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Simulink-based Modeling and Simulation Study of Iron Phosphate Lithium Batteries

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Abstract

As the most widely used secondary battery today, lithium iron phosphate battery has the advantages of high energy density, slow performance degradation and environmental friendliness, and has been widely used in unmanned devices, automobiles, electronic products and other fields. In order to solve the problem of LiFePO4 battery charge state is difficult to estimate, this paper selects the second-order RC equivalent circuit model as the research object, combines the hybrid pulse charge and discharge test and the least squares method to identify the parameters of the second-order RC model, and then establishes the state of charge (SOC) simulation model based on the extended Kalman filter algorithm in Matlab with Simulink. The simulation results show that the estimation method can estimate the state of charge of the battery compared with the actual state of charge values and the results are more satisfactory.

Keywords

Lithium iron phosphate battery; Extended Kalman filter; Battery charge state; Equivalent circuit model.

1. INTRODUCTION

With the development of the times, energy saving and emission reduction, low-carbon life, carbon neutrality, etc. have become the current development trend of the world, driving the rapid development of the new energy industry. Lithium batteries are used in various fields due to their high energy density, long life and high voltage. According to the classification of cathode materials, lithium batteries can be divided into lithium iron phosphate, lithium cobaltate, lithium manganate, lithium nickel acid and ternary materials and other types [1]. Lithium iron phosphate battery with its high energy density, long service life, large charge/discharge multiplier, high safety, good high temperature, good cycle performance and other advantages into the public eye. Its nominal voltage is 3.2V, the maximum charge voltage is usually 4.2V, high-performance lithium iron phosphate battery rated capacity is generally between 1000mAh to 5000mAh, the cut-off discharge voltage is generally about 2.5V [2]. It should be noted that the specific parameters will be affected by a variety of factors such as manufacturer, model and capacity. In the selection and use of high-performance lithium iron phosphate batteries, you need to choose according to the actual needs. Lithium iron phosphate market competition is also relatively fierce, many companies at home and abroad are developing and producing lithium iron phosphate batteries, such as Ningde Time, BYD, Panasonic batteries, etc., the market pattern is gradually taking shape.

Simulink is the main tool provided by Matlab and is most widely used in modeling and simulation of dynamic systems. In this paper, by establishing a second-order RC equivalent

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circuit model and building a simulation model in Matlab with the help of Simulink, a nonlinear system like a battery can be simulated.

2. EQUIVALENT CIRCUIT MODELING AND PARAMETER IDENTIFICATION

The battery is the main body in the battery management system, regardless of the method applied to SOC estimation, a reasonable battery model must be built. In the modeling and simulation of lithium iron phosphate batteries, the commonly used models include the electrochemical model and equivalent circuit model. The electrochemical model has the most detailed description of the internal processes of the battery, and the highest simulation accuracy, but is too complex [3]. Taking into account the model accuracy and modeling computation, the electrochemical model is more cumbersome in SOC estimation, therefore, the equivalent circuit model is selected to model the battery and used for SOC estimation.

2.1. Modeling of lithium iron phosphate batteries

Currently, the main battery equivalent circuit models that are commonly used in engineering and easy to implement are the Rint model, Thevenin model, PNGV model, and GNL model [4]. The Rint model is a simpler model that does not consider the polarization characteristics of the battery, so the accuracy of the model is low and is rarely seen in practical applications. The PNGV model is based on the Thevenin model with the addition of a capacitor, but it causes voltage fluctuations during the simulation, which affects voltage acquisition and is not suitable for long time charge/discharge simulations [5]. The second-order Thevenin model can better describe the dynamic output characteristics of the battery and is the most widely used. The circuit structure of the second-order Thevenin equivalent circuit model is shown in Figure 1. Where UOC is the battery open circuit voltage, at a certain temperature and the battery SOC has a fixed mapping relationship; U0 is the voltage across the ohmic resistor.R0 is the ohmic internal resistance of the battery; R1 and R2 are the polarized internal resistance of the battery; C1 and C2 are the polarized capacitance of the battery; Vb is the terminal voltage of the battery; I is the current in the equivalent circuit model; U0 is the voltage across the ohmic resistor; U1 and U2 are the voltages across the two RC networks, respectively. The time constant of the loop composed of R1 and R2 is larger and is used to describe the phase of slow change of terminal voltage during sudden change of current; the time constant of the loop composed of R2 and C2 is smaller and is used to describe the phase of faster change of terminal voltage during sudden change of current.

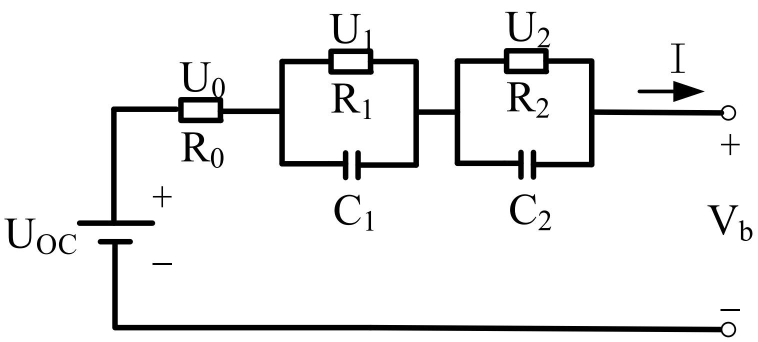

Figure 1. Second Order Thevenin Equivalent Circuit Model

According to the equivalent circuit model of the cell shown in Figure 1, from Kirchhoff's voltage law we get

$$U_{OC} - V_{\mathrm{b}} = U_0 + U_1 + U_2 \tag{1}$$

According to the equivalent circuit model of the battery shown in Figure 1, the equivalent mathematical model of the battery can be obtained as.

$$SOC = SOC_0 - \frac{1}{C_n}\int_{t_0}^{t_1} Idt t_1 \tag{2}$$

$$I = C_1\frac{dU_1}{dt} + \frac{U_1}{R_1} \tag{3}$$

$$I = C_2\frac{dU_2}{dt} + \frac{U_2}{R_2} \tag{4}$$

$$I = \frac{U_0}{R_0} \tag{5}$$

Where SOC0 is the SOC value at the moment t0; SOC is the SOC value at the moment t1; C_n is the rated capacity of the battery; I is the current discharge current of the battery.

2.2. Model parameter identification

The parameters to be identified in this paper include open-circuit voltage Uoc, ohmic internal resistance R0, battery electrochemical polarization capacitance C1, concentration polarization capacitance C2, battery electrochemical polarization resistance R1 and concentration resistance R2 [6]. The test object is a lithium iron phosphate battery with a nominal voltage of 3.2 V and a capacity of 1600 mA-h. The test equipment is Xinwei's BTS-8000 battery test system. Under the condition of 25℃ (room temperature), the mixed pulse charge/discharge test was conducted at 10% SOC interval. The OCV and SOC relationship curve relationship was obtained, as shown in Figure 2.

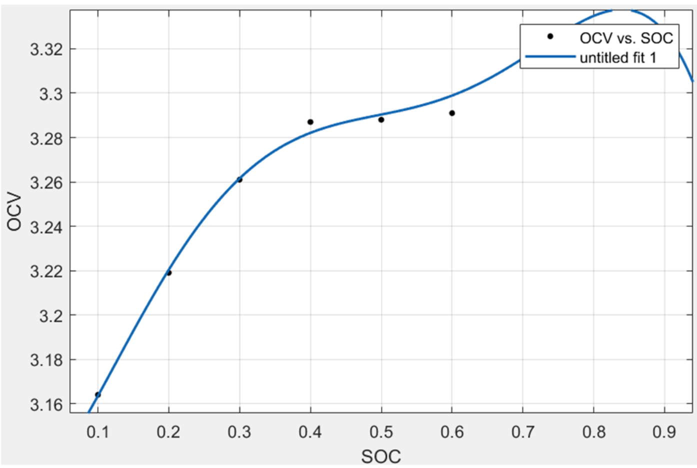

Figure 2. OCV-SOC curve of LiFePO4 battery

The parameters in the second-order RC model are identified using the least squares method, and the results are shown in Table 1.

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Table 1. Results of battery parameter identification

SOC	U_{OC}/V	R_0/Ω	R_1/Ω	C_1/F	R_2/Ω	C_2/F
0.1	3.164	0.00355	0.001	785632	0.0000789	845632
0.2	3.219	0.00352	0.0012	785264	0.0000647	774862
0.3	3.261	0.0035	0.00089	45635	0.0000879	754855
0.4	3.287	0.0033	0.000845	896542	0.0000216	1745654
0.5	3.288	0.0036	0.001	156354	0.0000216	765849
0.6	3.291	0.0035	0.00099	998551	0.0000520	786548
0.7	3.328	0.0031	0.0008	95445	0.0000618	685741
0.8	3.328	0.0031	0.000794	685452	0.0000426	786523
0.9	3.329	0.003	0.000699	852011	0.0000875	963542

3. BATTERY CHARGE STATE ESTIMATION METHOD

The value of SOC reflects the usable capacity of the battery, and since it cannot be measured directly, it is generally obtained through the implied relationship between external parameters such as current and voltage and SOC. The main battery SOC estimation methods are the ampere-time integration method, the open-circuit voltage method, the Kalman filter method and the neural network method [7].

3.1. Ampere-time integration method

This method is a method of integrating current over time to detect changes in battery capacity and subsequently estimate the SOC value. The integration of current over time is actually the amount of power charged or discharged. If the battery is considered as a closed system, it is only necessary to calculate the capacity of the incoming and outgoing battery cumulatively, and then compare the calculation result with the battery's fully charged state power to obtain the remaining power that the battery has. The calculation accuracy of this method depends on the initial value and the accuracy of the current sensor, and the small errors can produce large deviations after a long time of accumulation, which can lead to the damage of the battery. Therefore, the SOC values need to be calibrated periodically [8].

3.2. Open circuit voltage method

The open-circuit voltage method uses the correspondence between the open-circuit voltage of the battery and the depth of discharge of the battery to estimate the SOC by measuring the open-circuit voltage of the battery. for lithium-ion batteries, the open-circuit voltage has a certain proportional relationship with its SOC, which can be used to obtain the SOC of the battery more directly, and the method is relatively simple. However, it requires a long period of standstill to obtain a stable open-circuit voltage, so it is difficult to estimate the SOC of the battery in real time [9]. Therefore, it is generally not applied in battery management systems alone, but often used to complement other algorithms.

3.3. Kalman filtering method

The purpose of Kalman filtering is to remove noise disturbances from the data stream, predict the new state and its uncertainty, and then calibrate the predicted value with the new measured value to achieve SOC estimation. Theoretically the Kalman filtering method is able to maintain very high accuracy in the estimation process and can correct the errors very effectively. The drawback of the Kalman filter method is that it requires a large number of operations and the availability of an accurate mathematical model of the battery to ensure the accuracy of SOC estimation [10].

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3.4. Neural network method

The neural network method consists of three main layers, as shown in Figure 2. When SOC estimation is required, the function of each layer is as follows: the first layer is the input layer, which inputs the measured data such as open circuit voltage (OCV), current, temperature, and discharge multiplier of the power cell; the second layer is the hidden layer, which stores the input data based on the mapping relationship, and creates and trains the error feedback (BP) neural network; the third layer is the output layer, which is the artificial neural network passed with the output after the computation. This method is a series of external features such as: current, voltage, temperature, etc. through the neural network to establish a mapping relationship with the SOC, the accuracy depends on the selection of the network and the number of hidden layers, which is still in the experimental research stage [11].

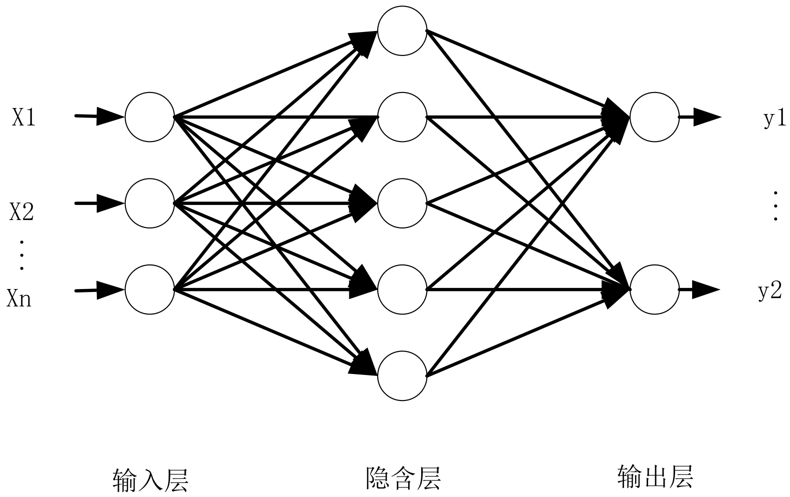

Figure 3. Neural network schematic

4. EXTENDED KALMAN FILTER METHOD FOR ESTIMATING SOC

The classical Kalman filtering method requires that the system must be linear, that is, there is a linear relationship between input variables and output variables. In such a system, Kalman filtering method will get a good filtering effect. However, in practical application, many systems are not only linear, but also show very strong nonlinearity. At this time, Kalman filtering method will have great limitations, and the filtering effect will be poor.

4.1. Extended Kalman filtering algorithm

Due to the complex internal structure of lithium batteries, the estimated data often exhibit strong nonlinearity in the process of operation. And the Kalman filter method is applied to linear systems, which makes it difficult for the traditional lithium battery SOC estimation algorithm to obtain real-time and accurate lithium battery charge states. In order to apply the Kalman filter to the field of nonlinear systems, the Extended Kalman Filter (EKF) has been proposed to perform Taylor series expansion and discard the higher order components. Based on the linear Kalman filter, the EKF forces the nonlinear relationship into a linear one. It enables a more accurate estimation of the battery state [12]. The algorithm is based on a state-space model that provides a priori estimates for the next moment by updating the predictions of the state variables through the system state equations. Then the system observations are used to correct the deviation of the predicted values and update the estimates to finally achieve state estimation. The state equation as well as the observation equation are discretized according to modern control theory and further rewritten as

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$$x_{k+1} = f(x_k, u_k) + w_k \tag{6}$$

$$y_k = g(x_k, u_k) + v_k \tag{5}$$

Where $f(x_k, u_k)$ and $g(x_k, u_k)$ are nonlinear transfer functions, w_k and v_k are mutually independent Gaussian white noise, whose satisfaction conditions are consistent with the Kalman filtering method.

4.2. Simulink Simulation Analysis

The algorithm simulation model is built based on the second-order RC equivalent circuit model of a single battery, and the model is shown in Fig. The leftmost part of the model represents the input current, which is usually considered to be positive for battery discharge. Here a negative gain is given to the current to make it positive and allow the battery to discharge. The second-order RC model is built with a mathematical model. The left input of this module is the current, and the right output is the true value of SOC using the ampere-time integration method, which will be compared with the extended Kalman filter to estimate the SOC value. The other output is the value of the terminal voltage simulated by the second-order RC model and will be compared with the real measured voltage. subsystem1 module is the extended Kalman filter estimated SOC and will be compared with the real SOC value.

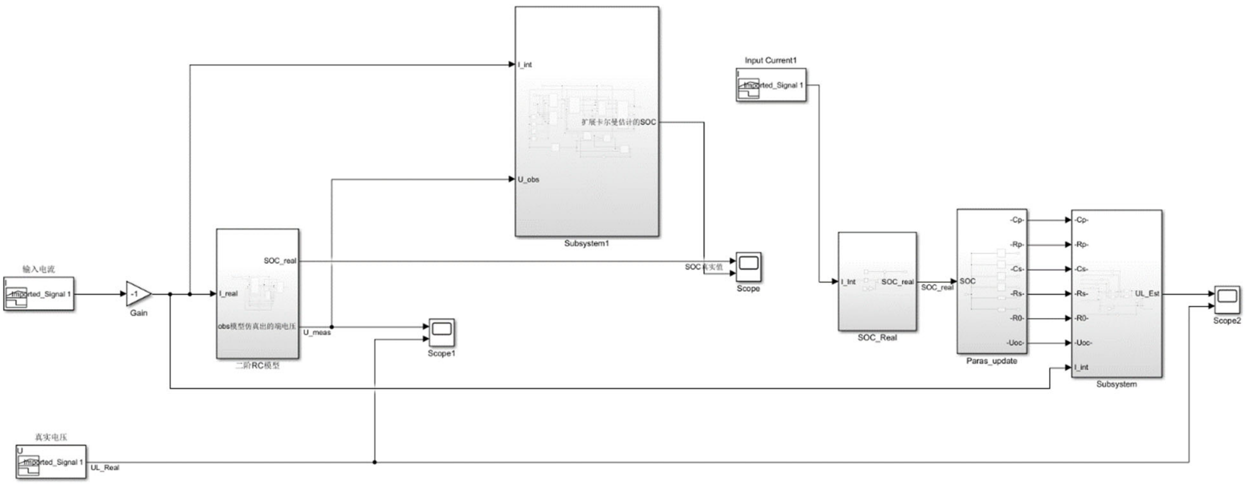

Figure 4. Single battery extended Kalman filter algorithm Simulink simulation model

The figure represents the SOC simulation results. The yellow line represents the real value of SOC, and the blue line represents the value of SOC estimated by the extended Kalman filter. It can be seen that the extended Kalman filter still converges quickly to near the true value when the initial value is inaccurate. The error between the simulated estimated SOC and the actual measured SOC fluctuates within a certain range, which verifies the accuracy of the simulation model.

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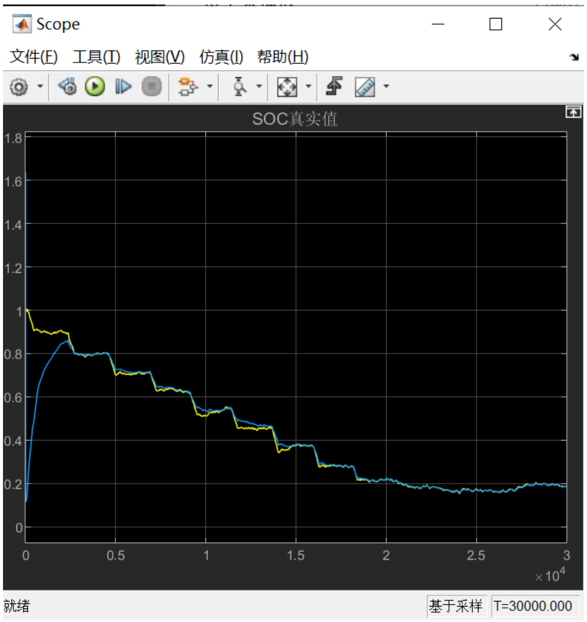

Figure 5. SOC simulation results

5. CONCLUSION

In this paper, the equivalent circuit model of the battery is established, the parameters in the model are identified using the least squares method, and the simulation model of the lithium iron phosphate battery is established in Matlab/Simulink. The measured current and voltage are input into the model, and the SOC values obtained by the extended Kalman filter algorithm are compared with the real values, showing that the algorithm can effectively estimate the SOC values.

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