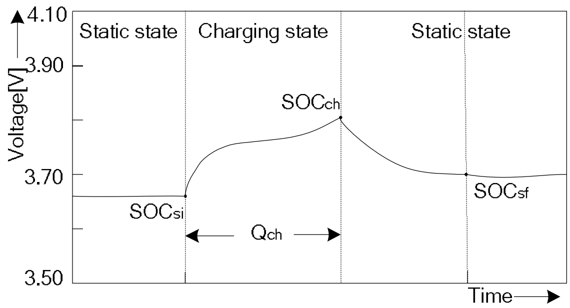


Fig. 6. Capacity updating in charging state

recalculated using correspondence curve between updated V_{OC} and capacity.

The battery capacity identification module will online update Q_{max}, the maximum available capacity, in different measuring voltage ranges.

$$Q_{\max} = \frac{100}{SOC_{sf} - SOC_{si}} \times Q_{ch} \tag{12}$$

where SOC_{sf} and SOC_{si} represent the SOC in static state before and after charging, respectively, and Q_{ch} represents the integral of the current during charging stage (Ah).

In this paper, the aging characteristics of batteries are simulated by frequent charging and discharging at given temperature, so as to shorten the test cycle.

3.2 SOC calculation

The SOC is estimated by the combination of current integration method and open circuit voltage method, that is to say, using the open circuit voltage method when the voltage status can accurately reflect the battery capacity, otherwise, choosing the current integration method.

3.2.1 Open circuit voltage method

When the li-ion battery is quietly placed for a long period of time, the open circuit voltage has an exact corresponding relationship with the SOC, so it's suitable for calculating SOC. The relation between the measured voltage, the open circuit voltage, internal resistance and current is given in Eq. (13). The BMS can measure the charge and discharge current I_{Batt} and the terminal voltage V_{Batt}, obtain the batteries OCV-SOC curve by estimating the value of $R_{(T, SOC, SOH)}$.

$$V_{Batt} = V_{OC(T,\ SOC,\ SOH)} - I_{Batt} \times R_{(T,\ SOC,\ SOH)} \tag{13}$$

At present, the $R_{(T, SOC, SOH)}$ estimation problem is solved mainly by establishing a reasonable impedance model of batteries. As shown in Fig. 7, charging and discharging experiments of Li-ion battery are carried out with current of 0.05C under the same temperature. For the same SOC condition, the internal resistances in the charging mode and discharging mode are approximately equal. The relationship between the measured terminal voltage and V_{OC} are presented in Eqs. (14) and (15), for charging and discharging respectively. V_{OC} can be deduced on 0.05C current as formula (16).

$$V_{Batt\_ch} = V_{oc} + I_{Batt\_ch} \times R_{(T,\ SOC,\ SOH)} \tag{14}$$

$$V_{Batt\_dch} = V_{oc} + I_{Batt\_dch} \times R_{(T,\ SOC,\ SOH)} \tag{15}$$

$$V_{oc} = (V_{Batt\_ch} + V_{Batt\_dch}) / 2 \tag{16}$$

where V_{Batt_ch} and V_{Batt_dch} are the measured terminal

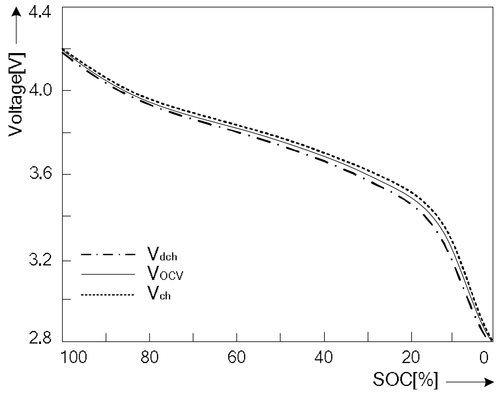


Fig. 7. Voltage curve at 0.05C charge-discharge rate

voltages for charging and discharging state, respectively.

3.2.2 Current integration method

The current integration method is characterized with local high precision, which calculates the current integral value $\int_{k-1}^{k} i(t)dt$ from the time k-1 to time k, through accurately measuring the current *i*(t) that flows through the battery pack during that time period. It's necessary to determine the initial SOC of batteries and efficiency coefficient η at present discharge rate. The SOC can be obtained by

$$SOC_k = SOC_{k-1} + \int_{k-1}^{k} \eta \times i(t)dt \tag{17}$$

The SOC is calculated to have higher accuracy based on the capacity update data, and the equation is

$$SOC(t) = (\frac{Q_n - \int_0^t i(t)dt}{Q_n}) \times 100\% \tag{18}$$

Where Q_n is the rated capacity of the battery which measuring methods determined by the types and characteristics of the core; and *i*(t) refers to the current flowing through the battery, and is positive when charging.

3.3 DC internal resistance tests

R_0 reflects the DC internal resistance property of the battery, which tends to increase with the increase of the number of cycling and aging of the battery. The OCV-SOC test data stored in BMS should be modified according to the change tendency of internal resistance, because of the estimation accuracy of SOC is directly affected by the estimation accuracy of R_0.

The response of DC internal resistance R_0 to pulse current is relatively fast, but the polarization resistances R_n and polarization capacitances C_n(n=1, 2, 3) have relaxation characteristics, such as the pulse response characteristics

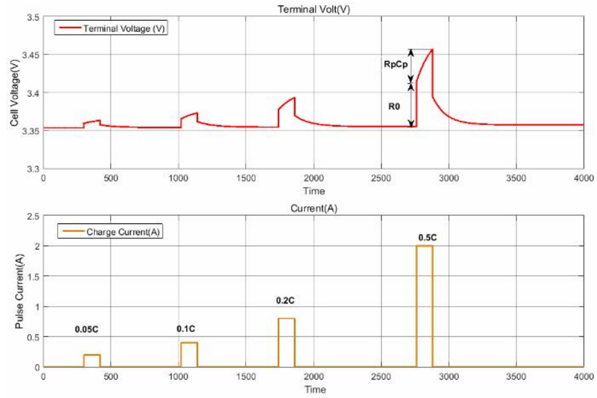


Fig. 8. Battery voltage response characteristics under pulse currents

shown in Fig. 8 of the measured terminal voltage by the action of impulse electric current.

The R_0 of the battery is calculated by impulse current experiment. The li-ion battery with nominal capacity of 4.1 Ah is charged at room temperature with discharge current at different rates (0.05C, 0.1C, 0.2C and 0.5C) and different voltage range, as shown in Fig. 8, so as to improve the estimation accuracy of R_0. The ohmic resistance R_0 for battery voltage within the range between 3.35V and 3.42V is calculated according to formula (1), and the measurement data are shown in Table 1.

Table 1. Parameter R_0 under different charge C rate

C	V_{st}	V_{chrg}	$T_{standby}$	Δ V	R_0
0.05C	3.354	3.359	10min	5mV	25mΩ
0.1C	3.354	3.365	10min	11mV	27.5mΩ
0.2C	3.354	3.377	10min	23mV	28.7mΩ
0.5C	3.355	3.414	15min	181mV	29.5mΩ

R_0 is a function of SOC, T, and SOH.
$R_0 = Lookuptable3D(SOC, T, SOH)$

R_0 is updated through online calculation, and the internal resistances of each voltage point within the cut-off charging and discharging interval are stored as arrays in the EEPROM chip of BMS. During the operation of the battery, the data matrix of internal resistance is updated continuously, providing parameters supporting the estimation of V_{OC}.

3.4 Relaxation characteristics test

R_n and C_n (n=1, 2, 3) represent voltage relaxation properties of V-I characteristics with the relaxation time constant $\tau = R_nC_n$. Due to the complexity of the battery relaxation characteristics, R_n and C_n are determined and corrected by analyzing and comparing the response characteristics data of battery terminal voltage, based on the equivalent model with 3 R-C branches constructed in Simscane software. Both R_n and C_n are functions of SOC,

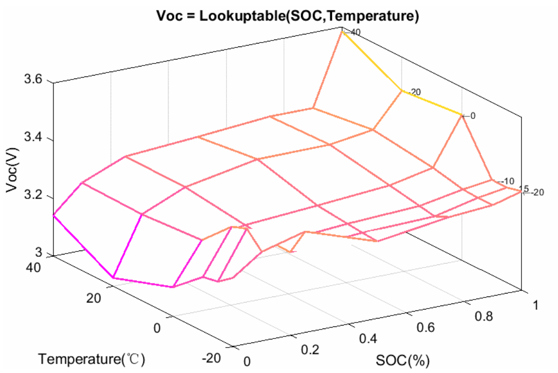


Fig. 9. V_{OC} data model

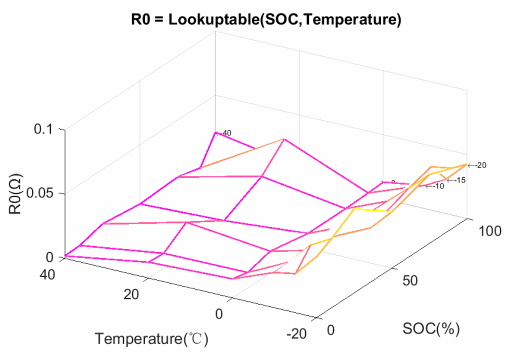


Fig. 10. R_0 data model

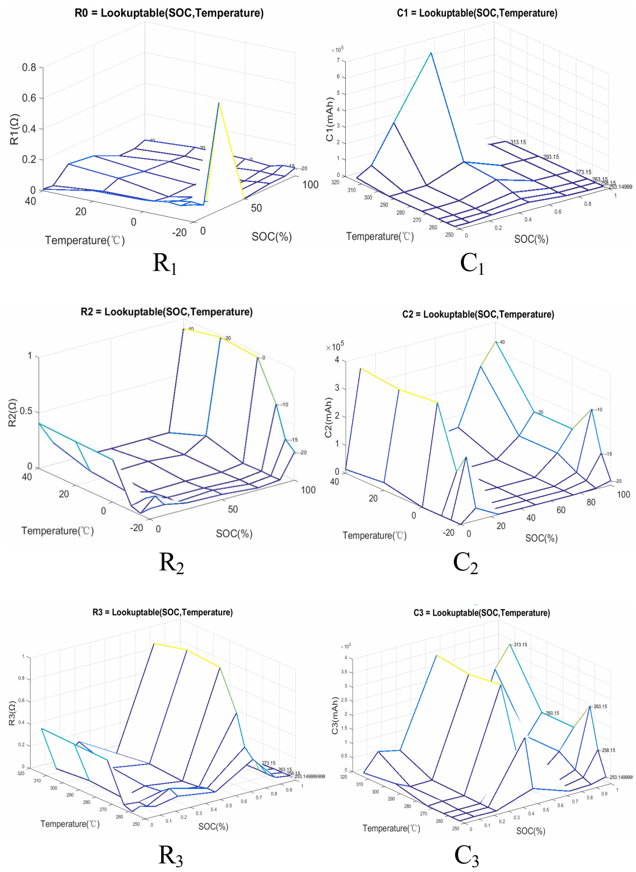


Fig. 11. Data model of R_n and C_n

T, and SOH.

$$C_n = Lookuptable3D(SOC, T, SOH)$$
$$R_n = Lookuptable3D(SOC, T, SOH)$$

The current characteristic of C_n satisfies $i_{cn}=C_n \times dV/dt$, and the voltage characteristic of R_n satisfies $V_{Rn}=i \times R_n$. The circuit equation is established with Simscane software. It is difficult to estimate the Rn and Cn on line. Usually, the database is constructed by collecting specific parameters of Rn and Cn, which are related to SOC and determined in the experiment.

3.5 parameter model

When the remaining capacity of li-ion batteries is below 80% of the rated capacity, the parameter models of R_0, R_1, C_1, R_2, C_2, R_3, C_3 and V_{OC} in the equivalent circuit model with 3 R-C branches are as follows. The V_{OC} model contains voltage characteristic data associated with the current temperature, SOH and SOC. The V_{OC} model is built by look-up table, as shown in Fig. 9.

R_0 reflects the immediate response characteristics of voltage related to the current temperature, SOH and SOC. The R_0 model is established by look-up table, as shown in Fig. 10.

Polarization resistances (R_1, R_2 and R_3) and polarization capacitances (C_1, C_2 and C_3) are related to temperature, SOH and SOC. The model is established by look-up table, as shown in Fig. 11. The voltage drop and power consumption of polarization resistances are calculated according to the current. The power consumed is converted into heat to calculate the temperature change of the battery.

4. Parameter Identification Driven by On-line data

The parameter identification method, driven by real-time measured current, voltage and temperature data of batteries, can be used to update the model parameters online. The method of parameter identification driven by on-line data updates and calibrates parameters by using data stored in BMS, which is different from the traditional method.

The parameters of the battery model are vulnerable to the effects of aging. However, the least square method based on forgetting factor algorithm is able to overcome the uncertainty of model parameters through regular calibration and updating, so as to accurately capture the real-time characteristics of the system. To ensure the accuracy of the equivalent circuit model with 3 R-C branches, the least square method based on forgetting factor algorithm is adopted with the following equation:

$$y_k = \mathbf{\Phi}_k \mathbf{\theta}_k + e_{Ls,k} \tag{19}$$

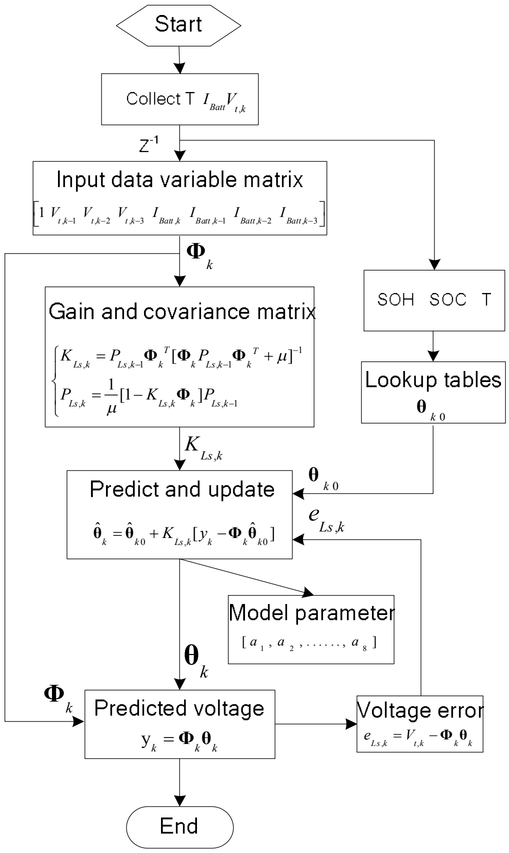


Fig. 12. Flow chart of online parameter identification based on forgetting factor

Where $e_{Ls,k}$ represents stationary white noise with zero mean value. The gain formula of the optimization algorithm is expressed by

$$\begin{cases} K_{Ls,k} = P_{Ls,k-1}\Phi_k^{\ T}[\Phi_k P_{Ls,k-1}\Phi_k^{\ T} + \mu]^{-1} \\ P_{Ls,k} = \dfrac{1}{\mu}[1 - K_{Ls,k}\Phi_k]P_{Ls,k-1} \end{cases} \tag{20}$$

Where μ is a forgetting factor, $K_{Ls,k}$ is the algorithm gain, and $P_{Ls,k}$ is the error covariance matrix of state estimation. $\boldsymbol{\theta}_{k0,}$ the initial value of system parameter variables $\boldsymbol{\theta}_k$, is determined by look-up table method, and the parameter variables are optimized by calculation $e_{Ls,k}$ and positive feedback.

$$\hat{\boldsymbol{\theta}}_k = \hat{\boldsymbol{\theta}}_{k-1} + K_{Ls,k}[y_k - \boldsymbol{\Phi}_k \hat{\boldsymbol{\theta}}_{k-1}] \tag{21}$$

According to Eqs. (8), (20) and (21), the Flow chart of online parameter identification based on forgetting factor is determined, as shown in Fig. 12. Based on the voltage, current and temperature data obtained from real-time sampling, the input data variables are constructed.

Independent variables including T, SOH and SOC are determined by regular updating and calibration of the BMS. The model parameter variables are determined to provide the initial value for the least square method, based on the look-up table method of life cycle database. At the same time, the gain covariance matrix calculated by the data variable matrix is combined with voltage error to optimize parameter variables, and the equations of the 3R-C equivalent circuit model are finally determined.

Table 2. Performance parameters of the li-ion battery

Performance index	Value	Performance index	Value
working voltage (V)	3.6	cycling life (times)	600~1200
rated capacity (Ah)	50	self-discharge rate (%/month)	6
gravimetric energy density (wh/kg)	160	memory effect	nothing
volumetric energy (wh/L)	270	Security	low
working temperature (℃)	-20~60	pollution	nothing

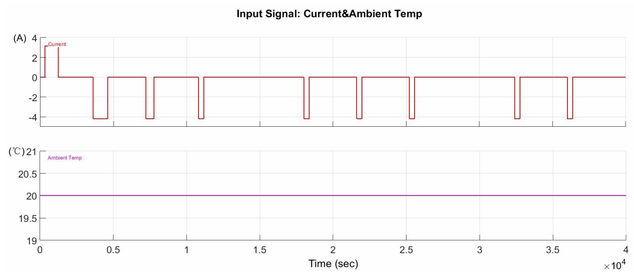


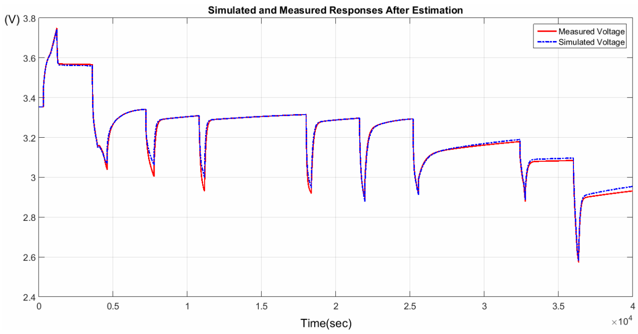
Fig. 13. Input data of simulation model

5. Case Study

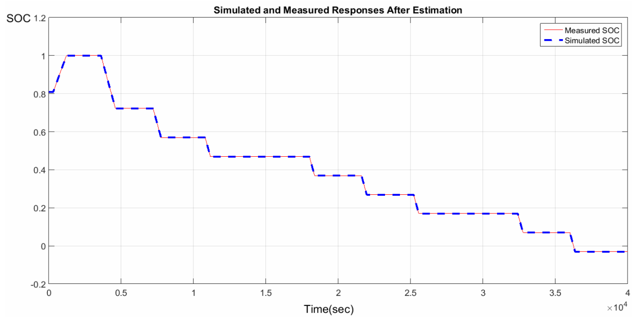
The simulation and measurement of li-ion batteries under pulse charging and discharging are compared and analyzed. The parameters of the li-ion batteries used in tests are shown in table 2.

The input signals for the equivalent model with 3 R-C branches of li-ion batteries are shown in Fig.13, including current signal and ambient temperature signal. The current signal is the pulse current for charging and discharging, which pulse width is usually set at 2% to 5% of the rated capacity. In low SOC stage, narrower discharge pulse width is usually used, so as to obtain better mutation parameters in the circuit. The temperature signal is the external temperature of the battery.

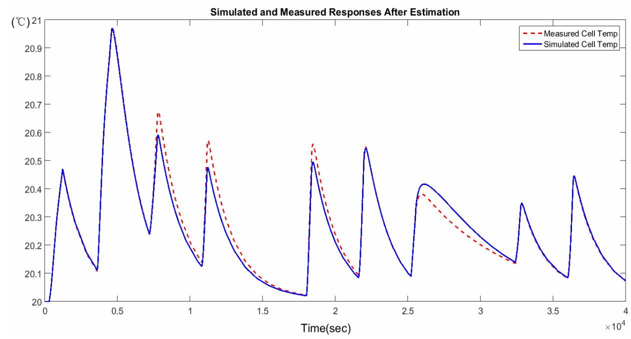
The simulation data including terminal voltage, SOC and temperature state of the 3R-C equivalent model of the li-ion battery are compared with the measured data respectively, as shown in Fig. 14. The simulation waveforms and the measured waveform of open circuit voltage V_{OC} and SOC are matched well with errors ratio less than 0.5%. Although there is slightly difference between the simulated and measured waveforms for temperature, model accuracy is still satisfied. As a result, the 3R-C equivalent model based on the life cycle database of the li-ion battery has higher accuracy.



(a) Open circuit voltage Voc



(b) SOC



(c) Battery temperature

Fig. 14. Comparison of measured and simulated outputs

6 Conclusion

The energy density, power density and ohm resistance change significantly with the battery aging, which greatly affect the accuracy of the equivalent circuit model. Therefore, accurate modeling considering the influence of battery aging is essential for effective BMS design.

1) An online updating method is proposed to update the residual capacity of the li-ion battery in the charging state and static state. This method not only addresses the problem of accurate on-line estimation of battery residual capacity, but also provides a test database of battery life cycle for the equivalent circuit model with 3 R-C branches, to lay the foundation for the accuracy of the model.

2) The model parameters are identification by look-up table method by taking T, SOH and SOC as independent variables, and driven by real-time measurement of current, voltage and temperature. And the parameter matrix is optimized by the least square method based on the forgetting factor. This method regularly updates and calibrates the model parameters based on the test database stored in BMS. By comparing the simulation data with measured data, the effectiveness of the full life cycle database and the parameter identification method are verified.

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