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State of Charge Estimation of Li-Ion Battery Based on Improved Extended Kalman Filter

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Abstract—**Accurate battery state of charge (SOC) estimation can reflect the endurance of power batteries, which plays an important role in the battery management system (BMS). The extended Kalman filter (EKF) estimation of SOC is easily affected by the noise of sampling voltage and current, and there are problems such as low estimation accuracy and easy divergence. This paper adopts the improved EKF to estimate SOC recursively, and the estimation accuracy is improved. Firstly, the second-order RC equivalent circuit model of the battery is established, and then the pulse discharge test is performed to identify the parameters of the model. Finally, simulation verification is carried out based on the discharge conditions of the lithium-ion battery. The results show that improved EKF has better convergence and lower error than EKF, and the average absolute error is less than 0.01.**

Keywords—state of charge, second-order RC, parameter identification, improved extended Kalman filter

I. Introduction

As the core component of electric bicycle, lithium-ion batteries have the advantages of high output voltage, high specific energy, and no pollution. In order to prevent battery overcharging, overdischarging and other problems, BMS is particularly necessary [1]. In addition, SOC estimation is an important part of BMS, which has a major impact on improving the efficiency of the battery pack, extending service life, and ensuring driving safety. Therefore, it is vital to choose a suitable battery model and estimation method [2].

SOC represents the remaining battery power, which is difficult to be measured directly by the device. Therefore, it needs to be estimated. At present, the algorithms for estimating SOC mainly include ampere-hour integration method, open circuit voltage method, neural network method and Kalman filter method [3]. The ampere-hour integration method is simple, but it is difficult to eliminate the cumulative error caused by the measurement current error. The open circuit voltage method requires the battery to stand for long enough to accurately obtain SOC, which cannot estimate the SOC in real time. The neural network method can establish a predictive model from numerous experimental data. The model can automatically realize the mapping from input parameters (such as voltage and current) to the output SOC. It has the advantages of high estimation accuracy and real-time performance [4]. However, a large amount of data is not easy to obtain, and the training of the model is not easy to converge, which is not suitable for practical engineering. Kalman filter is an optimal estimation algorithm with the smallest linear estimation bias variance. Due to the nonlinearity of lithium-ion battery charging and discharging, EKF is widely used to estimate the SOC in practice [5,6]. However, the actual sampling voltage and current will have deviations and noise, which cause the accuracy of EKF estimation to decrease. In order to reduce the impact of noise, this paper adopts improved extended Kalman filter to estimate SOC and adaptively adjust the variance of the observed noise [7]. In other words, while the system is working, it constantly adjusts the noise statistics to improve the SOC estimation accuracy.

In this paper, the establishment and parameter identification of the second-order RC model are given in Section II. The process of improved algorithm to estimate the SOC is introduced in Section III. Simulation and comparative analysis of the SOC estimation results are discussed in Section IV, and conclusions are drawn in Section V.

II. Second-order RC Model

A. Battery State Equation

A suitable battery model can make a more accurate SOC estimation. At present, the equivalent circuit model uses resistors and capacitors to describe the external characteristics of battery, which has good practicability for various working conditions. In addition, It can derive the state equation of the model for easy analysis and application. Therefore, it is widely used in new energy vehicle modeling and simulation research. The paper adopts a second-order RC equivalent circuit model, as shown in Fig 1, consisting of a resistor and two RC in series. The model can more fully reflect the static and dynamic characteristics of lithium-ion batteries, and has higher accuracy than the Thevenin model [8].

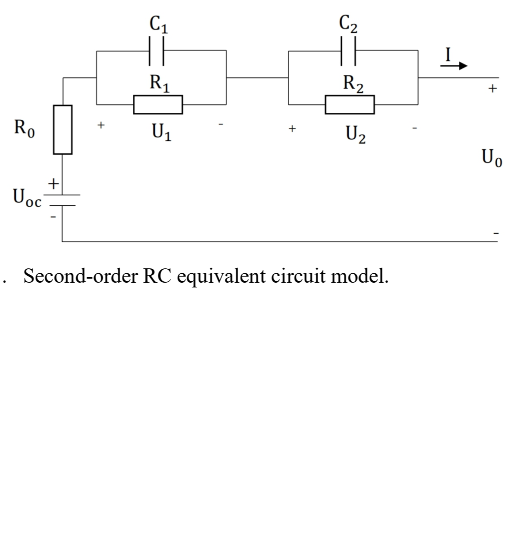

Fig. 1. Second-order RC equivalent circuit model.

In this model, U_{oc} represents the open circuit voltage and R_0 is the internal resistance. R_1C_1 and R_2C_2 in parallel show the electrochemical polarization effect. In addition, U_o is the load side voltage and I represents the real-time current in equivalent circuit. Based on Kirchhoff law, the equation of the circuit model is described as (1).

$$\begin{cases} \dfrac{dU_1}{dt} = \dfrac{I}{C_1} - \dfrac{U_1}{R_1C_1} \\ \dfrac{dU_2}{dt} = \dfrac{I}{C_2} - \dfrac{U_2}{R_2C_2} \\ U_o = U_{oc} - U_1 - U_2 - IR_0 \end{cases} \tag{1}$$

U_1 and U_2 are the voltages across R_1C_1 and R_2C_2 respectively. In addition, every parameter of the model can be approximated by the functional relationship of SOC. SOC is defined as follows,

$$SOC = SOC_0 - \frac{1}{C_n}\int \eta I dt \tag{2}$$

where SOC_0 is the initial state of charge, C_n represents the battery capacity. η is the Coulomb efficiency. For the convenience of calculation, η takes 1. Based on the above formula (1) and (2), the state equation can be discretized:

$$\begin{bmatrix} U_1(k+1) \\ U_2(k+1) \\ SOC(k+1) \end{bmatrix} = \begin{bmatrix} e^{-T/R_1C_1} & 0 & 0 \\ 0 & e^{-T/R_2C_2} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} U_1(k) \\ U_2(k) \\ SOC(k) \end{bmatrix} + \begin{bmatrix} R_1(1-e^{-T/R_1C_1}) \\ R_2(1-e^{-T/R_2C_2}) \\ -T/C_n \end{bmatrix} I(k) \tag{3}$$

the discrete measurement equation is as (4).

$$U_o(k) = U_{oc}(SOC(k)) - R_0 I(k) - U_1(k) - U_2(k) \tag{4}$$

B. Parameter Identification

In order to determine the parameter values of the model, pulse discharge test is performed to identify the parameters. When the battery is discharged once, it releases 10% of capacity, and then stands for one hour to eliminate the polarization effect as much as possible, so as to reciprocate. The voltage after standing still can be used as the open circuit voltage under the SOC, which is fitted with a polynomial. The fitting curve is shown in Fig 2.

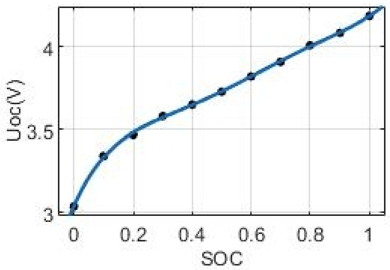

Fig. 2. U_{oc} -SOC curve

In order to identify the resistance and capacitance parameters in the model under different SOC values. The pulse experiment curve of one cycle is given in Fig 3 to illustrate t process of parameter identification.

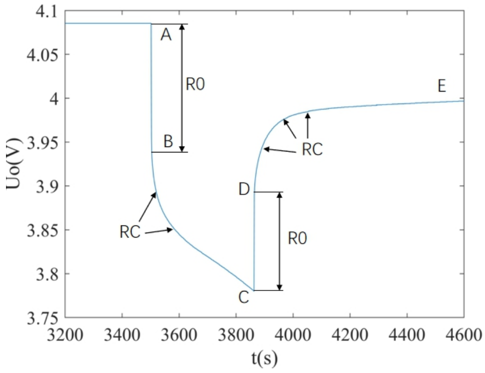

Fig. 3. Pulse discharge voltage curve

As shown in Fig 3, due to the ohmic resistance, the voltage will change suddenly, such as the change from A to B and C to D. Therefore, the R_0 can be expressed as (5).

$$R_0 = \frac{(U_A - U_B) + (U_D - U_C)}{2I} \tag{5}$$

The voltage change from B to C is mainly caused by the polarization reaction of the battery. At this stage, it is the zero state response of the RC circuit. Based on the second-order RC equivalent circuit model and pulse discharge, U_1 and U_2 can be shown as (6).

$$\begin{cases} U_1 = IR_1(1-e^{-t/R_1C_1}) \\ U_2 = IR_2(1-e^{-t/R_2C_2}) \end{cases} \tag{6}$$

Combining (4) and (6), the values of R_1, C_1, R_2 and C_2 under the SOC can be fitted and solved by the voltage curve at this stage. The identified parameters are shown in Table 1.

TABLE I. PARAMETER IDENTIFICATION RESULT

SOC	R_0/mΩ	R_1/mΩ	C_1/F	R_2/mΩ	C_2/F
0	111.51	27.039	12858	25.642	5119.6
0.1	78.26	26.065	2164.6	8.4738	3243.2
0.2	44.74	11.112	8937.5	4.447	12984
0.3	54.32	16.603	13885	5.8259	18704
0.4	55.38	16.73	11358	5.7242	18662
0.5	50.95	14.649	9171.9	5.5499	13649
0.6	49.37	13.691	9498.8	5.7543	12180
0.7	53.08	15.041	12437	5.6751	15503
0.8	50.61	14.663	10900	6.1564	13456
0.9	54.39	15.578	8125.1	6.9832	7621.1
1.0	51.48	12.092	326.15	8.0613	41729

III. Improved Algorithm for SOC Estimation

A. Second-order EKF Algorithm

The Kalman filter algorithm is an optimal estimation in the sense of a minimum variance in a linear system. It makes full use of the measurement data, and adopts recursive method to filter out the random noise, which can obtain the accurate spatial state value. In addition, when the initial values are given, based on the state value at time k-1, the input and observed value at time k, the state estimation at time k can be achieved by recursion. However, the state space of lithium-ion batteries is not linear. In order to get an approximate linearization relationship, EKF introduces Taylor expansion to linearize the battery model and omits high-order terms. Then EKF makes the optimal estimation under the Kalman algorithm. The battery space state equation and observation equation are described as (7).

$$\begin{cases} x_{k+1} = f\left(x_k, u_k\right) + w_k \\ y_k = h\left(x_k, u_k\right) + v_k \end{cases} \tag{7}$$

where x_k is the state vector of the system at time k. u_k is the input current, and y_k represents the observed value. h and f represent non-linear state function and observation function respectively. w_k is the white noise of the system with mean zero and its covariance is Q_k . v_k is the white noise of the measure with mean zero and its covariance is R_k . In addition, the two are independent of each other. After the state equation and observation equation in (7) is linearized, it can be expressed as (8).

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + w_k \\ y_k = Cx_k + Du_k + v_k \end{cases} \tag{8}$$

A represents the state transition matrix, and B is system control matrix. C represents the observation matrix, and D is feedforward matrix. They are as follows,

$$A = \begin{bmatrix} e^{-T/R_1C_1} & 0 & 0 \\ 0 & e^{-T/R_2C_2} & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} R_1(1-e^{-T/R_1C_1}) \\ R_2(1-e^{-T/R_2C_2}) \\ -T/C_n \end{bmatrix}$$

$$C = \begin{bmatrix} \text{-1, -1, } \dfrac{\partial U_{oc}(SOC)}{\partial U_{oc}} \end{bmatrix}, \ \mathrm{D} = \left[-R_0\right]$$

T is the sampling time, which is 1s. The EKF algorithm to estimate SOC mainly includes the following steps:

1. The initialization of state variables and error covariance P_k .

$$\begin{cases} \hat{x} = E(x_0) \\ \hat{P}_0 = E\left[\left(x_0 - \hat{x}_0\right)\left(x_0 - \hat{x}_0\right)^T\right] \end{cases} \tag{9}$$

2. The forecast of state variables and error covariance.

$$\begin{cases} x_{k+1|k} = Ax_{k|k} + Bu_k + w_k \\ P_{k+1|k} = AP_{k+1|k}A^T + Q_k \end{cases} \tag{10}$$

3. Kalman gain calculation.

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

4. The update of the correction state and covariance.

$$\begin{cases} x_{k+1|k+1} = x_{k+1|k} + K_{k+1}\left(U_o(k) - Cx_{k+1|k}\right) \\ P_{k+1|k+1} = \left(E - K_{k+1}C\right)P_{k+1|k} \end{cases} \tag{12}$$

B. Improved Extended Kalman Filter

Based on the iterative update of above-mentioned EKF algorithm, the SOC estimation value can be continuously revised. However, the main disadvantage of EKF is that the noise will not change during estimation process. If inaccurate noise variance is used in this process, it will cause system errors to accumulate, leading to system divergence and increasing errors. Therefore, we need improve the accuracy and robustness of the estimation system. In order to realize dynamic correction of the observed noise, the innovation e_k is introduced as (13).

$$e_k = y_k - h\left(\hat{x}_{k|k-1}, u_k\right) \tag{13}$$

Based on the first-order Taylor expansion, the observation equation can be shown as (14).

$$y_k = Cx_k + \left[h\left(\hat{x}_{k|k-1}, u_k\right) - C\hat{x}_k\right] + v_k \tag{14}$$

Combining (13) and (14), the covariance of innovation and innovation are as (15).

$$\begin{cases} e_k = C\left(x_k - \hat{x}_k\right) + v_k \\ E\left(e_k e_k^{\,T}\right) = CP_{k|k-1}C^T + R_k \end{cases} \tag{15}$$

Furthermore, the sampling average can be replaced by the time average [7]. Then the expression is given in (16) and (17).

$$y_k = CP_{k|k-1}C^T + R_k \tag{16}$$

$$\begin{aligned} y_k &= \frac{1}{k+1}\sum_{i=0}^{k} e_k e_k^{\,T} \\ &= \frac{1}{k+1}e_k e_k^{\,T} + \frac{k}{k+1}y_{k-1} \end{aligned} \tag{17}$$

The final observation noise variance is (18).

$$R_k = \frac{1}{k+1}e_k e_k^{\,T} + \frac{k}{k+1}y_{k-1} - CP_{k|k-1}C^T \tag{18}$$

Compared with the EKF, the observation noise of the improved extended Kalman filter is no longer a fixed value. It introduces dynamic observation noise, and then performs SOC estimation under the iterative process of EKF.

IV. SIMULATION VERIFICATION

In order to further compare the SOC estimation accuracy of EKF and improved EKF, this paper selects 18650 lithium-ion battery with 3.5AH capacity as the experimental object. Besides, the charge cut-off voltage is 4.2V. The discharge cut-off voltage is 2.7V, and the maximum discharge current is 10A. Based on 1C constant current discharge condition, we obtain experimental data, including sampled voltage, current and discharge time. The results of the SOC estimated by EKF and improved EKF, and actual SOC values are shown in Fig 4. The estimation error is shown in Fig 5.

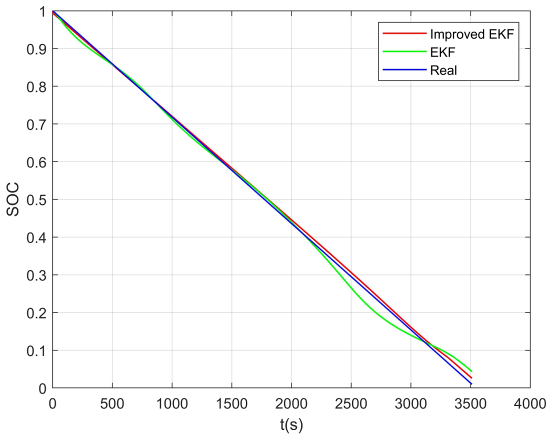

Fig. 4. The results of the EKF and improved EKF estimation.

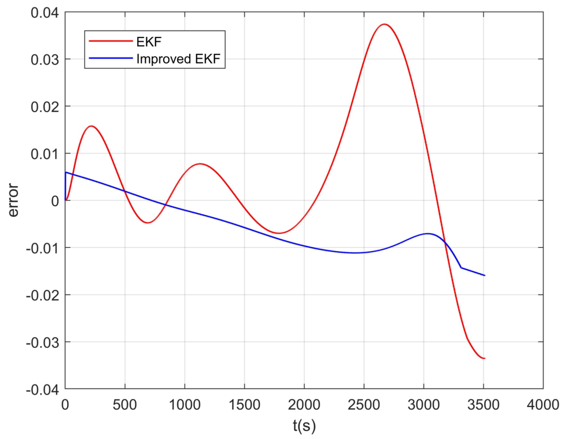

Fig. 5. The results of SOC estimation error.

As shown in Fig 4, the estimated SOC values of EKF deviate from the true SOC values for a period of time, and the degree of deviation is greater than the improved EKF. In addition, the error of EKF estimation is obviously larger than improved EKF for a long period of time. Through calculation and analysis, it can be known that the average absolute error of the SOC estimation based on EKF is 1.2%, and the maximum error is 3.74%. However, the average absolute error of the SOC estimation based on improved EKF is 0.69%, and the maximum error is 1.6%. Compared with EKF, the maximum error of SOC estimation by the improved EKF is reduced by 2.14%. This result shows that improved EKF has a better estimation performance than the EKF, which can prevent the divergence caused by the excessive estimation error.

V. CONCLUSIONS

In this paper, based on the pulse discharge test, the discharge voltage and current of the lithium-ion battery are collected. Then a second-order RC equivalent circuit model is established, and the model parameters are identified. Among various methods of battery state-of-charge estimation, the extended Kalman filter algorithm based on model is adopted. At the same time, in order to suppress the influence of noise and sampling error on the accuracy of SOC estimation, the improved extended Kalman filter algorithm is used for SOC recursive estimation based on the dynamical observation noise. Simulation verification shows that the improved extended Kalman filter has a better estimation effect, which enhances robustness and anti-interference.

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