Int. J. Electrochem. Sci., 15 **(2020)** 2226 – 2242, doi: 10.20964/2020.03.47

International Journal of
ELECTROCHEMICAL
SCIENCE
www.electrochemsci.org

A Novel State of Charge Estimation Method for Ternary Lithium Batteries Based on System Function and Extended Kalman Filter

Xiong Xin, Shun-Li Wang[*]*, Chun-Mei Yu, Jiang Cong, James Coffie-Ken*

School of Information Engineering, Southwest University of Science and Technology, Mianyang 621010, China;
[*]E-mail: 497420789@qq.com

Received: 15 October 2019 / *Accepted:* 14 January 2020 / *Published:* 10 February 2020

The Equivalent Thevenin model is establish to describe the external performance of ternary lithium ion battery base on Hybrid Pulse Power Characteristic experiment by identifying and verifying model parameters. The state of charge estimation model is built in SIMULINK using Extended Kalman Filter algorithm and system function of MATLAB. The Simulation results under the working conditions of the experimental data shows that, the maximum error of the Thevenin model is 0.08V and its average error is 0.04V. Based on the Thevenin model, the state of charge estimation result shows a better performance in accuracy and robustness compare with traditional coulomb counting method. The maximum error is less than 0.01 and the average error is 0.008 which shows the systematic process and the correctness of the estimation method in this paper.

Keywords: Ternary lithium battery；State of charge；Extended Kalman Filter；System function

1. INTRODUCTION

The rapid development of Electric Vehicle (EV) industry has greatly stimulated the development of lithium ion battery industry [1]. Ternary lithium ion battery is a kind of lithium ion battery whose anode material is composed of nickel, cobalt, manganese in a specified proportion, and the negative electrode is made of graphite material. With the great cost performance advantage and flexible performance of ternary lithium ion battery, it is widely used in the field of mobile energy storage system [2].

The accurate State of Charge (SOC) estimation for lithium ion battery is one of the most critical technologies in the Battery Management System (BMS) [3]. In the field of power battery, the accurate estimation of SOC is of great significance to ensure the safety of charge and discharge, improve the efficiency of energy utilization, and increase the endurance and service life of lithium ion battery [4]. However, the battery itself is a complex non-linear and time-varying system, and it is difficult to capture the change rule of battery parameters under the actual working condition [5]. It is by detecting the voltage, current, temperature and other information of the battery under the working condition that the state of charge be can estimated in real time. In estimating State of Charge, the process is prone to errors, due to this, the accurate estimation of the SOC as well as the real-time implementation of it have quickly become a new hot research topic and main evaluation indexes.

Some methods only use a single measurement data to estimate SOC [6]. For example, the discharge experiment method is used to measure the capacity of the battery to estimate SOC of the battery. The open circuit voltage method only detects the Open Circuit Voltage (OCV) of the battery to correlate the corresponding SOC [7]. The coulomb counting method can estimate SOC in real time through the current value, and the internal resistance method only uses the impedance parameters of the battery to estimate SOC [8]. This kind of methods only use the single monitoring information of the battery to realize SOC estimation, but the accuracy of estimation and the scope of application of estimation method are greatly limited. In order to make full use of accurate sensor measurement data, a data-driven SOC estimation method, such as BP neural network algorithm and support vector machine, is proposed [9]. After the learning model is selected, the battery accurate experimental data obtained in batch under the laboratory environment is used for training. These environmental conditions such as voltage, current, temperature, total battery capacity and corresponding SOC are used to establish measurable battery parameters, For example, the corresponding relationship among voltage [10], current, temperature and SOC can describe real-time SOC estimation[11], but it is greatly affected by the completeness of training set and is not easy to be embedded into the actual environment[12]. Some methods, based on the theory of signal estimation, regard the SOC of the battery as the disturbed signal. Using the theory of signal filter, such as Kalman filter, adaptive filter, particle filter, H-infinite filter [13-14], and introducing the prediction-correction mechanism, they all realized the real-time estimation of SOC of the lithium ion battery under the influence of noise. Considering the advantages of Kalman filter algorithm in anti-noise and low computational complexity, this paper designs a fusion algorithm based on Kalman filter theory [15], which is easy to understand and implement. It combines the battery equivalent model parameters, system function of MATLAB and Kalman filter algorithm skillfully, and the SOC estimation model based on system function and Extended Kalman Filter algorithm is built in MATLAB, which uses real-time estimation of the state of charge of lithium ion battery.

2. MATHEMATICAL ANALYSIS

The electrochemical principle of lithium ion battery is first introduced. On this basis, the establishing of the equivalent circuit model of lithium ion battery is analyzed. Then the identification principle and method of model parameters are also introduced. Finally, the principle and application of extended Kalman algorithm are explained.

2.1. Lithium ion battery

Lithium ion battery are mainly composed of three parts: positive material, negative material and electrolyte. The process of charging and discharging of lithium ion battery corresponds to the process of lithium ion embedding and getting rid of embedding in the battery [16]. When charging the battery, due to the effect of external power, lithium ions are generated at the positive pole of the battery. Under the effect of electromotive force, the lithium ions move to the negative pole through electrolyte. The negative pole material is often composed of carbon materials, which has many layered junctions. The positive charged lithium ions are embedded in the holes of the negative electrode material, and the charge of the battery is proportional to the number of these embedded ions. On the contrary, the lithium ion which is charged in the negative electrode before discharging will move away from the embedding to the positive electrode, and the more the number of ions that are discharged, the greater the discharge capacity. The positive and negative reactions are as follows:

$$Li(Ni_aCo_bMn_c)O_2 \underset{discharge}{\overset{charge}{\rightleftarrows}} Li_{(1-x)}(Ni_aCo_bMn_c)O_2 + xLi^+ + xe^- \quad (1)$$

$$6C + xLi^+ + xe^- \underset{discharge}{\overset{charge}{\rightleftarrows}} Li_xC_6 \quad (2)$$

Formula (1) and formula (2) are the positive and negative electrode electrochemical reaction formulas of a ternary lithium ion battery respectively. In some papers, the physical definition method of SOC is proposed, where the maximum number of lithium ions that can be transferred in a fully charged battery is used as denominator, and the remaining number of lithium ions that can be transferred in the negative electrode is used as molecule. Then a formula of SOC with practical physical significance is obtained. Generally, SOC is calculated by the capacity of battery, and the definition of SOC is given from the angle of coulomb counting [17].

$$SOC_t = \frac{Q_t}{Q_{origin}} \quad (3)$$

In formula (3), represents the current SOC of battery, represents the remaining capacity at this time, and represents the capacity when the battery is fully charged. The SOC of the battery can be estimated in real time by calculating the accumulated loss capacity of the battery.

2.2. Equivalent circuit model

In order to understand the working characteristics of lithium ion battery and the advance study of its state estimations, it is necessary to model the lithium ion battery and present the internal and external characteristics in an equivalent form. At present, in the study of power lithium ion battery modelling, models that can express the relationship between battery input and output mainly include electrochemical model, equivalent circuit model and neural network model. In the field of SOC estimation of lithium ion battery, the equivalent circuit model has the advantages of complexity and precision, and is widely used [18].

The electrochemical characteristics of lithium ion battery can be represented by some electronic components with energy storage function. Generally, the equivalent circuit of lithium ion battery includes voltage source, resistance and capacitance (energy storage elements). Several classical equivalent circuit models of lithium ion battery, such as RINT model, RC model and Thevenin model, can be established by these components. In order to select an equivalent circuit model suitable for SOC estimation with filter theory, the limitations of the above models are analyzed. The accuracy of RINT model is difficult to meet the requirements of SOC real-time estimation, and the parameters of RC model are difficult to determine the response to SOC. Thevenin model has the advantages of both models, and achieves a balance in model accuracy and complexity. Therefore, Thevenin model is selected for SOC estimation of lithium ion battery. Thevenin equivalent circuit model is shown in Fig. 1.

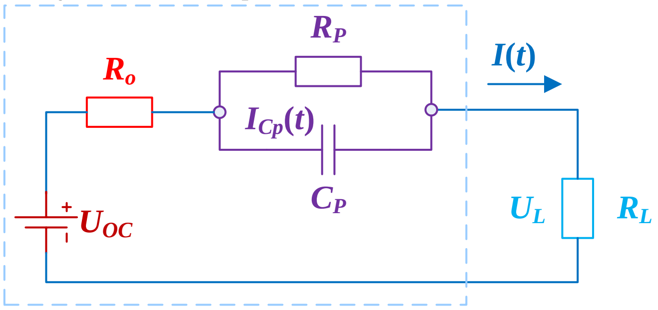

Figure 1. Thevenin Model

In the model of Fig. 1, the open circuit voltage is represented by DC voltage source Uoc, the ohmic internal resistance is represented by Ro, the polarization phenomenon occurring in lithium ion battery is represented by polarization internal resistance Rp and polarization capacitance Cp in parallel, the charging and discharging current is represented by I, and the battery terminal voltage is represented by UL. According to Kirchhoff's Voltage Law (KVL) and Kirchhoff's Current Law (KCL), the following formula is obtained:

$$KVL: U_L = U_{oc} + IR_0 + U_P \quad (4)$$

$$KCL: I = \frac{U_P}{R_P} + C_P \frac{dU_P}{dt} \quad (5)$$

In formula (4) and (5), UP represents the polarization voltage on the parallel circuit, according to these two formulas, the model parameter identification and state space expression of SOC estimation model are carried out in the following chapters.

2.3. Model parameter identification

Establishing an equivalent battery model is the basis of SOC accurate estimation in this approach. An accurate lithium ion battery model describes the relationship between SOC and battery parameters, the effects of temperature and aging degree should also be considered. According to equivalent model, the complex electrochemical reaction system of battery is equivalent to the Thevenin model. In short, the equivalent here means that the Thevenin equivalent model can be applied when the same current is applied to the battery system and the output terminal voltage is the same as or similar to the actual battery. The lower the error between the model terminal voltage and the actual terminal voltage, the higher the accuracy rate of the model. Model parameter identification works using electrochemical or physical knowledge and data analysis software when SOC and other conditions affecting model parameter values are given or known (such as battery capacity, charge and discharge rate, battery aging degree, and ambient temperature). The process of calculating the dependent variable value by the given system independent variable is the parameter identification process of the battery equivalent model. Similarly, when the conditions are gradually changed under the experimental environment, the corresponding model parameter values can be calculated one by one. When the obtained "condition-result", that is, the "independent-dependent variable" is obtained, the variation law between the variables can be learned. For example, to know the variation law of the open circuit voltage of the model, it is easy to know that the open circuit voltage is mainly affected by the SOC and temperature of the battery through the experiment of the external characteristics of the battery. When the temperature is constant, the open circuit voltage of the battery is tested at different SOC points, and the MATLAB software is used. The function of the open circuit voltage as a function of SOC can be achieved in the curve fitting tool in MATLAB.

In the equivalent Thevenin model, there are four model parameters open circuit voltage Uoc, internal resistance R0, polarization resistance Rp and polarization capacitance Cp that need to be identified. Under certain aging degree and temperature, these four parameters are mainly affected by SOC, it is easy to obtain the curve relationship between open circuit voltage and SOC through the Hybrid Pulse Power Characteristic (HPPC) experiment.

The identification of the internal resistance R0 of the equivalent model causes a sudden change in voltage during the charging and discharging period of the battery, as shown in figure3(b), and the internal resistance R0 can be obtained by following equation.

$$R_0 = \frac{(U_2 - U_1) + (U_3 - U_4)}{2I} \quad (6)$$

According to the zero-input response and zero-state response of the first-order RC circuit, Cp and Rp can be identified by combining the voltage response curves of the HPPC experiment [19]. The zero-input response of the circuit is as follows:

$$U_L = U_{OC} + U_P \quad (7)$$

$$U_P = U_P(0)e^{-t/\tau} \quad (8)$$

$$\tau = R_P C_P \quad (9)$$

Where Ul is the terminal voltage of the battery, which is obtained by the voltage response curve of the HPPC experiment, and the Uoc is the open circuit voltage of the battery. The response curve of the polarization voltage can be obtained according to formula (7), Up (0) is polarization voltage at the end of discharge, as the initial value of the polarization voltage and it is fitted to the polarization voltage response curve in MATLAB according to formula (8) to obtain the constant time parameter τ of the model. According to the zero-state response mechanism of 1-RC circuit, the following formula can be obtained analogously:

$$U_L = U_{OC} + IR_0 + U_P \quad (10)$$

$$U_P = IR_P(1-e^{-t/\tau}) \quad (11)$$

Using the zero-state response formula, the voltage-time data in the zero-state response stage in Figure 3 (b) can be fitted exponentially, and the polarization resistance Rp can also be fitted, the fitting result in the time constant τ is determined in the fitting process as a known parameter. Then Cp can be calculated according to formula (9). With the above identification method, we can use the data of HPPC experiment in each SOC point to identify the complete model parameters.

2.4. Extended Kalman algorithm

In order to use the EKF algorithm to estimate the SOC value of a lithium battery, firstly, an accurate battery model is established. The established Thevenin model is analyzed. The SOC and capacitance polarization voltage of the battery are selected to form a two-dimensional column vector, which is listed as a state variable of the system. The first-order response state equation of the circuit, the equations of the SOC are listed according to the chrono-integration method, and then an observation equation about the terminal voltage is listed according to the Kirchhoff voltage law. After discretization and linearization, two of the systems The equation is as follows:

Equation of state: $$\begin{bmatrix} S(k+1) \\ U_P(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1-\dfrac{\Delta T}{R_P C_P} \end{bmatrix} \begin{bmatrix} S(k) \\ U_P(k) \end{bmatrix} + \begin{bmatrix} -\dfrac{\eta \Delta T}{Q_0} \\ \dfrac{\Delta T}{C_P} \end{bmatrix} \left[I(k) \right] + \begin{bmatrix} w_1(k) \\ w_2(k) \end{bmatrix} \quad (12)$$

System observation equation: $$\left[U_L(k) \right] = \left[U_{OC} \right] - \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} S(k) \\ U_P(k) \end{bmatrix} - \left[R_0 \right] \left[I(k) \right] + \left[\upsilon(k) \right] \quad (13)$$

S(k) on the right side of the middle of equation (7) indicates the SOC value at the kth time, indicating the polarization voltage value at time k, and I(k) indicates the load current value at time k, indicating system noise, indicating different charge The effect of discharge rate on battery capacity is ignored in this paper, so it is taken as 1. In equation (8), the battery terminal voltage at time k is expressed, and the observation noise is expressed as a function of SOC. The data between the open circuit voltage and the SOC can be obtained from the previous HPPC experiment, and the functional relationship is obtained by fitting.

$$x_k = \begin{bmatrix} S(k) \\ Up(k) \end{bmatrix}, A_k = \begin{bmatrix} 1 & 0 \\ 0 & 1-\dfrac{\Delta T}{R_P C_P} \end{bmatrix}, B_k = \begin{bmatrix} -\dfrac{\Delta T}{Q_0} \\ \dfrac{\Delta T}{C_P} \end{bmatrix}, C_k = \begin{bmatrix} \dfrac{\partial (Uoc)}{\partial S(k)} \end{bmatrix}$$

Therefor the recursive process of the EKF filtering algorithm can be obtained:

$$x_{0/0} = E(x_0), P_{0/0} = \mathrm{var}(x_0) \quad (14)$$

$$x_{k/k-1} = A_k x_{k-1/k-1} + B_k I_k \quad (15)$$

$$P_{k/k-1} = A_{k-1} P_{k-1/k-1} A_{k-1}{}^T + Q_k \quad (16)$$

$$K_k = P_{k/k-1}C_k^T(C_kP_{k/k-1}C_k^T + R_k)^{-1} (17)$$

$$x_{k/k} = x_{k/k-1} + K_k\left[y_k - g(x_{k/k-1}, u_k)\right] \quad (18)$$

$$P_{k/k} = (I - K_kC_k)P_{k/k-1} \quad (19)$$

$$k = k+1 (20)$$

In the above iterative algorithm, equation (9) represents the initial state value and the initial error covariance. Equations (10) and (11) respectively represent the update of the state variable and error covariance of the system, equation (12) is the current Kalman gain K is calculated from the predicted error covariance, the matrix C, and the matrix R. Equation (13) corrects the predicted state vector using the gain K and the residual, and equation (14) updates the error covariance. The key of the algorithm is that each time the iterative updates, the state variables of the system are corrected by the input of the system observation, and the state variables are updated, where the SOC is continuously updated and corrected as the state quantity of the system, and the trend value is constantly updated.

2.5. System function

In the SIMULINK module of MATLAB, system function (S-function) is a function file with call format, which is usually used to describe the process of dynamic system. This function has a fixed framework structure, according to the needs of the described dynamic system, edit the sub functions in the framework of S-function [21]. The operation process of S-function is shown in the figure below.

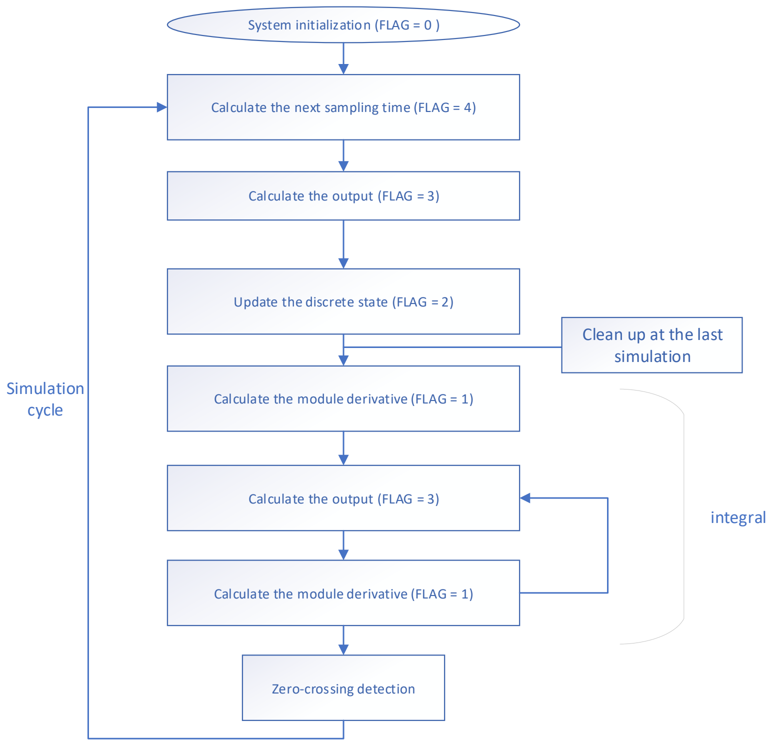

Figure. 2. Mechanism of S-function in SIMULINK

Each flag bit in the S-function corresponds to a sub-function. Inside the S-function, each sub-function runs in the order shown in Figure 2, each sub-function has different functions. When the flag bit is 0, the “mdlInitializeSizes” function is called to initialize the s function. When the flag bit is 4, the “mdlGetTimeOfNextVarHit” function is called to calculate the time of the next sampling point. When the flag bit is 3, the “mdlOutputs” function is called to calculate the output. When the flag bit is 2, the “mdlUpdate” function is called to update the discrete state in the system. When the flag bit is 1, the “mdlDerivatives” function is called to derive the state quantity. When the flag bit is 9, the “mdlTerminate” function is called to end the s function.

3. EXPERIMENTAL AND SIMULATION ANALYSIS

HPPC experiment is performed to analyze the pulse discharge characteristics of lithium ion battery and an equivalent circuit model is establish by identifying its parameters. The accuracy of the equivalent circuit model was verified by Beijing Bus Dynamic Stress Test (BBDST) working conditions. The SOC estimation simulation model based on EKF algorithm was constructed under SIMULINK environment and verified under BBDST working conditions too.

3.1. HPPC experiments

The parameter identification of Thevenin equivalent model of ternary lithium ion battery needs to be completed by experiments. This paper only conducts experiments at room temperature, where the apparatus included the ternary lithium ion battery (AVIC CFP50AH), battery testing equipment (YaKeyuan BTS200-100-10-4), thermostat (DGBELL) and a common computer.

The purpose of the Hybrid Pulse Power Characteristic is to obtain the parameters of the equivalent circuit model corresponding to different SOC values. At normal room temperature (25 degrees Celsius), a full battery is rested for some time and discharged for 10 seconds, then left for 40 seconds before charging again for 10 seconds. In this experiment, the current value of the pulse discharge and the charging current are both 1 C. The test is performed until the SOC is sequentially decreased by 10%, and the interval is 40 minutes after each experiment. The internal electrochemical reaction is balanced, so the process is performed in the same step at these different SOC points, and the voltage and current response data are obtained. In assuming the discharge current is negative, the results are the schematic diagram of the current and voltage profiles:

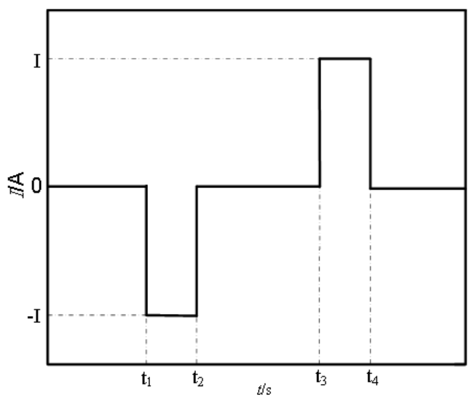

Figure 3. (a). HPPC experimental current

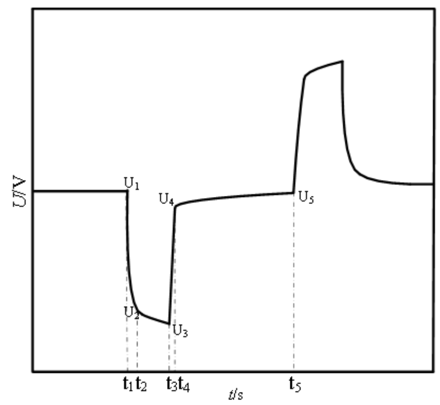

Figure 3. (b). HPPC experimental voltage

According to the curves in the above two figures, the value of the current and the voltage change suddenly at the time t1, which decreases sharply as it reflects the internal resistance characteristic of Thevenin model. From the time t2 to t3 in Fig. 3(b) it can be seen that the terminal voltage UL value shows a gradually decreasing change. According to the KVL of Thevenin circuit, the polarization of the polarization capacitor CP gradually reduces the terminal voltage, and the reverse polarization known as the polarization voltage Up gradually increases from 0v. In Fig. 3(b) the process from t4 to t5 is regarded as a zero-input response process in which the Cp capacity is gradually attenuated, and Up is gradually decreased and accordingly the UL gradually increases and finally equals the open circuit voltage. Finally, the corresponding voltage and current curves of the whole HPPC experimental pulse charge and discharge process correspond to the first-order RC link of Thevenin model, showing the polarization effect of the battery. It can be seen that the model is very related to the actual battery characteristics, so making it simple and easy to use. Parameter identification can be accomplished by establishing an equation for the zero-state and zero-input states of the first-order RC circuit.

According to the parameter identification method in Section 2.3, the results of the identification are shown in Table 1 below:

Table 1. Parameter identification result

SoC	$R_o(\Omega)$	$C_p(F)$	$R_p(\Omega)$	E(V)
1.000	0.0012	73021.9735	0.0062532	4.18
0.898	0.0012	38779.0975	0.0016404	4.05
0.795	0.0012	31237.4083	0.0019628	3.94
0.693	0.0016	38306.3389	0.0016788	3.84
0.590	0.0016	28407.8836	0.0011348	3.74
0.488	0.0012	77466.2222	0.0017468	3.65
0.385	0.0016	66796.6261	0.0015792	3.62
0.283	0.0012	48324.2877	0.0017932	3.58
0.180	0.0016	69167.8689	0.0015940	3.52
0.078	0.0016	22738.2283	0.0002188	3.43
0.000	0.0024	22738.2283	0.0002188	3.26

3.2 Model accuracy verification experiment

In order to verify the effect of parameter identification and verify the accuracy of the equivalent model, the equivalent circuit model of ternary lithium ion battery is built in MATLAB/SIMULINK [22]. The accuracy of the model is verified under HPPC experimental current condition, that is the constant-current discharge condition and BBDST conditions. The equivalent model parameters are shown in Fig. 4. In the diagram, the experimental IL module input load current condition is use to estimate the SOC value at each time by the time integral method. The SOC is then input into a LOOKUP TABLE and the online identification of the four parameters of the Thevenin model is achieved by the piecewise linear interpolation method. Finally, the closed-circuit voltage UL at each time is calculated as output by S-function, and then compared with the test voltage representing the experimental load current IL. The accuracy of the model is analyzed, and the validation of the model is completed.

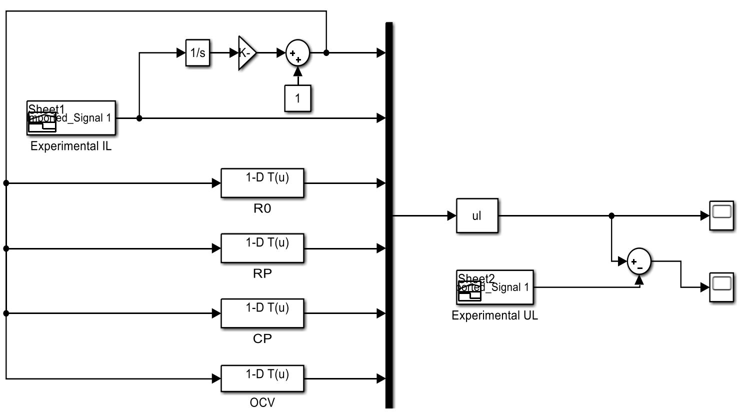

Figure 4. Model simulation

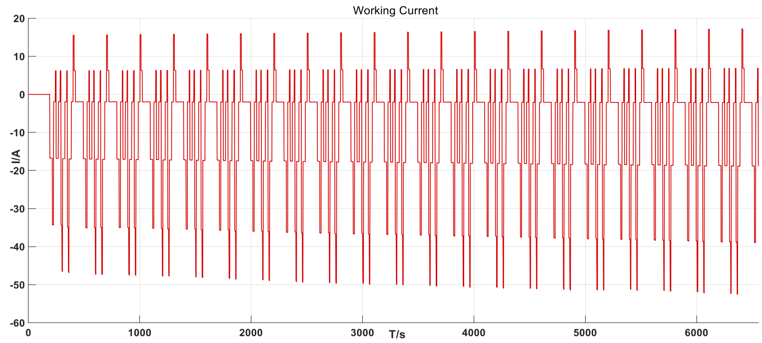

Figure 5. BBDST operating current

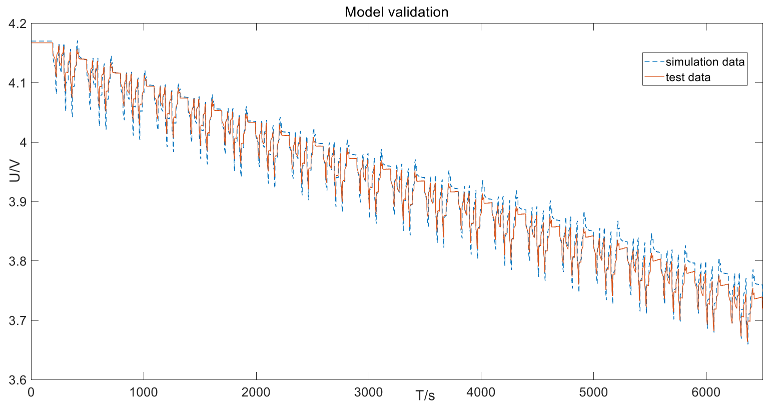

Figure 6. Model validation results

Fig. 6 shows the comparison of the simulation value of battery terminal voltage under BBDST current condition and the actual value of battery terminal voltage under the same current condition shown in Fig. 5. It can be seen that the simulation terminal voltage curve of the model can accurately follow the change of actual voltage in general. At each current mutation point, the simulation voltage and the actual voltage show the same trend of change, but in some mutations. There is a big deviation between the sudden change of the terminal voltage of point simulation and the change of the actual voltage. The reason is that the internal resistance identification of the model only considers the influence of SOC, ignores the factors such as charge-discharge ratio and temperature, which results in the inaccurate identification of the internal resistance. In addition, the zero input and zero state response of some simulation models do not accurately reflect the change of the actual battery terminal voltage. One reason is that they neglect. The factors such as charge-discharge ratio and temperature, polarization capacitance and polarization resistance in the selected equivalent model are also included. In the model building stage, the piecewise linear interpolation method is used to replace the actual CP and RP with SOC, which also causes errors. In a word, the equivalent Thevenin model with high accuracy is established by using relatively simple parameter identification method. The maximum error of the model is 0.08V and the average error is 0.04V.

3.3 Simulation Implementation of SOC Estimation Based on EKF

3.3.1 Application of EKF algorithm in S-function

In order to realize the real time estimation of lithium-ion battery SOC, in sections 2.2 and 2.3, we introduce the establishment of lithium ion battery equivalent model and parameter identification. In section 2.4, the principle of battery SOC estimation based on Extended Kalman Filter Algorithm is introduced. In order to build and implement the SOC estimation model based on Thevenin model and Extended Kalman Filter Algorithm[23], in section 2.5, the system function of MATLAB (S-function) is introduced, in this section, the system function is used as the carrier, based on MATLAB simulation environment A real-time estimation of lithium-ion battery SOC is realized by combining the lithium-ion battery model, Extended Kalman Filter algorithm and S-function together. The following diagram is a flow diagram of the algorithm[24].

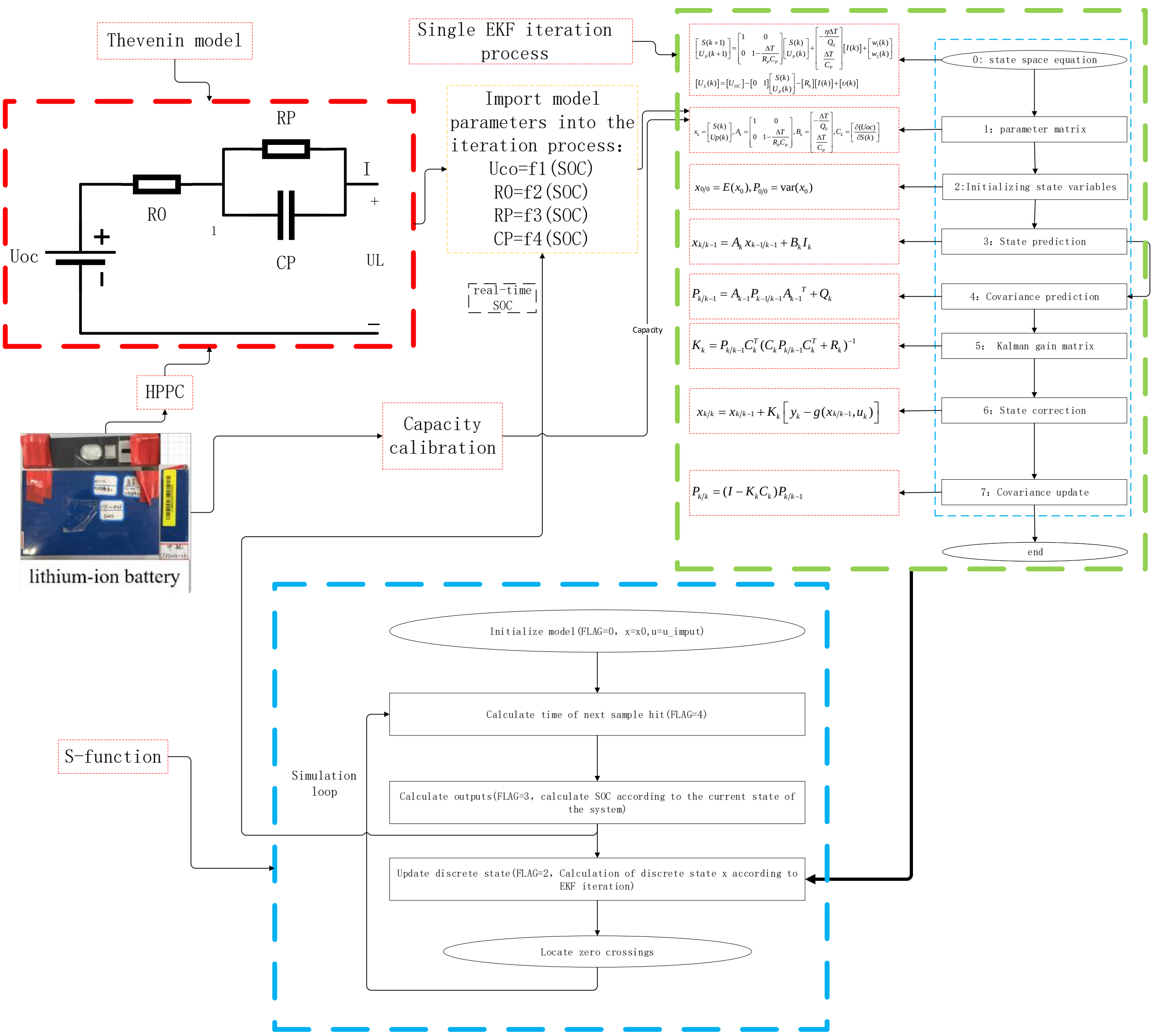

Figure 7. Simulating flow of S function

The three sections are shown in figure.7, the red dotted line is the equivalent model, the green dotted line is the single EKF iteration process, and the blue dotted line is the simplified S-function structure. The three sections seem to be independent, but they are closely related, the parameters of each part are closely related. The equivalent model parameters can update the Matrix A, B, C in EKF iteration in real time, which ensures that the EKF algorithm can iterate the optimal SOC estimation, while the EKF iteration formula is embedded in a sub-function of the S-function. The real-time estimation of lithium ion battery SOC based on SIMULINK is determined.

3.3.2 Simulation Architecture in SIMULINK

According to the analysis in the previous section which was based on a SIMULINK simulation environment, an SOC estimation model of lithium ion battery of the equivalent circuit model of lithium ion battery , with the Extended Kalman Filter theory as the core and the s function of MATLAB as the carrier is shown in Figure 8.

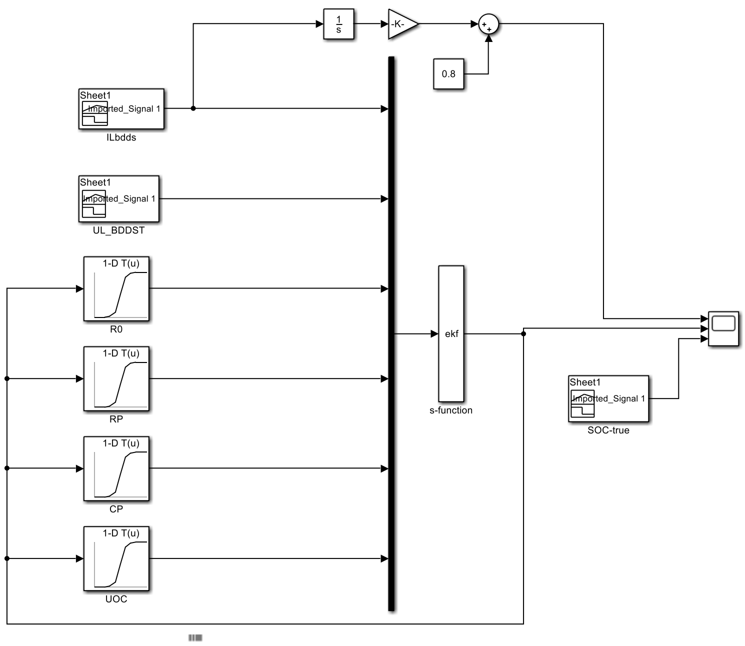

Figure 8. Simulating flow of S function

Figure 8 is a simulation model of real time estimation of the lithium ion battery SOC. The red region is an estimation model of SOC based on a coulomb counting method, 0.8 represents the false initial value of SOC (the true SOC value is 1). The real-time estimation of SOC is realized by accumulating the loss of coulombs by integrators. The blue region is a filter estimation model of SOC based on Thevenin equivalent model, Kalman filter theory and the S-function of SIMULINK as a carrier combined together. The four parameters of equivalent model are updated in real time with SOC by using the look up table method. The parameters of the model with the battery current and voltage are detected and used as the data base of the SOC filter estimation, through extended Kalman filter algorithm and the real-time filtering estimation of SOC is determined.

3.3.3 simulation results analysis

Based on the SOC estimation simulation model shown in figure 8 in the previous section, it analyzed the simulation results of SOC in a BBDST working condition and evaluates the performance of the SOC estimation model proposed in this paper.

The coulomb counting method is a widely used online SOC estimation method for lithium ion battery, because it is simple and it is in real-time [25]. The traditional Kalman filter algorithm has also been widely used in the field of SOC estimation of lithium-ion battery, which is more suitable for the actual working condition of lithium-ion battery [26-27]. Comparing the EKF algorithm based on S-function with the widely used coulomb counting method and the traditional Kalman algorithm, and evaluating the performance of the three SOC estimation methods from robustness and estimation accuracy of algorithms, the SOC estimation results are shown in the figure below.

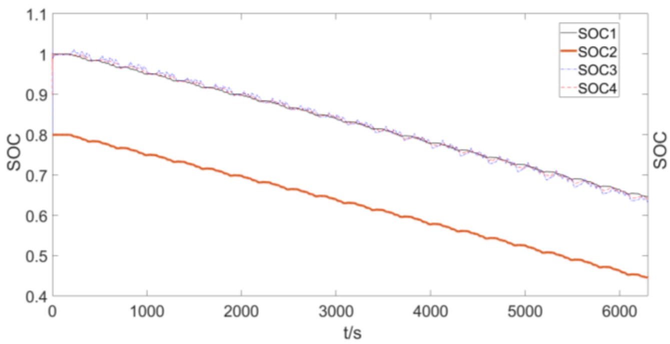

Figure 9 (a). SOC estimation results under BBDST

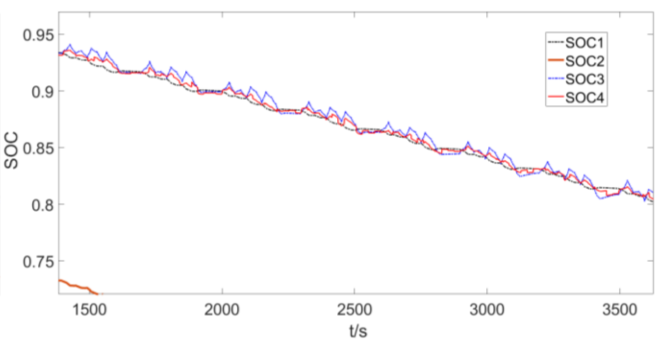

Figure 9 (b). Partial enlarged view of SOC

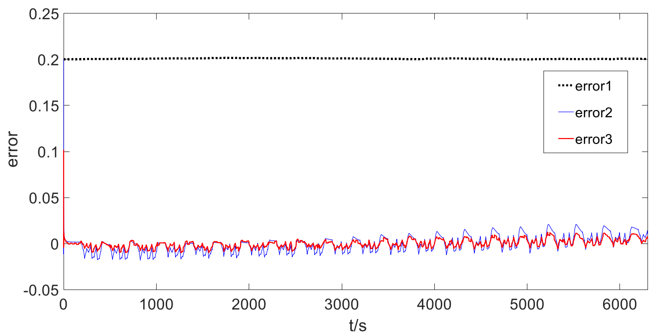

Figure 9 (c). SOC estimation error under BBDST

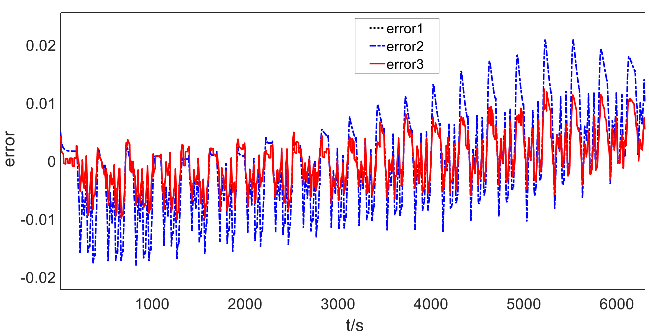

Figure 9 (d). Partial enlarged view of SOC error

Table 2. Error Statistics of SOC estimation

Estimation method	Maximum error	Mean absolute error
Coulomb counting method	0.2	0.18
Traditional EKF	0.02	0.015
EKF with S-function	0.01	0.008

As shown in figure 9(a) and figure 9(b), SOC 1 is the state of charge estimation of the battery detected by experimental equipment under working conditions, SOC 2 is the state of charge estimation of the traditional coulomb counting method, SOC 3 is the state of charge estimation of the traditional extended Kalman filter method, and SOC 4 is the state of charge estimation of the improved extended Kalman filter algorithm based on S-function.

In the case of the same SOC initial error, the coulomb counting result represented by the curve SOC2 keeps the SOC estimation error of about 0.2 all the time. After about 25 seconds adjustment, the traditional EKF algorithm can quickly track the SOC near the real value (5%), while the EKF filtering algorithm based on the S-function proposed in this paper only needs about 18 seconds to achieve accurate and fast SOC tracking. The results of SOC estimation error in Figure 9 (c) and Figure 9 (d) show that EKF algorithm is more suitable for the complex environment of lithium-ion battery in actual use than the widely used coulomb counting algorithm, where error curve 1, error curve 2 and error curve 3 respectively represent the SOC estimation error of coulomb counting method, traditional EKF algorithm and improved EKF algorithm based on S- function. The statistical results of SOC error in Table 2 show that the improved EKF algorithm, proposed in this paper, has lower error and stronger robustness than the traditional EKF algorithm, the average error is reduced by about 0.7%, and the maximum error fluctuation range is controlled within 1%. An improved UKF algorithm is proposed in [28], where the Mean Absolute Errors (MAE) of UKF algorithm and improved UKF algorithm are 1.7% and 1.1% respectively, which shows that the accuracy of SOC estimation is lower than that of the proposed algorithm. In [29], the square root unscented Kalman algorithm is used to estimate the SOC of ternary lithium-ion battery, but the maximum error of SOC estimation is more than 2%. Comparing with four typical SOC estimation methods, the improved EKF algorithm proposed in this paper realizes the real-time SOC estimation of lithium-ion battery in the actual working environment and the inaccurate SOC initial value condition.

4. CONCLUSIONS

In order to realize the real-time estimation of lithium ion battery SOC, the equivalent circuit model, state filter estimation theory and System function in MATLAB are combined and studied together in this paper. Thevenin equivalent circuit model of lithium ion battery was established based on HPPC experiment, and the parameters of the model were identified and verified by double exponential fitting method. The state space equations of SOC were established based on coulomb counting principle and equivalent circuit model, using the Kalman filter theory to design the iterative estimation algorithm of the SOC. The system function was built in MATLAB as the carrier, embedding the equivalent circuit model and the Extended Kalman Filter iterative algorithm into the SIMULINK environment and the estimation model of SOC filter was developed.

The conclusions drawn from the experimental results are as follows. Based on the HPPC experimental data, the parameters of the equivalent Thevenin circuit model are identified. The simulation results under BBDST condition show that the maximum error of the equivalent model terminal voltage is less than 0.08V, lithium-ion battery provides an idea for modeling and validation. Based on the equivalent circuit model and Kalman filter theory, taking MATLAB System function as carrier, a filter estimation model of SOC was also established in SIMULINK. The filter estimation method is compared with the coulomb counting method SOC estimation method under the same initial state error and the estimation error of the SOC is about 0.22 for the coulomb counting method while the estimation error of the SOC by the filter algorithm is less than 0.01.This means that the filter algorithm is more suitable for the estimation of the SOC under the operating condition in Shandong, the correctness of the proposed method is proved and an idea of lithium-ion battery estimation model suitable for MATLAB Environment is provided.

ACKNOWLEDGMENTS
The work was supported by National Natural Science Foundation of China (No. 61801407).

References

1. Y. Chaochun, *Int J Electrochem Sci.*, (2018) 1131.
2. Y. Zhang, W. Song, S. Lin and Z. Feng, *J. Power Sources*, 248 (2014) 1028.
3. L. Zhang, L. Zhang, C. Papavassiliou and S. Liu, *Wireless Personal Communications*, 102 (2018) 2063.
4. Y. Xing, W. He, M. Pecht and K.L. Tsui, *Applied Energy*, 113 (2014) 106.
5. M. Xiao, P. Liao, S. Yao, J. Cheng and W. Cai, *Journal of Renewable and Sustainable Energy*, 9 (2017) 054102.
6. F. Yan, *Int J Electrochem Sci*., (2018) 12360.
7. X. Wu, X. Li and J. Du, *IEEE Access*, 6 (2018) 41993.
8. Y. Wang, C. Liu, R. Pan and Z. Chen, *Energy*, 121 (2017) 739.
9. M. Charkhgard and M. Farrokhi, *Ieee T Ind Electron*., 57 (2010) 4178.
10. Z. Chen, L. Yang, X. Zhao, Y. Wang and Z. He, *Applied Mathematical Modelling*, 70 (2019) 532.
11. S. Cho, H. Jeong, C. Han, S. Jin, J.H. Lim and J. Oh, *Computers & Chemical Engineering*, 41 (2012) 1.
12. X. Dang, L. Yan, K. Xu, X. Wu, H. Jiang and H. Sun, *Electrochimica Acta*, 188 (2016) 356.
13. G. Dong, Z. Chen and J. Wei, *Ieee T Ind Electron*., 66 (2019) 8533.
14. M.B. Effat, C. Wu and F. Ciucci, *Asia-Pacific Journal of Chemical Engineering*, 11 (2016) 399.
15. T. Goh, M. Park, M. Seo, J.G. Kim and S.W. Kim, *Energy*, 159 (2018) 61.
16. H. Hongwen, X. Rui, Z. Xiaowei, S. Fengchun and F. JinXin, *IEEE Transactions on Vehicular Technology*, 60 (2011) 1461.
17. L. Lam and P. Bauer, *IEEE Transactions on Power Electronics*, 28 (2013) 5910.
18. S. Lee, J. Kim, J. Lee and B.H. Cho, *Journal of Power Sources*, 185 (2008) 1367.
19. J.X. Long, *Applied Mechanics and Materials*, 66-68 (2011) 583.

20. Y. Ma, Y. Chen, X. Zhou and H. Chen, *IEEE Transactions on Control Systems Technology*, 27 (2019) 1788.
21. T. Osaka, S. Nakade, M. Rajamäki and T. Momma, *J. Power Sources*, 119-121 (2003) 929.
22. C.-H. Piao, Q.-F. Yu, C.-X. Duan, L. Su and Y. Zhang, *Journal of Electrical Engineering and Technology*, 9 (2014) 1729.
23. F. Sun, R. Xiong and H. He, *J. Power Sources*, 259 (2014) 166.
24. J. Tian, R. Xiong and Q. Yu, *Ieee T Ind Electron*., 66 (2019) 1576.
25. R. Xiong, F. Sun, Z. Chen and H. He, *Applied Energy.* 113 (2014) 463-476.
26. H. Rahimi-Eichi, F. Baronti and M.-Y. Chow, *Ieee T Ind Electron.* 61 (2014) 2053-2061.
27. G.L. Plett, *Journal of Power Sources.* 134 (2004) 252-261.
28. X. Lai, C. Qin, W. Gao, Y. Zheng and W. Yi, *Applied Sciences*. 8 (2018) 1592.
29. M. Luo, Y. Guo, J. Kang, L. She and Z. Geng, *Ionics*. 24 (2018) 1907-1917.