Improved SOC Estimation Algorithm Based on Temperature Correction

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Abstract: In order to solve the problem of low accuracy of SOC estimation under complex operating environment, an improved SOC estimation algorithm based on temperature correction is proposed. First of all, considering the influence of temperature on the parameters of the battery model, the parameters of the model at different temperatures are obtained by the least square method, and the accuracy of the model parameters is verified. Secondly, under the FUDS conditions, the accurate estimation of SOC is realized by extended Kalman filter. Finally, the effect of temperature correction on SOC estimation accuracy is analyzed. The results show that the improved SOC estimation algorithm based on temperature correction improves the SOC estimation accuracy and robustness.

Introduction

The important functions of the battery management system are based on accurate SOC accuracy. The accurate estimation and high robustness of SOC are the core of the BMS, which play an important role in battery performance to prevent overcharging and overcharging, prolonging the battery life.

In the existing SOC estimation methods[1], the accuracy of the integration method depends on the sensor, and its calculation result depends on the initial value, and there is a cumulative error; The open-circuit voltage method needs a long time to stand and cannot meet the real-time requirements; The neural network method requires a lot of data training and is difficult to converge, heavily dependent on the sample size and accuracy[2]; The kalman filter can correct the initial error and is not sensitive to the initial value of SOC. The noise suppression effect is obvious and the convergence is fast, but the estimation accuracy depends on the accuracy of the battery model and the statistical characteristics of the noise[3]. The accuracy of the battery model is the key to improving the accuracy of EKF estimation.

In order to solve the problem that the current SOC estimation algorithm does not consider the influence of the working environment of the battery, resulting in a low estimation accuracy, an improved SOC estimation algorithm based on temperature correction is proposed. First, the model parameters at different temperatures are obtained by using the least square method, and the model parameters are verified. Secondly, under the condition of FUDS, the accurate estimation of SOC is realized according to the extended Kalman filter algorithm. Finally, the accuracy and robustness of the proposed algorithm are verified by compared considering temperature correction and not considering.

Create an equivalent battery model

In the battery SOC estimation, the equivalent battery model uses common circuit elements to simulate the external characteristics of the power battery. Compared with the related researches at domestic and abroad, the Rint model has the advantages of simple structure and easy to calculate, but it cannot reflect the dynamic characteristics of the battery and has lower accuracy. The Thevenin model adds a parallel RC circuit based on the Rint model, which has a simple structure and can reflect the dynamic characteristics of the battery with no accumulated error[4]; The PNGV model is based on the Thevenin model, and adds a capacitor to represent the load current cumulative voltage changes over time[5]; The second-order RC model adds an RC loop based on the Thevenin model to simulate the battery concentration difference and electrochemical polarization[6].

The n-order RC model based on Thevenin model can exactly simulate the polarization reaction of the battery, but it leads to the increase of the model complexity, the increase of computation amount and the decrease of real-time. After considering the accuracy and complexity of the battery model, this paper selects the Thevenin model for battery modeling, as shown in Figure 1.

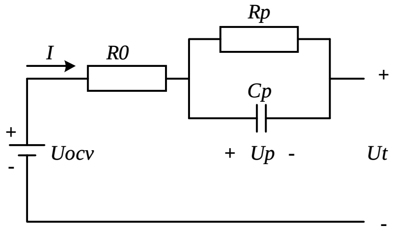

Figure 1 Thevenin equivalent circuit model

The battery's external characteristic description equation is as follows:

$$\begin{cases} U_t = U_{ocv} - U_p - I * R_0 \\ U_p = \dfrac{I}{C_p} - \dfrac{U_p}{R_p * C_p} \end{cases} \tag{1}$$

Where U_t is the operating voltage, U_{ocv} is the open circuit voltage, U_p is the polarization voltage, I is the load current, R_0 is the ohmic resistance, R_p is the polarization resistance, and C_p is the polarization capacitance.

Identify model parameters

Open circuit voltage and SOC

In order to get the SOC-OCV relationship of charge-discharge process, pulse charge-discharge test was used. The specific steps are as follows: 1) the battery is allowed to stand still at room temperature; 2) the standard charging is performed till the cut-off voltage, at this time, the SOC is 100%; 3) 1C discharged to the SOC as the target (SOC interval is 5%); 5) Repeat steps 3 and 4. The charging process is similar. In order to obtain the SOC-OCV relationship at different temperatures, experiments were performed at 0℃, 10℃, 25℃ and 40℃ respectively.

Figure 2 shows the SOC-OCV curves of charge and discharge at different temperatures. The influence of temperature on the open circuit voltage is mainly concentrated in low SOC and high SOC, and has a great impact.

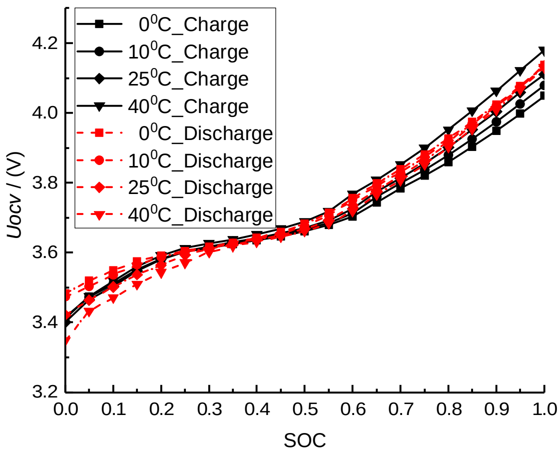

Figure2 SOC-OCV curves during charge and discharge at different temperatures

Least squares method to identify model parameters

The key to establishing the battery model lies in the identification of the model parameters, that is, calculating the ohmic resistance R_0, the polarization resistance R_p, and the polarization capacitance C_p. In the existing research, the methods of model parameter identification are mainly divided into two categories: one is to obtain the model parameters by using the terminal voltage curve during the static phase of the hybrid impulse experiment, which has strong physical meaning, but the deviation is large and can only be used in qualitative analysis; Second, through the discretization of the battery characteristic equation, using multiple linear regression algorithm or least squares method to calculate the model parameters, which has high accuracy and practicality. In this paper, the least square method is used to identify the model parameters.

Set the time constant as t_p :

$$t_p = R_p C_p \tag{2}$$

The relationship between continuous time s and discrete time t is:

$t = e^{sT}$, Where T is the sampling period.

The voltage drop inside the battery is Urc :

$$U_{rc} = U_{ocv} - U_t = U_p + IR_0 \tag{3}$$

Substituting the above formula (1) into Laplace transform, the transfer function of continuous time is as follows:

$$G(\mathrm{s}) = \frac{U_{rc}(s)}{I(s)} = \frac{(R_0 + R_p) + R_0 t_p s}{1 + t_p s} \tag{4}$$

From the relationship between continuous time and discrete time and (2), we get the transfer function of discrete time as follows:

$$G(t^{-1}) = \frac{Urc(t^{-1})}{I(t^{-1})} = \frac{a_1 + a_2 t^{-1}}{1 + a_3 t^{-1}} \tag{5}$$

Where the parameters are as follows:

$$\begin{cases} a_1 = R_0 \\ a_2 = \dfrac{(R_0 + R_p)T}{t_p} - R_0 \\ a_3 = \dfrac{T - t_p}{t_p} \end{cases} \tag{6}$$

The relationship between the model parameters and the estimated values is as follows:

$$\begin{cases} R_0 = a_1 \\ R_p = \dfrac{a_2 - a_1 a_3}{1 + a_3} \\ C_p = \dfrac{T}{a_2 - a_1 a_3} \end{cases} \tag{7}$$

The standard form of least squares is as follows:

$$z(k) = h^T(k) q + e(k) \tag{8}$$

where q is to be estimated parameters.

$$\begin{cases} z(k) = Urc(k) \\ q = \begin{bmatrix} a1 & a2 & a3 \end{bmatrix} \\ h(k) = \begin{bmatrix} -Urc(k) & I(k) & I(k-1) \end{bmatrix}^T \end{cases} \tag{9}$$

The criterion function is minimized, and the estimated value of the estimated parameters q is as follows:

$$\hat{q} = (H_L{}^T H_L)^{-1} H_L{}^T Z_L \tag{10}$$

Where, L is the total number of data.

$$\begin{cases} Z_L = \begin{bmatrix} z(1) & z(2) & \dots & z(k) \end{bmatrix}^T \\ H_L = \begin{bmatrix} h(1) & h(2) & \dots & h(k) \end{bmatrix}^T \end{cases} \tag{11}$$

Through the voltage and current sensor measurements obtained the operating voltage and current data at different times. However, the open-circuit voltage measurement requires a long time to settle. Therefore, the open-circuit voltage is obtained according to the real-time estimated SOC value based on extended Kalman filter algorithm and the *SOC-OCV* relationship. Run the above-mentioned least-squares calculation process in MatLab. After obtaining a_1, a_2, a_3, the model parameters R_0, R_p, C_p can be obtained from equation (7).

EKF estimated SOC

Battery SOC is affected by many factors and will vary with operating mode. The purpose of Kalman filtering is to remove noise interference from the data stream and to calibrate the predictions with new measurements by predicting the new state and its uncertainty. In classical Kalman filter, state variables, observed variables and system stimuli are linear, but in practical applications, the relationship between the three is not linear and requires the use of extended Kalman filter.

The state equation and observation equation of EKF are as follows:

$$\begin{cases} x_{k+1} = f(x_k, u_k) + w_k \\ y_k = h(x_k, u_k) + v_k \end{cases} \tag{12}$$

Where x is the system state variable, y is the system observation variable, u is the system excitation, w and v are the process excitation noise and the observation noise, respectively.

During battery operation, the current change will affect the other parameters (SOC, operating voltage), so the battery operating current is used as the system excitation u. In practice, changes in temperature also affect battery parameter. The sensor can be more accurately measure the battery voltage, so the operating voltage is used as the observation variable y. State variables refer to the amount of change over time under the system stimulus, so the voltage U_p of the RC loop and the battery SOC are used as the state variable x.

$$x = \begin{bmatrix} SOC & U_p \end{bmatrix}^T \ , \ y = U_t \ , \ u = I \tag{13}$$

$$SOC = SOC_0 - \frac{\int h I(t) dt}{C_N} \tag{14}$$

Where, h is the charge and discharge efficiency, C_N is the nominal capacity.

The equation of state based on Thevenin model is:

$$\begin{cases} x_k = Ax_{k-1} + Bu_k + w_k \\ y_k = U_{oc}(SOC) - U_p - R_0 u_k + v_k \end{cases} \tag{15}$$

$$A = \begin{bmatrix} 1 & 0 \\ 0 & e^{\frac{T}{R_p C_p}} \end{bmatrix} \ , \ B = \begin{bmatrix} -\frac{T}{C_N} \\ R_p(1 - e^{\frac{T}{R_p C_p}}) \end{bmatrix} \tag{16}$$

EKF estimates the specific steps are as follows:

1) initialize the relevant parameters and initial value;

2) Calculate the predicted value of state variables and covariance matrix P_k

$$\hat{x}_k = Ax_{k-1} + Bu_k \tag{17}$$

$$\hat{P}_k = A_k P_{k-1} A_{k-1}^T + Q \tag{18}$$

3) Calculate the observation matrix H_k and the Kalman gain K_k

$$H_k = \frac{\partial U_{oc}}{\partial SOC} \tag{19}$$

$$K_k = \hat{P}_k H_k^T (H_k \hat{P}_k H_k^T + R)^{-1} \tag{20}$$

4) Correcting the state estimate and covariance matrix according to the measurements at k and the Kalman gain K_k

$$x_k = \hat{x}_k + K_k(\hat{U}_t - U_t) \tag{21}$$

$$P_k = (I - K_k H_k)\hat{P}_k \tag{22}$$

where, Q and R are the covariance matrix of the excitation noise and the covariance matrix of the observation noise respectively, and I is the unit matrix.

5) Loop iterative process 2) ~ 5), to obtain SOC estimation values at different moments.

Analysis of results

In order to verify the accuracy of the model parameters identified by the least square method, and the effectiveness of the proposed algorithm, the Federal Urban Operating Conditions (FUDS) were used. At the same time, the battery temperature was introduced to verify the effect of temperature change on SOC estimation. Figure 3 and Figure 4 are the FUDS current curve and temperature curve, respectively.

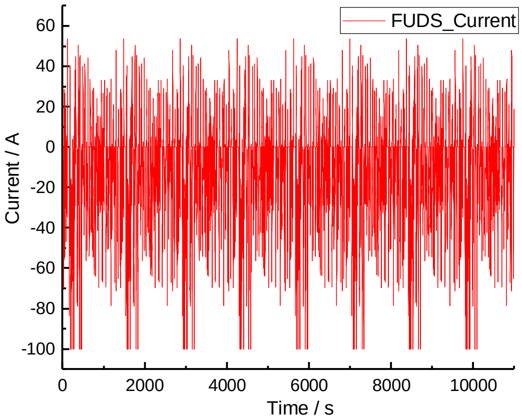

Figure 3 operating current under FUDS conditions

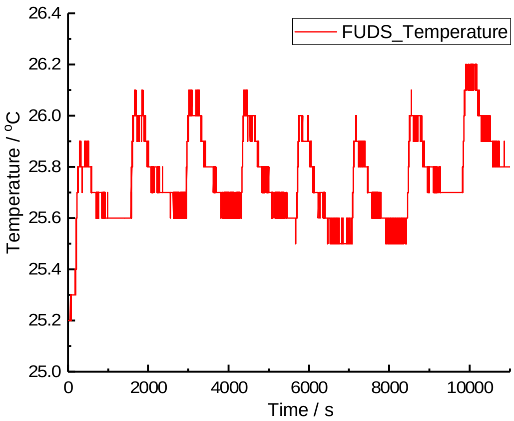

Figure 4 battery temperature under FUDS conditions

Parameter identification results

Figure 5 is the ohmic resistance R_0, the polarization resistance R_p and the polarization capacitance C_p at different temperatures, respectively, obtained through the least square method. It is found that the temperature has a great influence on the model parameters. The ohmic resistance and the polarization resistance decrease with increasing temperature, but the polarization capacitance increases with temperature. At -25ºC, Ohmic resistance and polarization resistance have increased significantly. The impact of SOC on model parameters is limited, and the model parameters vary significantly with SOC only when SOC is small.

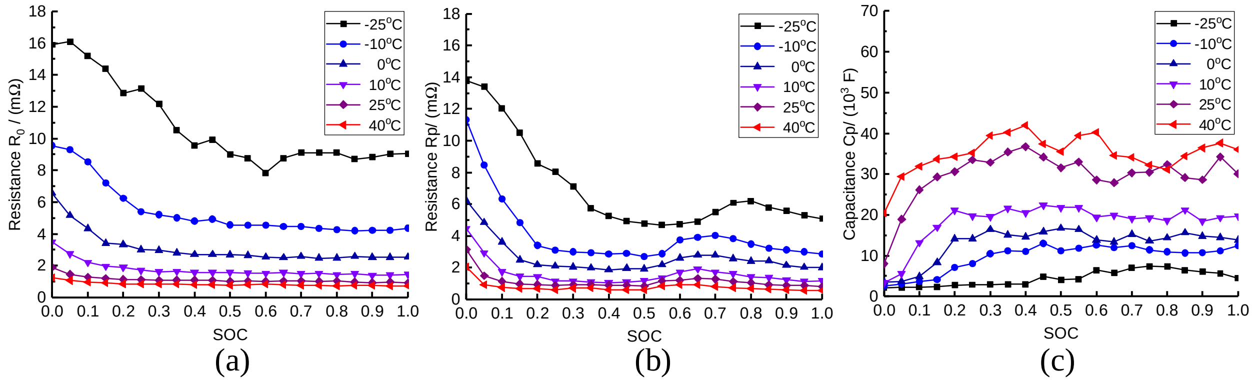

Figure 5 model parameters at different temperatures

Model parameter verification

The model parameters of the model were substituted into the equivalent battery model. The current data of FUDS was used to calculate the model operating voltage, which was compared with the working voltage to verify the accuracy of the model parameters.

Figure 6 is the comparison of the simulation working voltage and the actual operating voltage under the FUDS conditions. Figure 7 is the error of the simulation working voltage and the actual operating voltage.

It is found that the simulation voltage and the actual voltage basically coincide, and the error is roughly within the upper and lower 0.01V. However, when the voltage variation is large, the load voltage error increases greatly. In the latter part of simulation, the error increases rapidly due to the lower terminal voltage. Considering, the error is within the allowable range, indicating that the parameters of the identified model have higher accuracy and can be used for SOC estimation.

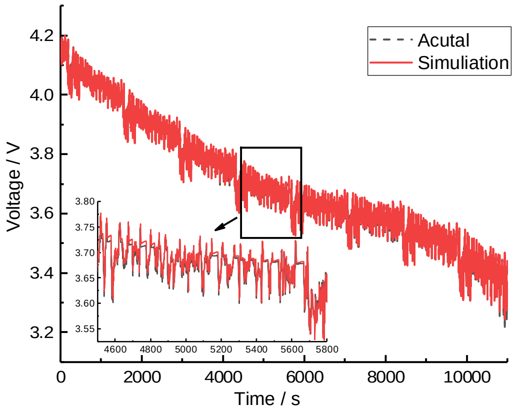

Figure 6 Operating Voltage Comparison

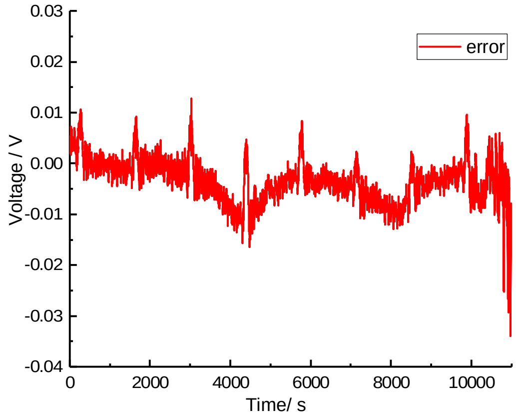

Figure 7 Operating voltage error

SOC estimation result

The SOC value based on the accurate initial SOC and safety integration is taken as SOC true value. The extended Kalman filter algorithm is used to estimate the SOC when considering the temperature factor and not considering the temperature factor, respectively, to compare with the SOC true value.

Figure 8 shows the comparison of SOC estimates and real values under FUDS conditions. Figure 9 shows the SOC estimation error. The results of EKF algorithm considering the temperature factor are closer to the true values. The maximum error is 3.45%, the mean error is 1.93% , and the root mean square error is 2.21%. In the later period, the error becomes smaller and the estimated value converges to the true value. However, the estimation results of EKF without considering the temperature factor obviously deviate from the real value, and the cumulative error is obvious. The maximum error is 6.38%, the mean error is 3.44% and the root mean square error is 3.99%.

Temperature has a great influence on the equivalent battery model parameters, and accurate model parameters are the key of EKF algorithm. Compared with considering temperature correction and without consideration, the estimation accuracy of SOC is improved by 46%.

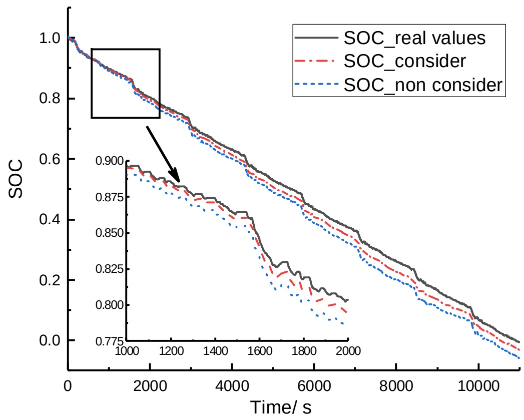

Figure 8 Comparison of SOC estimates with real values

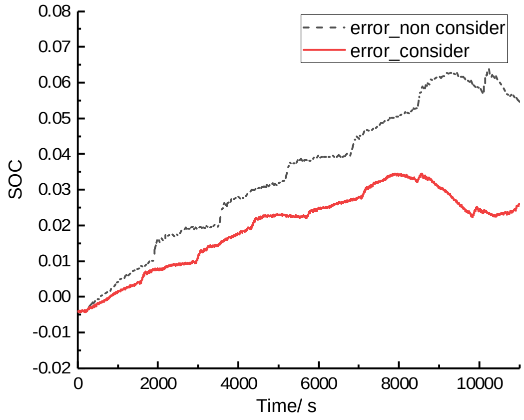

Figure 9 SOC estimation error

Table 1 SOC estimation error statistics（%）

Error Analysis	improve algorithm	Traditional algorithm
Maximum error	3.45	6.38
Mean error	1.93	3.44
Root mean square error	2.21	3.99

Conclusion

1) Based on the Thevenin model, the least square method is used to identify the equivalent battery model parameters at different temperatures, which improves the accuracy of the model parameters and is closer to the actual parameter values.

2) Under the FUDS condition, the simulation working voltage obtained by substituting the identified model parameters is calculated, and compared with the actual working voltage to verify the accuracy of the model parameters.

3) Under the FUDS conditions, the accurate estimation of SOC is realized by extended Kalman filter, including considering temperature correction and not considering.

4) Comparing the SOC estimate with the SOC true value, The experimental results show that the improved SOC estimation algorithm based on temperature correction is obviously superior to the traditional SOC estimation algorithm based on EKF algorithm, and the accuracy and robustness are obviously improved.

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