International Journal of Smart Grid and Clean Energy

SOC estimation of lithium-ion battery at low temperature

Wenkang Gao, Shenghui Wang, Xipeng Miao

School of Electrical and Electronic Engineering, Changchun University of Technology, Changchun, 130012, China

Abstract

The evolution of interfacial compatibility, stability of electronic impedance, ion migration mechanisms at grain boundaries and molecular dynamics properties within lithium-ion batteries under low-temperature conditions greatly challenges the prediction of the state of charge. In the present study, considering that the lithium-ion battery is susceptible to the operating temperature environment, an improved second-order RC equivalent circuit model is developed, and the parameters of the temperature model are identified by the least squares method to verify the accuracy of the model parameters. The extended Kalman filter algorithm is used to estimate the SOC value. The improved model and algorithm have high accuracy in a low-temperature environment, which is a method for battery SOC prediction under low-temperature conditions of lithium-ion batteries and an effective guarantee for stable operation and safe use of lithium-ion batteries at low temperatures.

Keywords: Lithium-ion battery, SOC, Extended Kalman filter, low temperature

1. Introduction

With the rapid development and progress of society, the consumption of energy increases rapidly, and the energy crisis spreads to the whole world. The transportation sector has become the industry with the fastest growth of fuel consumption in the world [1]. In recent years, lithium-ion batteries have been widely used in electric vehicles with the advantages of high energy density, low self-discharge performance, fast charging speed, long life and no pollution, and have become the mainstream power source of electric vehicles [2]. The State of Charge (SOC) estimation of batteries is the most basic and primary task in the battery management system, which is related to the working state of batteries and personal safety of users [3]. Considering the advantages and disadvantages of various estimation methods, this paper adopts the extended Kalman filter method combined with the proposed improved second-order RC battery model to complete the dynamic estimation of battery SOC in cold and high temperature environment.

2. Establish an Equivalent Model

The existing battery models include Rint, RC, Thevenin, PNGV、DP models, all of which belong to ECM or electrochemical models. And then there's the EM equivalent circuit model. The change of temperature affects the internal reaction of the battery, and the internal reaction of the battery is slow in low temperature environment, which affects the charging and discharging characteristics of the battery, and then affects the SOC estimation of the battery. The second-order equivalent RC circuit is shown in Fig. 1. Where: U_{oc} is the open-circuit voltage; U_T is the terminal voltage; $U_1(t)$ and $U_2(t)$are the voltages at both ends of R_1 and R_2, respectively; R_0, R_1 and R_2 are ohmic internal resistance, ohmic polarization resistance and electrochemical polarization resistance, respectively. C_1 and C_2 are ohmic polarization capacitance and electrochemical polarization capacitance, respectively. Kirchhoff's voltage law (KVL) and current law

* Manuscript received October 9, 2022; revised October 10, 2022.
Wen Kang Gao. Tel.: 15516919417; *E-mail address:* 451353068@qq.com
Sheng Hui Wang. Tel.: 18686517333; *E-mail address:* wangshenghui@ccut.edu.cn
Xi Peng Miao. Tel.: 17854335187; *E-mail address:* 1728723772@qq.com
doi: 10.12720/sgce.11.4.135-140

(KCL) are used to describe the relationship between capacitance, voltage and current in the improved cell model. The specific relationship is as follows:

$$\dot{U}_1 = \frac{I_t}{C_1} - \frac{U_1}{R_1C_1} \quad , \dot{U}_2 = \frac{I_t}{C_2} - \frac{U_2}{R_2C_2}, U_t = U_{oc}(SOC,T) - U_1 - U_2 - I_tR_0 \tag{1}$$

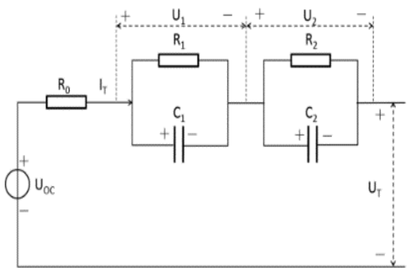

Fig. 1. Second-order RC equivalent circuit

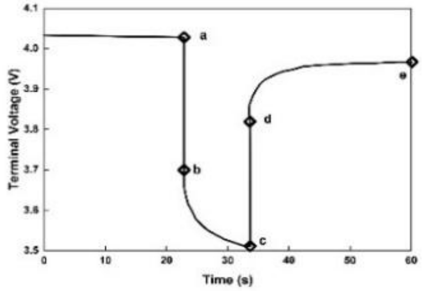

Fig. 2. Enlarged view of a pulse of HPPC

3. Model Parameter Identification and Verification

Accurate parameter identification is crucial to the accuracy of SOC prediction results. The charging and discharging device is used to collect battery current, voltage and other data, and then the approximate mathematical model of battery available capacity is obtained by fitting the data of battery available capacity. Finally, the least square method is used to complete the battery parameter identification [4].Considering the relaxation phenomenon of battery open-circuit voltage OCV under charge and discharge conditions, and using the HPPC test curve for parameter identification, the ohmic resistance R_0 value was obtained. The relevant parameters of R_1、R_2、C_1、C_2 can be obtained by using the least square method[5]. An enlarged view of a pulse is as Figure2For the second order RC model shown in figure1, once the charge/discharge current execution or stop, terminal voltage will fall or rise immediately, but the voltage of capacitor $C_1$and C_2、$U_1$and U_2 are not at the start of discharge/charge moment of sudden change, so from the beginning of discharge/charge moment the change of the terminal voltage R_0 ohm resistance can be determined. Therefore, R_0 ohm resistance can be represented by the type:

$$R_0 = \frac{|U_T(t_b) - U_T(t_a)| + |U_T(t_d) - U_T(t_c)|}{2|I_t|} \tag{2}$$

Parameter R1、R2、C1、C2 identification is divided into two steps. The first step to determine the time constant $\tau_1 = R_1C_1, \tau_2 = R_2C_2$. According to the identified time constants, R1、R2、C1、C2 are further identified in detail.

$$U_t = U(t_0)e^{-\frac{t-t_0}{\tau}} + IR(1 - e^{-\frac{t-t_0}{\tau}}) \tag{3}$$

t_0 is the initial time. The current is equal to zero during the relaxation process c−d−e. Depending on the type, can calculate the voltage U_1、U_2 as follows:

$$U_1(t) = U_1(t_c)e^{-\frac{t-t_c}{\tau_1}} ,U_2(t) = U_2(t_c)e^{-\frac{t-t_c}{\tau_2}} ,\ U_T(t) = U_{oc}(SOC) - U_1(t_c)e^{-\frac{t-t_c}{\tau_1}} - U_2(t_c)e^{-\frac{t-t_c}{\tau_2}} \tag{4}$$

$$\text{To:} U_T(t) = \alpha_1 - \alpha_2 e^{-\frac{t-t_c}{\beta_1}} - \alpha_3 e^{-\frac{t-t_c}{\beta_2}} \tag{5}$$

Among them, the α_1、α_2、α_3、β_1、β_2 as the unknown coefficients, Need recognition at the end of the relaxation process measurement $\alpha_1 = U_T(\infty)$, namely, point e. Using the MATLAB function "Custom Equations" in the Curve Fitting Toolbox, Can get the optimal coefficient α_1、α_2、α_3、β_1、β_2Therefore, to determine the time constant τ_1，$\tau_2$and voltage$U_1(t_c)$，$U_2(t_c)$. The second step is to determine the parameters in the discharge process a - b – c R_1、R_2、C_1、C_2. Notice that point a is the end of the relaxation process. Then $U_1(t_a) = 0, U_2(t_a) = 0$.According to Equation (4), it can be known that:

$$U_1(t) = I_T R_1\left(1 - e^{-\frac{t-t_a}{\tau_1}}\right),\quad U_2(t) = I_T R_2(1 - e^{-\frac{t-t_a}{\tau_2}}) \tag{6}$$

Therefore, the resistance R_1、R_2 be determined by the following formula:

$$R_1 = \frac{U_1(t_c)}{I_T(1-e^{-\frac{t_c-t_a}{\tau_1}})},\quad R_2 = \frac{U_2(t_c)}{I_T(1-e^{-\frac{t_c-t_a}{\tau_2}})} \tag{7}$$

3.1. Experimental procedure

(1) Capacity characteristic test (Capacity test at different temperatures)

① Place the battery at the appropriate temperature for 1 hour. Ensure that the internal temperature of the battery is consistent with the preset temperature.

② Set six groups of experiments, the temperature is -20, -10, 0, 25℃.Charge the battery at constant current and constant voltage (0.5C) at different temperatures, charge to cut-off voltage, stand for 1h, and then reach cut-off voltage with constant current of 0.5C

(2)HPPC test

The following experimental steps were carried out at -20, -10, 0, and 25℃, respectively

① 0.5C constant discharge for 10S, standing for 50S;0.5C constant current charge for 10S and stand 50S

② 1C constant current charge for 10S and stand 50S;1C constant current charge for 10S, stand 50S

③ 1.5C constant discharge for 10S, stand 50S;1.5C constant current charge for 10S, standing 50S

④ 2C constant current discharge for 10S, standing 50S;2C constant current charging for 10S, standing for 50S;

⑤ 10%SOC(measured by the above capacity characteristics experiment) constant current discharge up to the cut-off voltage.

Repeat the above experimental steps to obtain 90%SOC, 80%SOC.......After fitting and identification of the one-to-one correspondence between 10%SOC and open-circuit voltage OCV, the parameter values of the second-order RC circuit model are obtained, as shown in Table 1.

Table 1. Identification results at each temperature parameter

T/℃	R_0/mΩ	R_1/mΩ	R_2/mΩ	C_1*10^3F	C_1*10^3F
25	78.83	9.74	17.38	2.38	10.22
0	278.6	10.72	24.40	1.55	5.09
-10	299.5	16.91	30.51	1.39	4.27
-20	302.7	18.3	32.89	1.00	3.88

4. EKF Algorithm

In order to apply EKF algorithm to SOC estimation of battery model considering the influence of ambient temperature. Firstly, for the battery model in Figure 1, equation (1) needs to be discretized as:

$$\begin{aligned} U_{1,k} &= exp(-T_s/\tau_1)U_{1,k-1} + R_1(1 - exp(-T_s/\tau_1))I_{t,k-1} \\ U_{2,k} &= exp(-T_s/\tau_2)U_{2,k-1} + R_2(1 - exp(-T_s/\tau_2))I_{t,k-1} \\ U_{t,k} &= U_{oc}(SOC,T) - R_0 I_{t,k-1} - U_{1,k} - U_{2,k} \end{aligned} \tag{8}$$

T_s as the sampling interval. Secondly, define the system state , $x_k$measured values for y_k and input matrix U_k as follows:

$$x_k = [SOC_k \ U_{1,k} \ \ U_{2,k}]^T, y_k = U_{t,k}, U_k = I_{t,k} \tag{9}$$

The SOC_k for time step k observed SOC, its calculation formula is:

$$SOC_k = SOC_{k-1} - \frac{I_{t,k}\eta T_s}{C_{cap}} \tag{10}$$

Where, C_{cap} is the rated capacity, η is the Coulomb efficiency (assumed to be 1 under charging condition and 0.98 under discharge condition); $I_{t,k}$ is the load operating current. Finally, the discrete-time state space equation of the battery model considering the influence of ambient temperature is:

$$x_k = Fx_{k-1} + BU_{k-1} + \omega_{k-1}, y_k = Hx_k + DU_k + \upsilon_k \tag{11}$$

The system matrices F, B, H and D are defined as follows: $F_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & exp\left(-\frac{T_s}{\tau_1}\right) & 0 \\ 0 & 0 & exp\left(-\frac{T_s}{\tau_2}\right) \end{bmatrix}$

$$B_k = \begin{bmatrix} \frac{\eta T_s}{C_{cap}} \\ R_1(1 - exp\left(-\frac{T_s}{\tau_1}\right)) \\ R_2(1 - exp\left(-\frac{T_s}{\tau_2}\right)) \end{bmatrix}; H_k = [\alpha \quad -1 \quad -1]; D_k = [-(R_0 + R_{temp})]$$

α is OCV - SOC under different environmental temperature curve of the slope, usually by linear interpolation to calculate.

5. Experiment and Analysis

According to the discharge condition, four temperatures such as -20℃, -10℃, 0℃ and 25℃ were selected for comparison. In order to reduce the errors caused by individual differences in batteries, experimental methods and data processing, the same batch of batteries were selected for the experiment.

5.1. Analysis of experimental results and error analysis

The curves of battery discharge and SOC estimation results at -20, -10, 0, 25 degrees Celsius are drawn as Figure 3:

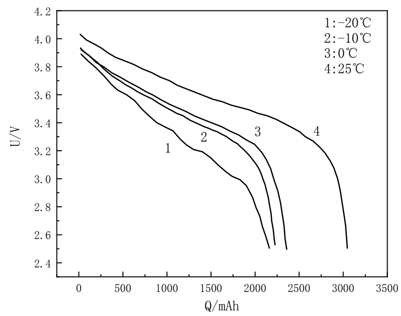

Fig. 3. Discharge diagram at different temperatures

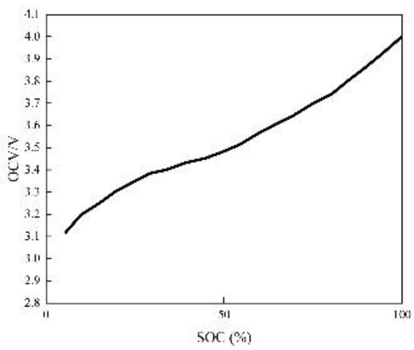

Fig. 4. OCV-SOC curve

There are few researches on improving SOC estimation accuracy in low temperature environment. CAI Yi shan et al. [6] estimated battery SOC based on adaptive two-step filtering (ATSF) algorithm and reduced the estimation error to less than 2% by improving the robustness of measurement noise. Li Jia bo et al. [7] established an online SOC estimation model using Gaussian regression, and checked the calculation and found that the error of SOC estimation at room temperature was less than 2%.J.safi et al. [8] introduced the noise factor in voltage sensors and the collective estimation temperature change factor into the collective estimation method, and improved the SOC estimation accuracy to about 98%.I.u.khalil et al. [9] equivalent the battery pack model to the state space equation of the second-order Davinan circuit model, and used the state space integral and extended Kalman filter (EKF) algorithm to estimate SOC. Under the condition of model height matching and normal temperature, the error was less than 1%.J.W et al. [10] established a model of lithium iron phosphate positive lithium ion battery based on low temperature by calibrating battery capacity and determining battery parameters, verified the accuracy through simulation, and then used EKF algorithm to estimate SOC at different temperatures. The simulation results show that the SOC estimation error is less than 2%, but the algorithm is complicated and the computation is large.Y.j.wang et al. [11]

In order to verify the effectiveness and accuracy of the algorithm, the above methods are integrated into the following error analysis. Compare the capacity of the actual value (Q_{real}) and estimate (Q_{est}) capacity error $Q_{error} = \frac{Q_{real}-Q_{est}}{Q_{real}} \times 100\,\%$ to calculate the data in figure3, from the global perspective, a global error average and maximum global error, Table 2 lists the results.

Table 2. Global error and maximum error in each environment

The environment temperature /℃	The global error /%	Maximum error /%
-20～-10	2.48	9.72
-10～0	2.46	9.32
0～25	1.76	5.48

Under the condition of low temperature, the error of prediction result is relatively large, because the electrolyte in the battery will partially condense at low temperature, the chemical reaction of the battery will lag, and the polarization and impedance will increase, which will enhance the nonlinear relationship between the input quantity and the estimator, thus leading to the increase of error [12].

6. Conclusion

Under the low temperature condition of -20 ~ -10℃, the global error of SOC estimation of the established estimation model is 2.48%, and the maximum error is 9.72%. The accuracy is high, and the data of current, voltage and ambient temperature during battery discharge are easy to obtain, so the data-driven method has certain engineering application value [12].

References

[1] Chengyong Z. SOC and SOH estimation method of power Lithium-ion batter. Chongqing University of Posts and Telecommunications, 2019.

[2] Chuang Y. Research on State of Charge Estimation algorithm of ternary lithium ion Battery based on dynamic model. Harbin Institute of Technology, 2019.

[3] Wenjie F. 18650 Lithium ion Battery Safety Performance Research under Mechanical Abuse. Taiyuan University of Technology, 2019.

[4] Hui P, Long G, Longxing W, Jiamin J, Kai L. An improved dual-polarization model and its State of charge estimation for lithium ion battery considering the influence of ambient temperature. *Transactions of China Electrotechnical Society*, 2021.

[5] Lianjing M, SOC and SOH estimation of automotive lithium ion battery considering the influence of ambient temperature and cycle times.

[6] Yishan C, Lin Y, Zhongwei D, et al. Battery SOC estimation algorithm based on adaptive two-step filtering. *Power Supply Technology*, 2019;43(6):1022-1026.

[7] Jiabo L, Meng W, Min Y, et al. SOC estimation of lithium ion battery based on gaussian process regression. *Energy Storage Science and Technology*, 2020;1(9):131-137.

[8] Safi J, Beeney M, Kehs M, et al. Improving SOC accuracy using collective estimation for lithium ion battery cells in series. Portland: In: *Proc. of* American Control Conference, 2014:254-259.

[9] Khalil IU, Ahsan M, Ullah I，et al. SOC prediction of li-thium-ion battery using extended Kalman filter. *Islamabad:* In: *Proc. of International Symposium on Recent Advances in Electrical Engi-neering(RAEE)*, 2018:1-5.

[10] Wu J, LI T, ZHANG H, et al. Research on modeling and SOC esti-mation of lithium iron phosphate battery at low temperature.

Energy Procedia, 2018; 152:556-561.

[11] Wang YJ, Zhang CB, Chen ZH. A method for state-of-chargeestimation of Li Fe PO4batteries at dynamic currents and temperatures using particle filter. *J Power Sources*, 2015; 279:306-311.

[12] Niu XQ, Tian JJ, Zhao F, Wang Y. SOC estimation of lithium ion batteries under different ambient temperatures. *Battery*, 2021.