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SOC estimation of sodium-ion batteries based on EKF

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Abstract. As a new generation of energy storage devices, sodium-ion batteries have promising applications in renewable energy storage and electric vehicles. However, the state-of-charge (SOC) estimation of sodium-ion batteries is limited by their complex electrochemical properties and dynamic responses. In this paper, we propose a SOC estimation method for sodium-ion batteries based on extended Kalman filter (EKF). Firstly, a second-order RC equivalent circuit model is established for the characteristics of sodium-ion batteries, and the feasibility of the open-circuit voltage-based accurate estimation of the state of charge of sodium-ion batteries is verified through the open-circuit voltage (OCV) test experiments, and the experimental data-driven method is adopted for the parameter identification; furthermore, a system model is constructed in the Matlab/Simulink simulation platform, and the applicability of the model is verified through the online simulation. Secondly, the state space equations are constructed based on the model, and the improved EKF algorithm is used to realize the online estimation of SOC. Finally, the effectiveness of the proposed method is verified by the stage discharge condition. The simulation results show that the method can accurately track the SOC changes of sodium-ion batteries, and the estimation error is controlled within 2.5%, with high estimation accuracy and robustness. Through accurate parameter identification and model optimization, this paper significantly improves the accuracy of SOC estimation of sodium-ion batteries, provides an efficient and reliable solution for the sodium-ion battery management system, and provides important technical support for its promotion in practical applications.

Keywords: Sodium-ion Battery, SOC Estimation, Extended Kalman Filter, Equivalent Circuit Model, Parameter Identification.

1 Introduction

Energy storage technology is a key supporting technology to realize the goal of "carbon peak and carbon neutral". With the aggravation of global climate change, countries have put forward the carbon neutral target, and promote the transformation of energy structure from fossil energy-based to renewable energy-based [1]. Energy storage technology plays an important role in this process, which can effectively solve the problem of intermittency and uncertainty of renewable energy, improve the efficiency of energy utilization, and reduce the dependence on traditional fossil energy. With the advancement of power system reform and smart grid construction, the role of energy storage technology in the power system is becoming more and more prominent. Energy storage technology can enhance the flexibility and stability of the power system, support the large-scale access of new energy sources, and at the same time meet the peak and valley differences in power demand[2].

Currently, lithium-ion batteries, which are highly commercialized, have limitations in terms of safety, cycle life, material cost and environmental impact. In contrast, sodium-ion batteries have become a strong contender for next-generation energy storage devices by virtue of their abundant resources, low cost, high energy conversion efficiency, and environmental friendliness[3]. Sodium is a richly abundant element on the earth, its abundance is about three times that of lithium, and it is inexpensive, which makes sodium-ion batteries have a significant advantage in cost [4], and become one of the important research directions in the field of energy storage. However, the commercial application of sodium-ion batteries still faces many challenges, such as low energy density and poor cycling stability [5], so improving their performance and reliability is the focus of current research.

Compared with lithium-ion batteries, sodium-ion batteries have significant differences in material properties and working principles. For example, the ionic radius of sodium ions is larger and the diffusion rate is slower, which leads to its energy storage mechanism and performance characteristics are different from those of lithium-ion batteries [6]. Therefore, the unique physicochemical properties of sodium-ion batteries need to be fully considered for the estimation of their state of charge (SOC). At present, the development of sodium-ion batteries is still in the primary stage, and the key technologies of their battery management system (BMS), especially the accurate estimation of SOC, still need further in-depth research. By solving these problems, sodium-ion batteries are expected to realize wider applications in the field of energy storage.

As a key parameter reflecting the remaining battery charge, the estimation accuracy of SOC directly affects the formulation of battery charging and discharging strategies by the BMS, which in turn affects the service life and safety of the battery[7]. However, the charging state of a battery cannot be directly measured and can only be indirectly estimated based on externally measurable parameters such as terminal voltage, current and temperature. In addition, the inherent electrochemical characteristics of sodium-ion batteries, such as large polarization voltage and complex dynamic response, further increase the difficulty of SOC estimation. Currently, the main research methods for SOC include equivalent circuit model-based, data-driven, joint estimation of physical characteristics, and novel algorithms and optimization strategies. Wu Shengli et al [8] based on the equivalent circuit model approach achieved high accuracy SOC estimation through the second order RC model, introducing the multiple new holographic theory combined with extended Kalman filtering (EKF), especially in the wide temperature range. Xiong et al[9] based on the data-driven approach combined with the LSTM-RNN model in the hybrid neural network approach, and combined with the historical data to achieve a high accuracy prediction. Shuai Jiang et al [10] joint estimation method based on physical properties further improved the estimation accuracy through SOC-SOH joint estimation and temperature adaptive method. Yunhai Peng et al [11] utilized particle volume Kalman filtering (PF-CKF) to solve the estimation challenges in nonlinear systems and high noise environments. Overall, SOC estimation research is developing towards high accuracy, strong robustness and multi-dimensional joint estimation, which provides important support for the optimization of battery management systems.

Extended Kalman Filter (EKF) [12], as a classical nonlinear state estimation algorithm, is widely used in the field of SOC estimation for lithium-ion batteries due to its advantages such as small computational effort and high estimation accuracy. However, there are relatively few studies on the EKF algorithm for sodium-ion batteries, and most of the existing methods use simple battery models, which are difficult to accurately describe the dynamic characteristics of sodium-ion batteries.

Aiming at the above problems, this paper proposes an extended Kalman filter-based method for estimating the state of charge of sodium-ion batteries. Firstly, the second-order RC equivalent circuit model is used to model the sodium-ion battery, the open-circuit voltage test is used to verify the feasibility of estimating the SOC of the sodium-ion battery through the open-circuit voltage, and the least squares method is used to identify the parameters. Next, the state space equation is constructed based on this model, and the EKF algorithm is used to realize the online estimation of SOC. Finally, the effectiveness of the proposed method is verified through simulation studies.

2 Modeling Of Sodium-Ion Batteries

Existing studies are rich in exploring battery models, which can be mainly categorized into four types: electrochemical model, energy model, coupling model and equivalent circuit model. Among them, the electrochemical model establishes mathematical equations by describing the chemical reactions inside the battery, but due to the complexity of the reaction process, the model has a large amount of computation, which is difficult to be applied to the real-time estimation of the state of charge (SOC) of the battery. The energy model focuses on analyzing the heat production characteristics of the battery during operation, providing a theoretical basis for the battery thermal management system. The coupled model integrates the characteristics of the electrochemical model and the energy model. It should be noted that the electrochemical model, the energy model and the coupled model are all constructed based on the internal chemical properties of the battery, and their model parameters are often difficult to identify accurately, which is not suitable for the simulation study of the model. The equivalent circuit model [13], on the other hand, has the advantages of high computational efficiency, easy parameterization, and strong adaptability, and is suitable for state estimation algorithms to be combined to achieve high-precision SOC estimation.

The battery equivalent circuit models mainly include the following typical structures: the Rint model, the Thevenin model, the PNGV model, the first-order RC model, the second-order RC model, and the GNL model. In terms of the working principle, sodium-ion batteries are similar to lithium-ion batteries in that they both realize energy storage and release through the embedding/de-embedding reaction of sodium ions in the positive and negative materials. Specifically, its charging and discharging process contains several key mechanisms: sodium-ion migration in the electrolyte, ion diffusion in the electrode material, and electrochemical reaction kinetics and other complex processes. These processes exhibit different dynamic properties on the time scale and can be roughly categorized into two types, one dominated by the ion migration in the electrolyte and the electrochemical reaction on the electrode surface, which usually corresponds to a shorter time constant, and the other dominated by the diffusion of sodium ions in the electrode material, which usually corresponds to a longer time constant. The second-order RC model describes the fast and slow dynamic characteristics of the battery through two RC parallel loops, respectively, which can better capture the electrochemical behavior of sodium-ion batteries on different time scales, and thus provide accurate mathematical descriptions of the voltage response of the battery. Moreover, the second-order RC model has a simple structure, convenient parameter identification and strong adaptability, which is an efficient and reliable solution for modeling and state estimation of sodium-ion batteries. The second-order RC model [14] is shown in Fig. 1.

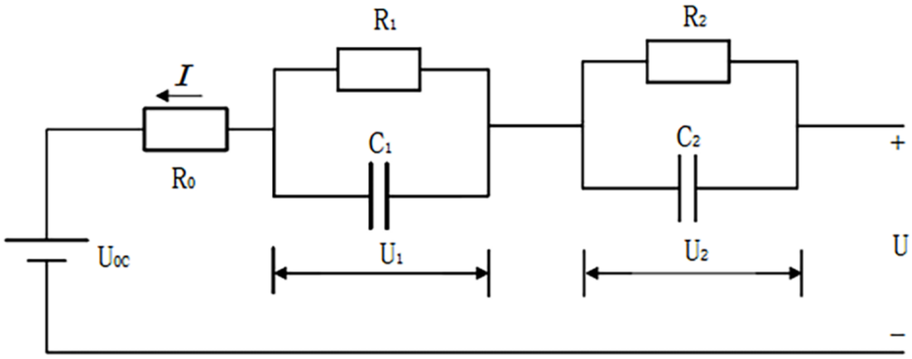


Fig. 1. Second order RC circuit equivalent model.

The second-order RC equivalent circuit model consists of a voltage source Uoc, an ohmic internal resistance R0, an electrochemical polarization internal resistance R1 and capacitance C1, and a concentration polarization resistance R2 and capacitance C2. The equivalent circuit dynamic equations are established according to Kirchhoff's law as shown in Equation 1.

$$\begin{cases} \dot{U}_1 = \dfrac{1}{C_1} - \dfrac{U_1}{R_1C_1} \\ \dot{U}_2 = \dfrac{1}{C_2} - \dfrac{U_2}{R_2C_2} \\ U = U_{oc} + U_1 + U_2 + IR_0 \end{cases} \tag{1}$$

3 Parameter Identification

Battery parameter identification [15] refers to the process of determining unknown parameters (internal resistance, capacitance, open-circuit voltage) in a battery model through experimental data or algorithms. These parameters are the core of the battery model and directly affect the accuracy and predictive ability of the model. The purpose of parameter identification is to enable the battery model to accurately reflect the actual behavior of the battery, thus supporting battery state estimation (SOC, SOH), performance prediction and optimal control.

The experimental object of this paper is the 26700 sodium-ion battery produced by Zhongke Haina, and the main performance parameters of this battery are listed in Table 1. The experimental platform built in this paper is shown in Fig. 2, which consists of four main parts: a computerized data processing system, a 26700 sodium-ion battery, a DC charging power supply and a discharge electronic load.

Table 1. Basic parameters of sodium-ion battery monomer

Item	Specification	Note
Nominal capacity/Ah	3.0	23℃，0.5C
Nominal Voltage/V	3.0	——
Cut-off charging voltage/V	4	——
Cut-off discharging voltage /V	1.5	T: 0~+60℃
Standard charging mode	0.25C CC to 4V	——
Dimension/mm	CV to 0.05C	——

Fig. 2. Experimental platform

3.1 Open-circuit Voltage Test

In order to obtain the correspondence between the open-circuit voltage and the state of charge (OCV-SOC curve) of a battery, an open-circuit voltage test is required. In this paper, the intermittent discharge test was conducted at room temperature (25°C), using 1C discharge multiplication, and the resting time under each SOC point was 30 min. To investigate the difference between the OCV-SOC curves of sodium-ion batteries and lithium-ion batteries, this test is conducted to determine the sodium-ion batteries and lithium-ion batteries with the model number of 18650 under the same conditions.

The relationship between SOC and open-circuit voltage under the corresponding point is obtained from the test as shown in Tables 2 and 3. Polynomial fitting of SOC and open-circuit voltage under the corresponding point is carried out, and in order to ensure the accuracy and continuity, this paper adopts a fifth-order polynomial for the fitting, and the relationship between OCV-SOC of sodium-ion and lithium-ion batteries is obtained as shown in Eqs. (2) and (3). The function fitting curves are shown in Figs. 3 and 4.

Table 2. Sodium-ion battery open circuit voltage test results

SOC/%	0	10	20	30	40	50	60	70	80	90	100
OCV/V	1.892	2.294	2.552	2.737	2.895	3.088	3.264	3.431	3.58	3.734	3.882

Table 3. Lithium-ion battery open circuit voltage test results

SOC/%	0	10	20	30	40	50	60	70	80	90	100
OCV/V	2.923	3.206	3.251	3.281	3.287	3.289	3.299	3.324	3.325	3.325	3.363

$$\begin{aligned} OCV = 8.67\times SOC^5 - 25.58\times SOC^4 + 28.16\times SOC^3 \\ -14.5\times SOC^2 + 5.246\times SOC + 1.891 \end{aligned} \tag{2}$$

$$\begin{aligned} OCV = 12.05\times SOC^5 - 34.36\times SOC^4 + 36.66\times SOC^3 \\ -18.03\times SOC^2 + 4.113\times SOC + 2.927 \end{aligned} \tag{3}$$

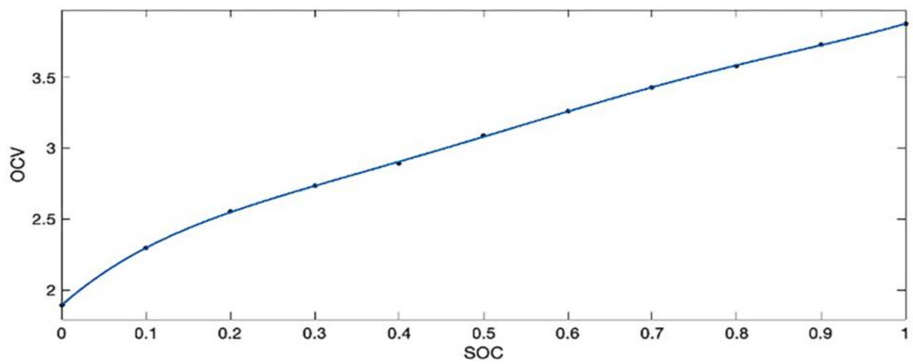


Fig. 3. OCV-SOC polynomial fitting curves for sodium-ion batteries

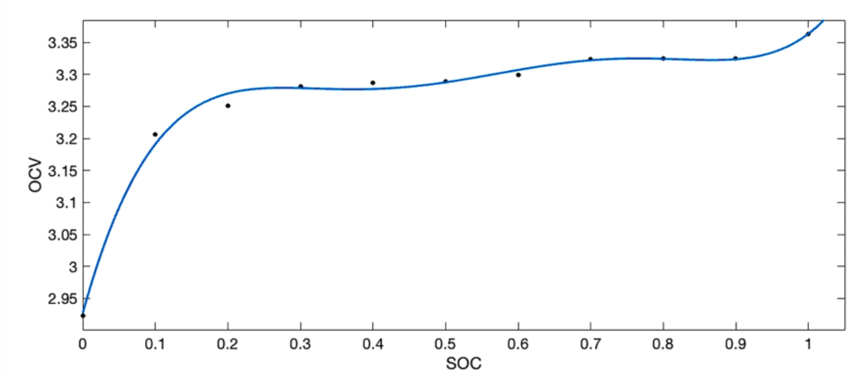


Fig. 4.OCV-SOC polynomial fitting curves for Lithium-ion batteries

The linear trend of the OCV-SOC relationship of sodium-ion batteries can be preliminarily observed through the fifth-order polynomial fitting curves in Fig. 3. In order to further quantify the highly linear characteristics of the OCV-SOC relationship of sodium-ion batteries, this paper adopts linear regression methods to linearly fit the open-circuit voltages (OCVs) of the sodium-ion batteries at different SOC points in order to accurately characterize the linear properties of their OCV-SOC relationship and to provide high-precision mathematical model support for subsequent SOC estimation. The results are shown in Fig. 5.

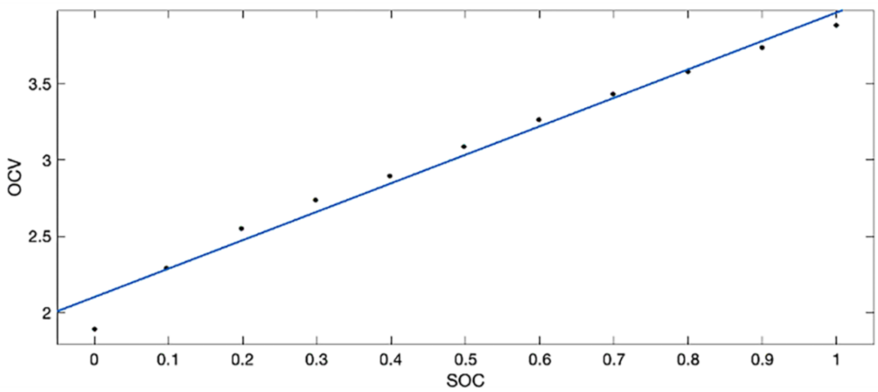


Fig. 5. OCV-SOC linear fitting curve for sodium-ion batteries

The results of comparative analysis show that there is a significant difference between the open-circuit voltage-state of charge (OCV-SOC) relationship curves of sodium-ion batteries and lithium-ion batteries. Meanwhile, the linear fitting curve of the sodium-ion battery shows that the OCV-SOC curve of the sodium-ion battery exhibits good linear characteristics and does not have the voltage plateau phenomenon common in lithium-ion batteries. This highly linear OCV-SOC relationship allows the open-circuit voltage of sodium-ion batteries to more directly and accurately reflect their SOC state, thus significantly improving the accuracy of SOC estimation. In contrast, the OCV-SOC relationship of lithium-ion batteries exhibits strong nonlinearity due to the existence of multiple voltage platforms, resulting in a certain limitation of the SOC estimation accuracy. This characteristic of sodium-ion batteries not only simplifies the complexity of battery modeling, but also reduces the design difficulty of battery management system (BMS) algorithms, enabling them to exhibit higher applicability and reliability in dynamic application scenarios such as electric vehicles. Therefore, sodium-ion batteries have obvious advantages in terms of SOC estimation accuracy and BMS adaptability, which provide important technical support for their large-scale application in electric vehicles and energy storage systems.

3.2 Open-circuit Voltage Test

Offline parameter identification [16] refers to the process of determining the parameters of a battery model by means of experimental data and algorithms when the battery is not in its actual operating state (i.e., offline). Offline parameter identification is usually performed in a laboratory or controlled environment and can provide highly accurate parameter estimates that provide the basis for battery modeling, state estimation, and performance optimization[17]. Since this paper has verified that the OCV-SOC curves of sodium-ion batteries exhibit good linear characteristics through the open-circuit voltage test, and their dynamic response varies less, which significantly reduces the modeling complexity, the offline parameter identification is used for the five parameters of the second-order RC model, namely, R0, R1, R2, C1, and C2.

In this paper, HPPC experiments are used for parameter identification. Here, a complete cycle experiment with SOC of 60% is selected for illustration.

In figure 6, A~B stage is the pulse discharge process, and B~D stage is the discharge resting phase.

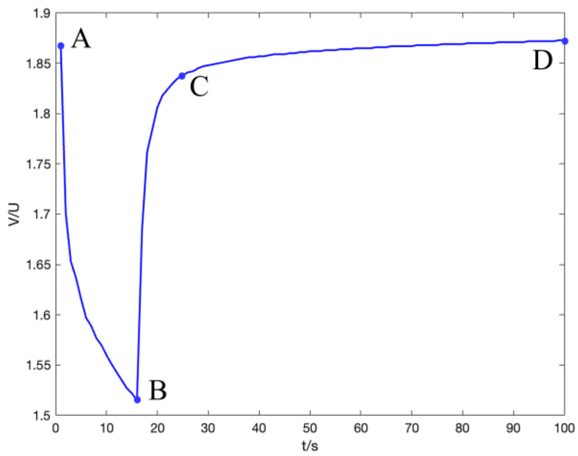


Fig. 6. HPPC voltage curve at SOC=60%

Parameter identification of polarization resistance and capacitance

In the resting phase after pulse discharge, the phenomenon of slow voltage recovery is mainly affected by the combined effect of polarization resistance and polarization capacitance inside the battery. This process is reflected in the figure is the B~C stage, this process is the second-order RC circuit of the zero input response, in the B~C stage at any moment of the battery's operating voltage is:

$$U = OCV_D - IR_1 e^{-\tau_1 t} - IR_2 e^{-\tau_2 t} \tag{4}$$

The rebound voltage curves of stages B to C are fitted by a customized second-order exponential function called “Custom Equations” in the fitting toolbox in Matlab:

General model:

$$f(x) = A - B * \exp(-ax) - C * \exp(-bx) \tag{5}$$

Coefficients:

A =3.734, B =0.02671, C =0.01281, a =0.03705, b =0.00244

Equating Eq. (4) with Eq. (5) correspondingly the parameters of the model can be obtained as follows: Therefore, through the above identification method, the identification results of the equivalent impedance parameters of the battery at each SOC point can be obtained as shown in Table 4.

Table 4. Second order RC model parameter identification results

SOC	R1	R2	C1	C2	R0
0.1	0.445	0.0331	11.6242	12990	0.2776
0.2	0.0134	0.011	2442.7	47064	0.1501
0.3	0.0094	0.0109	56792	3265.4	0.1377
0.4	0.005	0.0116	114280	3002.2	0.1326
0.5	0.0107	0.0051	3216.8	94744	0,1294
0.6	0.0092	0.005	3310.1	86078	0.1284
0.7	0.0085	0.0041	3162.5	100060	0.1271
0.8	0.0033	0.0075	166020	3863.3	0.1342
0.9	0.0074	0.0027	4165	227580	0.1271
1.0	0.0026	0,0069	139480	3337.3	0.1265

3.3 Matlab/Simulink Based Model Simulation and Comparative Validation

In order to verify the accuracy of the model and parameter identification, this study compares the measured voltage data with the simulation results for verification. As shown in Fig. 7, the battery simulation model and its parameter settings are constructed in the Matlab/Simulink environment.

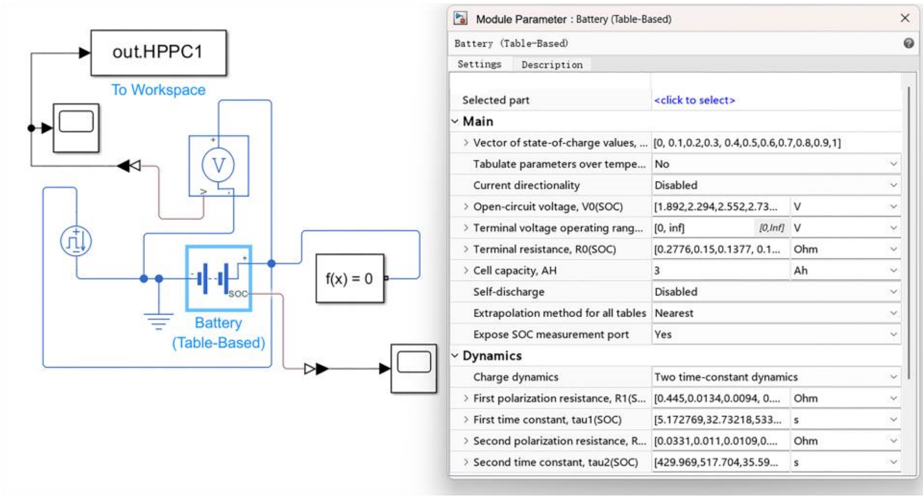
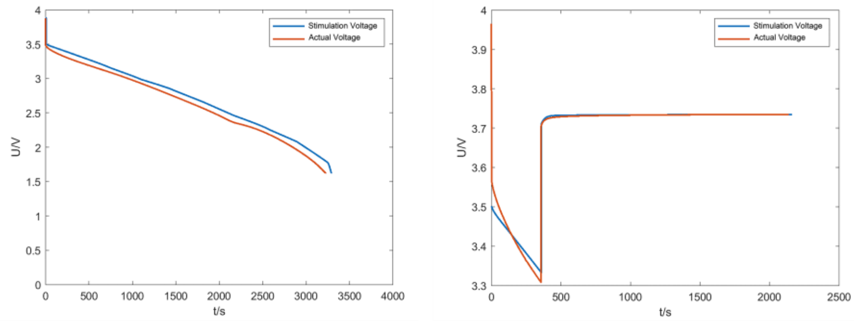


Fig. 7. Battery Simulation Model and Battery Parameter Setting

In this study, two discharge conditions are used to verify the accuracy of the simulation model: constant current discharge and pulse discharge. The constant-current discharge is verified using a 1C discharge multiplier, and the simulation curve obtained under this condition is shown in Fig. 8(a). In the pulse discharge validation stage, the experimental data of one complete cycle was selected for analysis in this study, and the specific test conditions are set as follows: 3A pulse current was used, and the discharge is left for 30 minutes after 6 minutes, and the simulation result curve is obtained as shown in Fig. 8(b).



（a） （b）

Fig. 8. Simulation Result Curve

Constant current terminal voltage simulation results show that the simulation voltage and the actual voltage in the initial moment (t = 0s) are close to 3.5V, the error is very small, providing an accurate starting point for the subsequent analysis; in the interval from t = 0s to t = 2500s, the simulation voltage and the actual voltage trend is highly consistent with that of the actual voltage, although the simulation voltage is slightly lower, but the error is stable and smaller, indicating that the model can effectively capture the change rule of the actual voltage; To t = 3500s, the two voltages are reduced to a lower level, the error is still maintained in a small range, the simulation voltage decreases slightly faster, but the overall error on the model analysis and prediction of the impact can be ignored.

The simulation results of the pulse-terminal voltage show that at the initial moment, the actual voltage is slightly higher than 3.5 V, and the simulated voltage is about 3.5 V, with a small gap. Subsequently, the actual voltage drops rapidly to 3.3V, and the simulated voltage then drops but is slightly higher, which is a short period of time and a small error. After that, the actual voltage rises rapidly, and the simulated voltage rises synchronously, and both of them are close to 3.7V in 500s, almost coinciding, which indicates that the model can accurately follow the voltage change in the rapid phase. After the stabilization stage, both voltages are stabilized at about 3.7V, and the curves almost overlap with negligible error, indicating that the model has very high accuracy in the steady state. Overall, despite the transient differences in the initial phase, the simulation model can accurately reflect the actual voltage changes in the recovery and stabilization phases, showing high reliability and accuracy.

Specific analysis of the experimental data shows that the average relative error between the output voltage and the experimental data is less than 4%, of which the root mean square error is 4.2% in the constant current discharge condition and 0.5% in the pulse discharge condition, which indicates that the battery model can accurately reflect the actual dynamic characteristics and has good dynamic performance.

4 SOC Estimation Of Sodium-ion Batteries

4.1 Extended Kalman Filter Algorithm

Extended Kalman Filter (EKF) is an extension of Kalman Filter [18] (KF) for nonlinear systems. Kalman filter as a recursive estimation algorithm is mainly applied to state estimation of dynamic systems. The algorithm has a wide range of applications in several engineering fields such as navigation systems, automatic control and signal processing. However, the standard Kalman filter assumes that both the dynamic and observation models of the system are linear, while the EKF deals with nonlinear systems by linearizing the nonlinear model[19]. Its system space state model is as follows:

$$\begin{cases} x_k = f\left(x_{k-1}, u_{k-1}\right) + w_{k-1} \\ z_k = h\left(x_k\right) + v_k \end{cases} \tag{6}$$

Where x_k is the state vector, u_k is the control input, z_k is the observation vector, w_k and v_k are the process noise and observation noise, respectively, which are usually assumed to be zero-mean Gaussian white noise.

The function is linearized, and the state transfer F_k and observation matrices H_k are computed using Jacobi matrices:

$$F_k = \left.\frac{\partial f}{\partial x}\right|_{x_{k-1|k-1}} \tag{7}$$

$$H_k = \left.\frac{\partial h}{\partial x}\right|_{x_{k|k-1}} \tag{8}$$

Projected state：

$$\hat{x}_{k|k-1} = f\left(\hat{x}_{k-1}, u_{k-1}\right) \tag{9}$$

Predicting covariances:

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{10}$$

Where Q_k is the process noise covariance matrix.

Update step:

Calculate the Kalman gain：

$$K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k\right)^{-1} \tag{11}$$

Update the status estimate:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(z_k - h\left(\hat{x}_{k|k-1}\right)\right) \tag{12}$$

Updated covariance estimates:

$$P_{k|k} = \left(I - K_k H_k\right) P_{k|k-1} \tag{13}$$

Where R_k is the observation noise covariance matrix.

4.2 SOC Estimation Of Sodium-ion Batteries Based On EKF

State of Charge (SOC) estimation of sodium-ion batteries based on Extended Kalman Filter (EKF) is a commonly used Battery Management System (BMS) technique [20].SOC is the percentage of remaining battery charge, and an accurate estimation of SOC is critical for battery performance optimization, lifetime management, and safety. EKF can efficiently estimate the SOC of a nonlinear battery system by combining a battery model and real-time measurement data, it is able to effectively estimate the SOC of a nonlinear battery system.

The EKF state space used in this paper not only considers the SOC, but also introduces two voltage decay terms (the voltages of the two RC links), which reflect the battery characteristics more realistically than the traditional first-order RC model. The SOC estimation accuracy is improved by using the dynamically changing battery parameters over time and fitting them by an eighth-order polynomial.

Equation of state:

$$\begin{bmatrix} SOC_k \\ U_{1,k} \\ U_{2,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-\Delta t}{R_1C_1}} & 0 \\ 0 & 0 & e^{\frac{-\Delta t}{R_2C_2}} \end{bmatrix} \begin{bmatrix} SOC_{k-1} \\ U_{1,k-1} \\ U_{2,k-1} \end{bmatrix} = \begin{bmatrix} -\eta \dfrac{\Delta t}{C} \\ R_1\left(1-e^{\frac{-\Delta t}{R_1C_1}}\right) \\ R_2\left(1-e^{\frac{-\Delta t}{R_2C_2}}\right) \end{bmatrix} I_{k-1} + w_{k-1} \quad (14)$$

Where: Δt is the experimental sampling period; $U_{1,k}$ and $U_{2,k}$ are the voltage values on C_1 and C_2 at time k, respectively; C is the cell capacity; η is the Coulombic efficiency of the cell.

$$U_k = \left[\frac{dU_{oc}(SOC)}{dSOC} -1 -1\right] \begin{bmatrix} SOC \\ U_{1,k} \\ U_{2,k} \end{bmatrix} - R_0 I_k + v_k \quad (15)$$

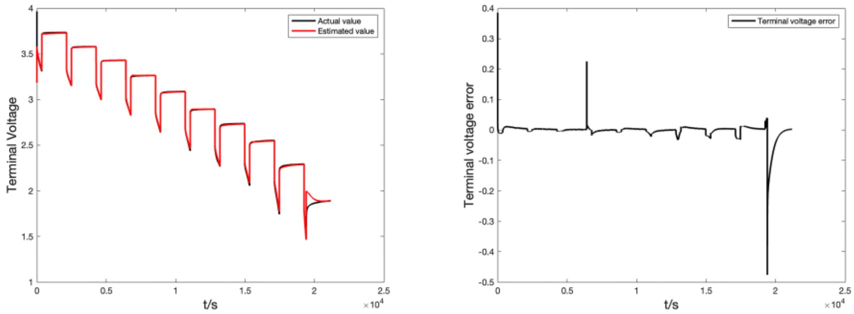
Among them:

$$
\begin{cases}
x_k = \begin{bmatrix} SOC_k \\ U_{1,k} \\ U_{2,k} \end{bmatrix} \\
A_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-\Delta t}{R_1 C_1}} & 0 \\ 0 & 0 & e^{\frac{-\Delta t}{R_2 C_2}} \end{bmatrix} \\
B_k = \begin{bmatrix} -\eta \dfrac{\Delta t}{C} \\ R_1 \left(1 - e^{\frac{-\Delta t}{R_1 C_1}} \right) \\ R_2 \left(1 - e^{\frac{-\Delta t}{R_2 C_2}} \right) \end{bmatrix} \\
C_k = \left[\dfrac{dU_{oc}\left(SOC\right)}{dSOC} -1 -1 \right] \\
D_k = -R_0
\end{cases} \tag{16}
$$

By substituting the above model parameters into the Kalman filtering algorithm, this study achieves an accurate estimation of the SOC of sodium-ion batteries.

5 Experimental Stimulation

In order to verify the estimation accuracy of the extended Kalman filter algorithm on the SOC of sodium-ion batteries, this paper selects the stage discharge condition as the verification, adopts 1C discharge multiplication rate, takes the measured current and voltage data as the input, and estimates the SOC of sodium-ion batteries based on the second-order RC equivalent circuit model. The estimation results and error analysis are shown in Figs. 9 and 10, respectively. The SOC obtained by the ampere-time integration method is chosen as the reference value. The simulated terminal voltage results are approximated as the simulated open-circuit voltage and linearly fitted to the corresponding SOC reference value, and the fitting results are plotted on the same graph with the linear fitting results obtained from the open-circuit voltage test, as shown in Fig. 11, which reveals that the simulation results are highly consistent with the experimental results, and further verifies the highly linear characteristics of the OCV-SOC curve of the sodium-ion battery.



（a）　　　　　　　　（b）

Fig. 9. Terminal Voltage Estimation Result Curve

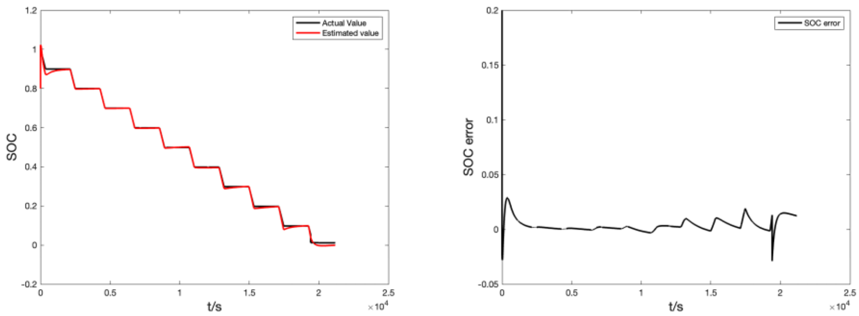


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Fig. 10. SOC Estimation Result Curve

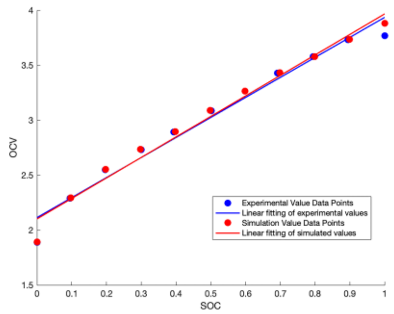

Fig. 11. Linear fitting results

The analysis results based on the experimental data show that the EKF algorithm exhibits good tracking accuracy and stability in sodium-ion battery SOC estimation. As shown in Fig. 9, the SOC curve estimated by the EKF algorithm fits well with the real value curve under the 1C stage discharge condition, and the estimation effect is good.

The mathematical calculation of the experimental data yields that its mean absolute error (MAE) is controlled within 0.9% and the root mean square error (RMSE) is lower than 2.5%, which verifies the effectiveness of the algorithm. However, in the interval where the SOC is lower than 10%, there is a significant nonlinear relationship between the open-circuit voltage (OCV) and the SOC, and at the same time, the complex electrochemical polarization effect inside the cell is more significant in the low SOC region, which together lead to the decrease of the SOC estimation accuracy. The experimental data show that the estimation error increases about 0.7%-1.2% in the interval of SOC<10% compared with other intervals, which is consistent with the theoretical analysis. From the perspective of the overall error distribution and change trend of the images, the error between the simulation results and the actual measurements is always kept at a low level, and the fluctuation range of the error is small, with no obvious deviation or accumulation phenomenon. In addition, the change trends of the simulation curve and the actual curve during the discharge process are highly consistent, especially during the rapid voltage change and stabilization phases, which are almost completely overlapped. This indicates that the proposed SOC estimation method can effectively capture the dynamic characteristics of sodium-ion batteries and maintain a stable estimation performance under different operating conditions. Therefore, the method not only meets the accuracy requirements of SOC estimation for sodium-ion batteries, but also demonstrates good robustness and reliability, which provides strong support for its application in practical battery management systems.

6 Conclusion

In this study, a second-order RC equivalent circuit model based on dynamic characteristics is proposed to address the technical difficulties in estimating the state of charge (SOC) of sodium-ion batteries. The model can accurately characterize the polarization effect of the battery. The simulation experiments are carried out under two typical working conditions of constant current discharge and pulse discharge, and the results verify that the model has high estimation accuracy and reliability. On this basis, an SOC estimation method based on extended Kalman filter (EKF) is proposed, and combined with the open-circuit voltage (OCV) test experiments, the feasibility of realizing the accurate estimation of SOC based on OCV for sodium-ion batteries is verified. The experimental data-driven parameter identification method is adopted to ensure the accuracy and reliability of the model parameters, and the state-space equations are constructed to realize the online estimation of SOC using the improved EKF algorithm. Simulation results show that the method can accurately track the SOC changes of sodium-ion batteries, and the estimation error is controlled within 2.5%, exhibiting high estimation accuracy and robustness.

In this paper, the accuracy of SOC estimation of sodium-ion batteries is significantly improved through accurate parameter identification and EKF model optimization, providing an efficient and reliable solution for sodium-ion battery management system (BMS). The results provide a theoretical basis and technical reference for the development of the BMS state estimation module, which is not only suitable for the laboratory environment, but also able to meet the demand for high accuracy of SOC estimation in practical applications, and provides important technical support for the promotion of sodium-ion batteries in the fields of renewable energy storage and electric vehicles. Future research will further optimize the adaptive ability of the model parameters to cope with more complex working conditions and promote the practical application and development of sodium-ion battery technology.

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