SOC Estimation of Ternary Lithium Battery Based on Interpolation Method and Online Parameter Identification

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Abstract. SOC estimation is currently a function of the energy management system for new energy vehicles. Based on the SOC of batteries, the remaining available capacity of batteries can be directly determined to determine the remaining driving range of electric vehicles. Aiming at this problem, this paper use the two Resistance and Capacitance equivalent circuit model for the ternary lithium-ion battery, and then obtains the OCV-SOC curve by using spline interpolation. The improved recursive least squares (FFRLS) method with forgetting factor is used to identify parameters of the battery model. Due to the nonlinear state of the external characteristics of the battery, the linear kalman filter would lead to a large error in the estimation, which cannot meet the need for accuracy. Therefore, in this paper, EKF is improved in this paper, and spline interpolation is used to optimize the relationship between open circuit voltage and SOC in data processing, thus improving the estimation accuracy.

Keywords: SOC estimation · Spline interpolation · Recursive least squares · Extended kalman filter

1 Introduction

Nowadays, electric vehicles (EV) have gradually begun to promote the application. For the power batteries of electric vehicles, lithium batteries have higher working voltage, excellent performance, durable quality and other characteristics. Both domestic and foreign countries strongly support the domestic electric vehicle industry.

Lithium battery already used in EV are lithium iron phosphate (LiFeO4) and ternary lithium ion batteries (batteries with elements Ni, Co and Mn). LiFePO4 is a very popular lithium battery electrode material with a large discharge capacity. It is often used in new energy vehicles as a power battery [1]. But the performance of lithium iron phosphate batteries is subject to changes in temperature. Ternary lithium-ion batteries are not as safe as lithium iron phosphate batteries, but have higher energy density than lithium iron phosphate batteries. Ternary lithium-ion batteries are still subject to resource bias due to the energy density of vehicle power batteries.

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There have been basically four estimation methods for SOC. The first is to use the Coulomb method. Up to now, the utilization rate of Coulomb counting method has not been much in engineering, because it has a big limitation. The first is that the Coulomb counting method needs a sufficiently accurate initial value [8]. However, the sensor is not interference-free, so the reliability is not as high. The second is the open circuit voltage method, but this method is too high for experimental conditions, and the relationship between the open circuit voltage and the charged state may be different for different batteries. The third approach is to use machine learning or artificial neural networks. Neural network method has been applied to the estimation of SOC [2, 3]. The fourth is to use the battery equivalent model to estimate SOC. Another method is to convert the electrochemical reaction of the battery into the form of circuit for analysis by using the equivalent Thevenin model. As a kind of model convenient for SOC analysis, the Thevenin equivalent model has been widely used [4].

The state equation of two Resistance and Capacitance equivalent model of the battery is used in this paper, and then use spline interpolation to obtain the relationship curve between OCV and SOC, which can be used to estimate SOC by combining improved least square method based on forgetting factor and extended kalman filter (EKF). Experiments under UDDS conditions is used to estimate battery parameters by RLS method.

The structure of the paper can be divided into five parts. The second part is to apply the battery equivalent model to establish the equation, which lays a foundation for the following work. In the third part, the model parameters of the second part are measured based on the experiment and parameter identification algorithm. The fourth part use EKF to estimate SOC. The fifth part gives the conclusion.

2 The Establishment of Battery Model

For lithium-ion batteries, it is impractical to model them directly, because charging or discharging a battery is not a linear time-invariant model, and the equations used to describe internal chemical reactions cannot be used directly in engineering [5]. The two Resistance and Capacitance equivalent circuit model takes into account the characteristics of the inside of the battery and can accurately describe its dynamic characteristics.

Figure of two Resistance and Capacitance model is shown in Fig. 1. C_b is an ideal voltage source, and the voltage across it is the battery's open circuit voltage. I_t represents the terminal current of battery; The two sets of RC represent the polarization characteristics of the cell in the Thevenin model.

According to the battery equivalent model, the mathematical expression can be obtained as follows,

$$\begin{cases} U_o = U_{oc} + U_1 + U_2 + I_t R_0 \\ I_t = U_1/R_1 + C_1 dU_1/dt = U_2/R_2 + C_2 dU_2/dt \end{cases} \tag{1}$$

where U_t is port voltage, U_{oc} is open circuit voltage, and U_1, U_2 is voltage of the two RC parts respectively.

According to the time integration method, the expression of the battery SOC is as follows,

$$SOC = SOC_0 - \frac{\eta}{Q_c} \int_0^t i(\tau) d\tau \tag{2}$$

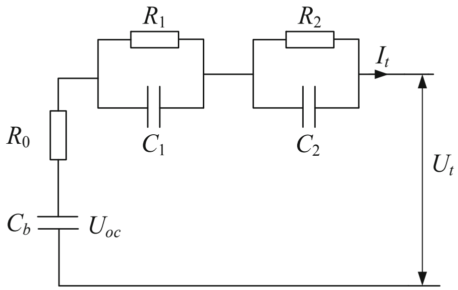

Fig. 1. Cell model equivalent circuit diagram

where SOC_0 is the initial value of SOC, and Q_c is battery capacity. Parameter η is the Coulomb efficiency. The equations in the discrete state of two RC model are,

$$\begin{bmatrix} SOC_{k+1} \\ U_{1k+1} \\ U_{2k+1} \end{bmatrix} = A \begin{bmatrix} SOC_k \\ U_{1k} \\ U_{2k} \end{bmatrix} + BI_{t,k} + \begin{bmatrix} w_{1,k} \\ w_{1,k} \\ w_{1,k} \end{bmatrix} \tag{3}$$

$$U_{t,k} = U_{oc}(SOC_k) - U_{1,k} - U_{2,k} - R_0 I_{t,k} + v_k \tag{4}$$

where $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-T}{\tau_1}} & 0 \\ 0 & 0 & e^{\frac{-T}{\tau_2}} \end{bmatrix}$, $B = \begin{bmatrix} -\eta T/Q_c \\ R_1(1 - e^{\frac{-T}{\tau_1}}) \\ R_2(1 - e^{\frac{-T}{\tau_2}}) \end{bmatrix}$. The product of each set of resistance and capacitance values corresponding to the time constant τ. System noise is w, and observation noise is v.

3 Identification of Battery Model Parameters

The capacity of lithium battery is 32 Ah. The functional relationship between the open circuit voltage (OCV) and SOC can be displayed through a polynomial fitting method, but it still has its limitations for the polynomial fitting, so the fitting method is changed to use spline interpolation method.

In this paper, piecewise spline interpolation is adopted to fit the experimental data. The advantage of using spline interpolation to establish OCV model is to make the data smoother, and the whole OCV curve is continuous, so that the accuracy is higher.

According to the sampled data points, two different methods are used for data fitting. It can be seen that the degree of fitting of the 6th polynomial is significantly less than that of the cubic Spline interpolation. Therefore, Spline interpolation is used to fit the OCV-SOC curve. The interpolation results are shown in Fig. 2.

The experiment uses HPPC working conditions to identify the parameters. The test data of HPPC is brought into the FFRLS algorithm for identification, and the battery parameters can be obtained. Finally, the performance of SOC algorithm combining spline interpolation and EKF is tested under UDDS condition. Figure 3 shows the terminal voltage variation of the battery under typical UDDS operating conditions.

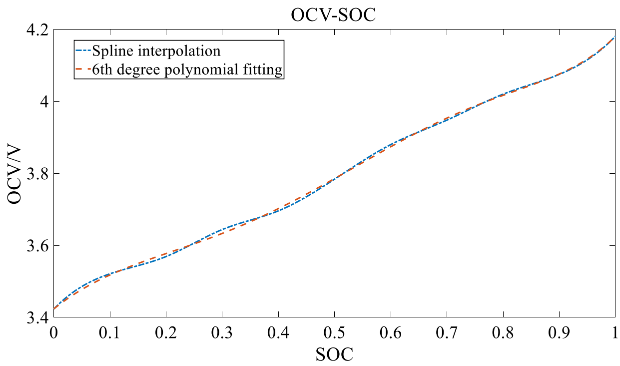

Fig. 2. OCV - SOC curve

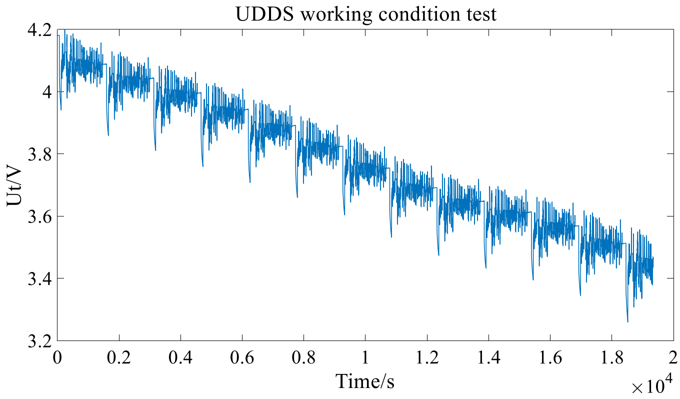

Fig. 3. Battery terminal voltage under UDDS condition

The characteristic of least square method is that it can be widely used for system identification [7]. The RLS method is an improvement on the LS method. In order to solve the problem that the number of recursive steps of least square method is too large to be corrected normally, the forgetting factor is added to eliminate this effect. The process of RLS is as follows:

If a system expression in discrete form can be written:

$$\theta_k = \sum_{i=1}^{n} m_i \theta_{k-i} + \sum_{i=1}^{n} p_i u_{k-i} + v_k \tag{5}$$

The parameter to be estimated is m_i, p_i. F is the sum of the squares of the residuals:

$$F(\psi) = \sum_{i=1}^{N} (\theta - \Phi\psi)^2 \tag{6}$$

The purpose of recursive least squares is to minimize $F(\psi)$. The equation after combining the recursive least square method with the battery model is as follows:

$$U_t = U_{oc} + (\frac{R_1}{\tau_1(x_k - x_{k-1})/T + 1} + \frac{R_2}{\tau_2(x_k - x_{k-1})/T + 1})I_t + R_0 I_t \tag{7}$$

Equation (8) can be simplified into the following form:

$$m_1 U_t v^2 + m_2 U_t v + U_t = m_1 U_{oc} v^2 + m_2 U_{oc} v + U_{oc} + m_1 R_0 I v^2 + m_3 I v^2 + m_4 I \tag{8}$$

where $m_1 = \tau_1 \tau_2$, $m_2 = \tau_1 + \tau_2$, $m_3 = R_0 + R_1 + R_2$, $m_4 = R_0 m_1 + R_1 \tau_1 + R_2 \tau_2$, $v = (x_k\text{-}x_{k\text{-}1})/T$.

Finally, the equation can be converted to the following form:

$$\begin{cases} U_{t,k} - U_{oc,k} = a_1(U_{oc,k-1} - U_{t,k-1}) + a_2(U_{oc,k-2} - U_{t,k-2}) + a_3 I_k + a_4 I_{k-1} + a_5 I_{k-2} \\ a_1 = \frac{-(2m_1 + m_2 T)}{T^2 + m_2 T + m_1} \\ a_2 = \frac{m_1}{T^2 + m_2 T + m_1} \\ a_3 = \frac{m_1 R_0 + m_3 T^2 + m_4 T}{T^2 + m_2 T + m_1} \\ a_4 = \frac{-(2m_1 R_0 + m_4 T)}{T^2 + m_2 T + m_1} \\ a_5 = \frac{m_1 R_0}{T^2 + m_2 T + m_1} \end{cases} \tag{9}$$

After a_1–a_5 are identified, the parameters of two RC model can be obtained according to the parameter relationship. The recognition image is shown below. The identification results of R_0 is shown in Fig. 4, and other parameter identification results are shown in Fig. 5, Fig. 6.

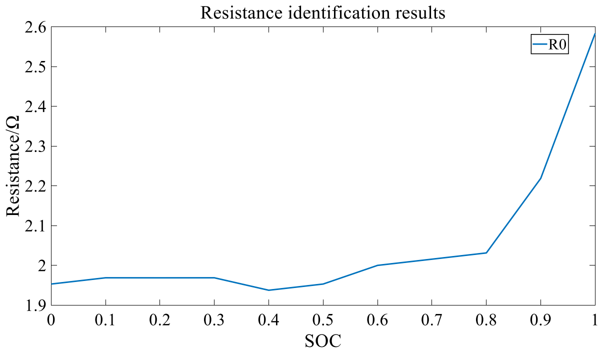

Fig. 4. R_0 identification

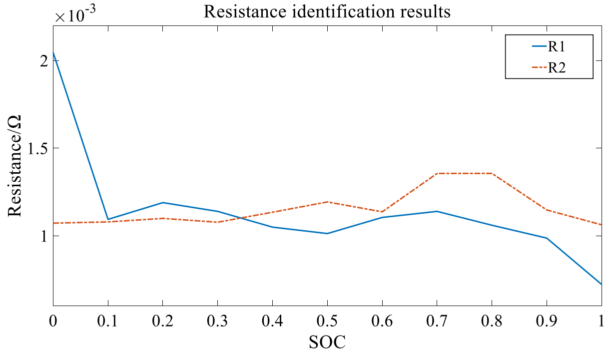

Fig. 5. $R_{1,2}$ identification

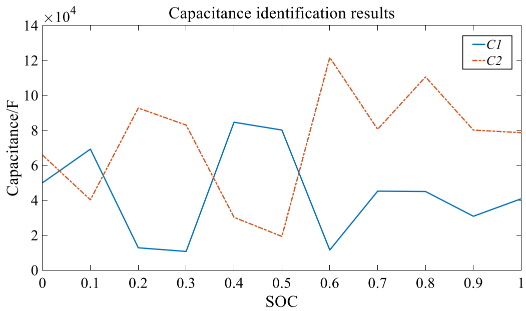

Fig. 6. $C_{1,2}$ identification

4 Battery SOC Estimated by EKF

Due to the immeasurability of SOC, in order to have a relatively accurate monitoring of battery state, a specific algorithm is needed to calculate the accurate SOC. Kalman filter algorithm is widely used in system control. The filter of the system is realized by using the principle of recursion [6]. The basic principle of kalman filter is as follows,

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + w_k \\ z_k = Mx_k + Nu_k + v_k \end{cases} \tag{10}$$

where A, B, M, N are the coefficient matrixs, and w and v are the process noise and measurement noise.

State prediction, covariance prediction and K gain are shown below:

$$\begin{cases} \hat{x}_{k+1} = A_k \hat{x}_k + B_k u_k \\ P_{pre,k+1} = A_k P_k A_k^T + Q \\ K_{kal} = P_{pre,k+1} C_{k+1}^T \left(C_{k+1} P_{pre,k+1} C_{k+1}^T + R \right)^{-1} \end{cases} \tag{11}$$

At the end of these steps, the latest state and the estimation of the covariance of the states can be calculated with the following equation:

$$\begin{cases} \hat{x}'_{k+1} = \hat{x}_{k+1} + L_{k+1}[z_{k+1} - M_{k+1}\hat{x}_{k+1} - N_{k+1}u_{k+1}] \\ P'_{pre,k+1} = (I - L_{k+1}M_{k+1})P_{pre,k+1} \end{cases} \tag{12}$$

At first, the initial value is set for the whole nonlinear system. After the initial value is set, the state of the system is predicted and its covariance is estimated for the next prediction. After iteration, the estimated result can be obtained as follows,

$$x_{k+1} \approx A'_k x_k + f(u_k, x_k) - A'_k x_k + w_k \tag{13}$$

$$z_{k+1} \approx M'_k x_k + h(u_k, x_k) - N'_k x_k + v_k \tag{14}$$

where f and h are nonlinear functions respectively, and the partial derivative of the state variable x_k is taken to carry out Taylor expansion. Their first partial derivatives are respectively used as the new coefficient matrix:

$$\begin{cases} A'_k = \dfrac{\partial f}{\partial x_k}\Big|_{x_k=\hat{x}_k}(x_k - \hat{x}_k) \\ M'_k = \dfrac{\partial h}{\partial x_k}\Big|_{x_k=\hat{x}_k}(x_k - \hat{x}_k) \end{cases} \tag{15}$$

The iteration of status updates is complete. The images of SOC accuracy value, estimated value of the battery tested under UDDS condition and the images of error curve are shown in Fig. 7, Fig. 8.

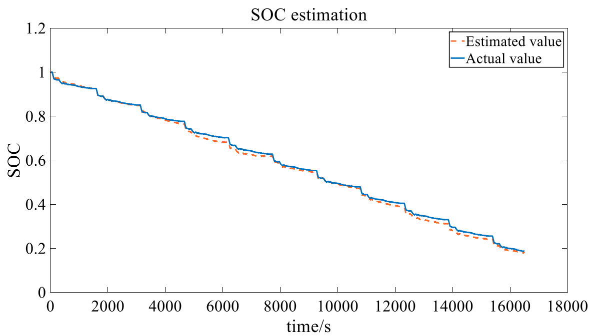

Fig. 7. SOC estimation curve

It can be seen that the estimated value at the beginning of the image still maintains a good tracking effect, but the error gradually increases at the middle and the end of the image, and the error at the end of the image decreases. After analysis, it may be related to OCV There is a problem with the fitting of the OCV-SOC curve relationship. In the interpolation curve of OCV-SOC, the curve inputted by the sample point and then spline interpolation is not accurate enough. In the subsequent work, it is necessary to use the OCV-SOC curve. Better methods will improve its accuracy in order to expect more accurate estimation results.

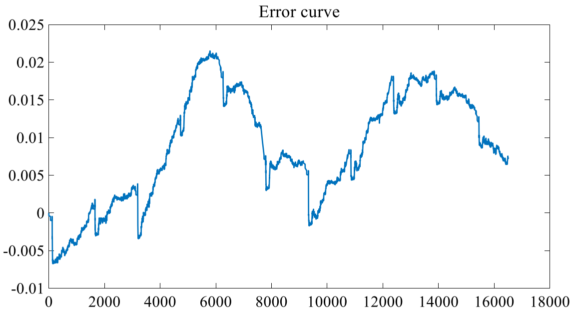

Fig. 8. SOC estimation relative error curve

5 Conclusion

For the ternary lithium-ion battery of this experiment, an equivalent two RC model is established for its characteristics, and its resistance and capacitance were identified using an improved RLS regression method with a forgetting factor for its equivalent circuit. Compared with offline parameter identification, the accuracy of this method is improved, and online parameter identification has the advantages of simple operation and less program volume. For the non-linear battery model, EKF is used to estimate the SOC, which improves the shortcomings of the extended Kalman filter that uses offline parameter identification for the estimation accuracy of the non-linear system.

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