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EXPERIMENTAL STUDY ON THE EFFECTS OF MODEL PARAMETERS ON STATE OF CHARGE ESTIMATION OF LITHIUM-ION BATTERIES

Yong Tian, Rucong Lai, Zhibing Zeng, Xiaoyu Li, Jindong Tian*

College of Physics and Optoelectronic Engineering, Shenzhen University, Shenzhen 518060, China

ABSTRACT

An appropriate battery model is crucial for accurate state of charge (SOC) estimation of lithium-ion batteries. A complex battery model can improve the accuracy, however, it leads to high computational cost. In this paper, the second-order resistor-capacitor (RC) model is selected due to its superiority in good balance between accuracy and complexity. Different factors, including RC parameters of battery model, relationship between open circuit voltage (OCV) and SOC, and measurement noise are investigated to extract the ones that significantly affect the accuracy of SOC estimation based on Kalman filters. The results revealed that in comparison with the resistors, the polarization capacitors have no obvious influence on the SOC estimation. In addition, the voltage measurement noise has greater influence on the SOC estimation compared with the current measurement noise. These results can be potentially used to guide us in deciding which parameters should be separately identified online and offline so as to achieve a proper balance between model accuracy and complexity.

Keywords: lithium-ion battery, state of charge, model parameters, Kalman filters

1. INTRODUCTION

Currently, development and application of electric vehicles (EVs) have become a global consensus [1]. Lithium-ion batteries (LIBs) are considered to be the most promising power battery for EV applications due to their high energy/power density, high voltage of a single cell, long lifespan and low self-discharge. However, LIB is relatively deficient in safety and anti-abuse ability, meaning that an inappropriate management or incorrect use is likely to cause serious hazards, e.g., leakage, combustion and explosion. To ensure the operating safety and reliability, the state of charge (SOC) of the LIBs must be accurately estimated online, and a number of approaches have been developed. These methods can be roughly divided into two categories, namely non–model–based methods and model–based methods.

The non-model-based methods typically include the Ampere-hour integral or Coulomb counting method [2], open-circuit voltage (OCV) method [3], machine learning based methods (e.g., the artificial neural network [4], fuzzy logic model and support vector machines [5]). The Ampere integral method suffers from large estimation error caused by the inaccurate initial SOC and current measurement noise. The OCV method requires high precise voltage measurement and it is not suitable for online application due to the long standing period before measuring the battery OCV. The machine learning based methods can realize the accurate SOC estimation through input/output data training and self-learning, but they usually require a large amount of training data covering all of the typical driving cycles of the EV, which is time-consuming. Moreover, their estimation accuracy highly depends on the quantity of training data, which limits their application in practice. Thus, the model-based methods are currently more popular and suitable for real-time application than the other methods. The adaptive filter-based methods have been widely used for battery SOC estimation, because of their merits in terms of self-correcting, online computing, and the availability of dynamic SOC estimation error range. The widely used Kalman filters (KF) based SOC estimation algorithms typically include the extended Kalman filter (EKF) [6-8], unscented Kalman filter (UKF) [9][10], and cubature Kalman filter (CKF) [11]. Other commonly used model-based methods include the particle filter (PF) [12][13], unscented particle filter (UPF) [14], cubature particle filter (CPF) [15], and H-infinity filter [16][17], etc.

Selecting an appropriate battery model is crucial to the model-based SOC estimation methods because it has

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prominent influence on both the estimation accuracy and computational complexity. Equivalent circuit models (ECMs) are rather suitable for SOC estimation application due to their simple structure and high computation efficiency. Lai et al [18] compared different typical ECMs in terms of stability, accuracy and robustness of the model and SOC estimation, and the results revealed that the first- and second-order RC models are the choice of priority because they perform good balance between the estimation accuracy and model complexity. Relationship between the OCV and SOC is a crucial element affecting the SOC estimation results. Zheng et al [19] compared two common OCV tests, namely the incremental OCV test and the low-current OCV test at three different temperatures for observing the influence of OCV on SOC estimation. It is indicated that the incremental OCV test is a better choice for predetermining the OCV-SOC for online battery SOC estimation.

Based on aforementioned reviews, many factors affect the SOC estimation results. However, the influence of different factors on accuracy of model-based SOC estimation methods has not been systematically investigated by existing publications. In this paper, the second-order RC equivalent circuit model is selected to simulate the dynamic behaviors of the LIB, and the exponential-function fitting method is used to determine the model parameters. The EKF and CKF algorithms are employed to estimate the SOC. Then, the impact of model parameters and measurement noise on the accuracy of SOC estimation, as well as the effect of the order of the polynomial function used for fitting the OCV-SOC relationship on SOC estimation are investigated.

2. EXPERIMENTS

A test bench was established as shown in Fig. 1 to collect data for evaluating the battery characteristics. It consists of a NEWARE BTS4000 battery test system, a host computer, and the tested LIB, INR18650-25R, which is produced by SAMSUNG SDI, Korea. The battery specifications mainly include nominal capacity 2500mAh, nominal voltage 3.6V, charging/discharging cut-off voltage 4.2V/2.5V and maximum continuous discharging current 20A.

In this paper, all experiments are carried out at room temperature. In order to acquire the battery OCV-SOC curve, the battery is rested for two hours at each 10% interval from 100% SOC to 0% SOC, so that the terminal voltage measured at the end of rest time can be considered as the OCV. The OCV-SOC curve is attained by the polynomial fitting between the corresponding SOC values and measured OCV values.

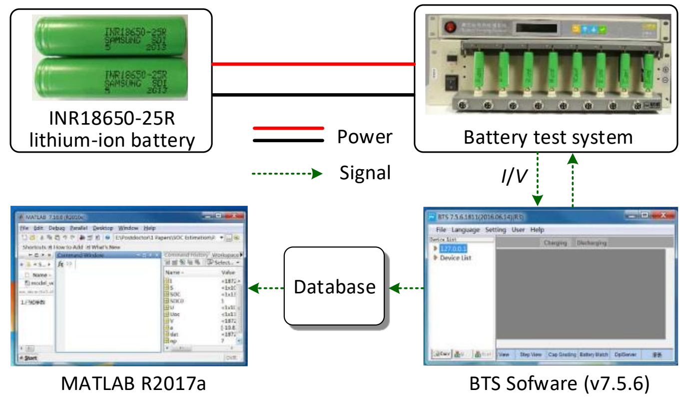

Fig 1 Configuration of the battery test bench.

3. SOC ESTIMATION METHODOLOGY

3.1 Battery model

To get balance between the complexity and accuracy for SOC estimation, the second-order resistor-capacitor (RC) model is selected in this paper. The Schematic of the second-order RC model is shown in Fig. 2, where V_{oc} is the open circuit voltage, R_o is the ohmic resistance, R_{pi} and C_{pi} (i=1, 2) are the polarization resistance and capacitance, respectively, which are used to simulate the recovering voltage behaviors of the battery, V_{cpi} is the terminal voltage of $R_{pi}//C_{pi}$ parallel network, I_L represents the load current and V_t indicates the terminal voltage.

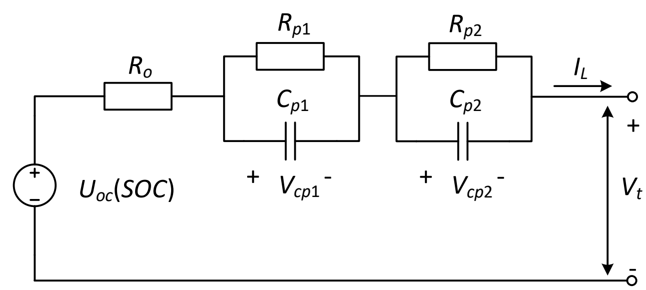

Fig 2 Schematic of second-order RC model.

The discrete space model of the second-order RC model in Fig. 2 can be formulated as

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

$$y_k = h(x_{k-1}, u_{k-1}) + v_k \tag{2}$$

where $f(x_{k\text{-}1},u_{k\text{-}1})$ and $h(x_{k\text{-}1},u_{k\text{-}1})$ are the sate transition function and measurement function, respectively, w_k and v_k are zero-mean white Gaussian stochastic processes with covariance Q_k and R_k, respectively.

To assess the incidence of model parameters on SOC estimation accuracy quantitatively. The EKF and CKF algorithms are employed for SOC estimation in this paper. The principle of the EKF and CKF algorithms are summarized in Fig. 3 and Fig. 4, respectively, where P is the error covariance.

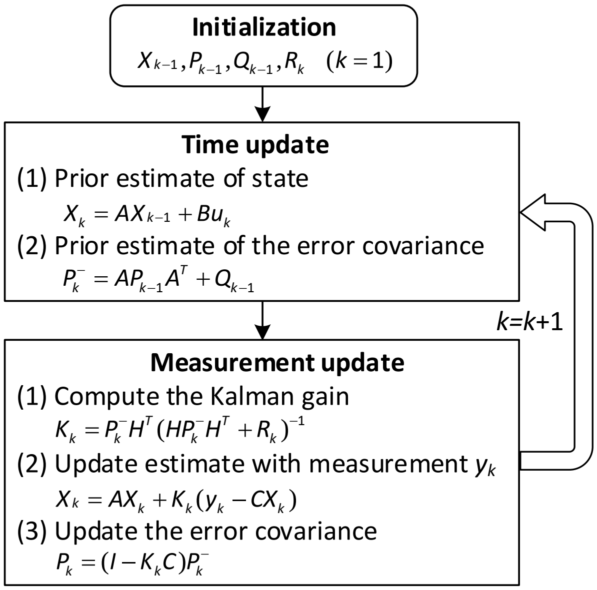

Fig 3 Flow chart of EKF.

In order to estimate the SOC using EKF, the nonlinear functions in Eqs. (1) and (2) must be transformed to the vector form as

$$f(x_{k-1},u_{k-1}) = \begin{pmatrix} \exp(-\Delta t/\tau_1) & 0 & 0 \\ 0 & \exp(-\Delta t/\tau_2) & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} U_{p1,k-1} \\ U_{p2,k-1} \\ SOC_{k-1} \end{pmatrix} + \begin{pmatrix} R_{p1}(1-\exp(-\Delta t/\tau_1)) \\ R_{p2}(1-\exp(-\Delta t/\tau_2)) \\ -\eta_c \Delta t / C_n \end{pmatrix} I_{L,k-1} \tag{3}$$

$$h(x_{k-1},u_{k-1}) = U_{oc}(SOC_{k-1}) - I_{L,k-1}R_o - U_{p1,k-1} - U_{p2,k-1} \tag{4}$$

where x=[U_{p1}, U_{p2}, SOC] is the state vector, u=I_L is the input variable, U_{p1} and U_{p2} are the terminal voltage of C_{p1} and C_{p2}, respectively, U_{oc}(SOC) indicates the nonlinear relationship between the OCV and SOC, τ_1=$R_{p1}C_{p1}$, and τ_2=$R_{p2}C_{p2}$.

Then, A and C in Fig. 3 can be obtained as

$$A = \frac{\partial f}{\partial x} = \begin{pmatrix} \exp(-\Delta t/\tau_1) & 0 & 0 \\ 0 & \exp(-\Delta t/\tau_2) & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$C = \frac{\partial h}{\partial x} = \begin{pmatrix} -1 & -1 & \dfrac{dU_{oc}(SOC)}{dSOC} \end{pmatrix}$$

More details about the EKF and CKF can be found in [6] and [11], respectively.

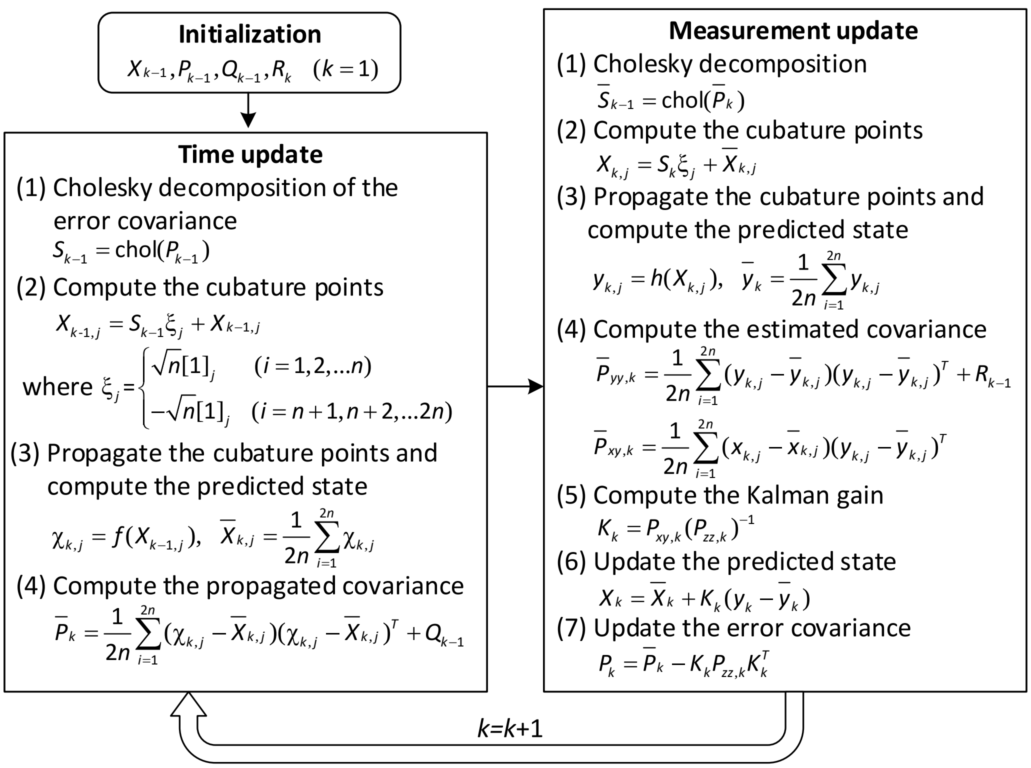

Fig 4 Flow chart of CKF.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Influence of model parameters on SOC estimation

In this Section, we analyze the influence of each resistor and capacitor on an individual basis. First, the values of R_o, R_{p1}, R_{p2}, C_{p1} and C_{p2} were acquired according to the offline identification method, and then a bias error was added to one of the five parameters in turn but the others keep constant. The root mean square error (RMSE) of SOC estimation for each parameter is obtained by the CKF and EKF algorithms under the NEDC cycle. The results are shown in Figs. 5 and 6.

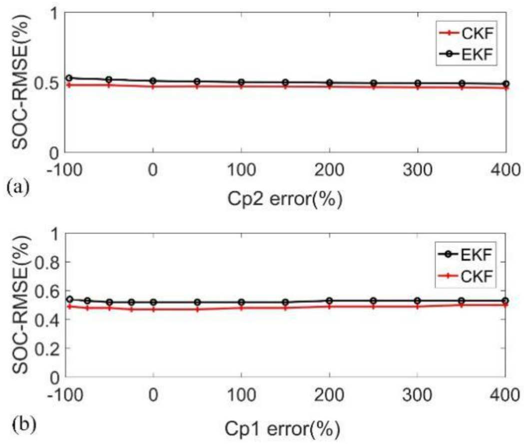

Fig 5 Influence of polarization capacitors on SOC estimation: (a) C_{p2}; (b) C_{p1}.

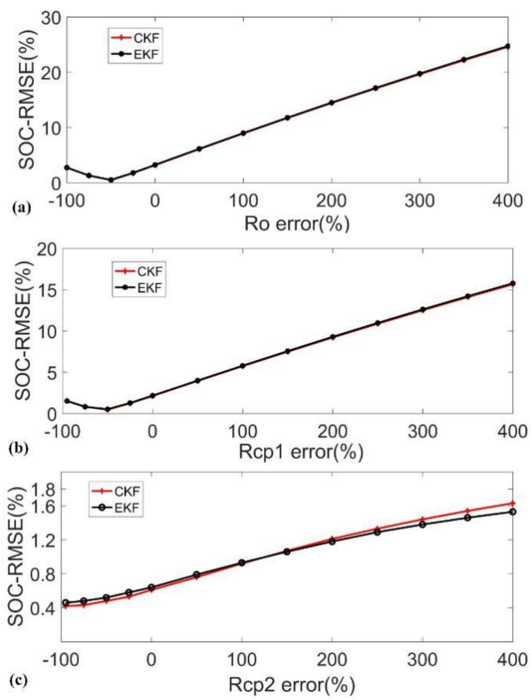

Fig 6 Influence of resistors on SOC estimation: (a) Ohmic resistor R_o; (b) polarization resistor R_{p1}; (c) polarization resistor R_{p2}.

It can be seen from Fig. 5 that the polarization capacitor C_{p1} and C_{p2} have very slightly influence on SOC estimation accuracy, even though these parameters suffer from error of 400%. However, according to Fig. 6, it is clear that the variation of resistors has larger influence on the SOC estimation comparing with the polarization capacitors, especially for the R_o and R_{p1}. These conclusions are useful and valuable to the online parameters identification. For example, taking the constant capacitors value which obtained from the offline parameter identification into the online parameter identification model can reduce the computation cost and cut down the cost of the battery management system (BMS) hardware.

4.2 Influence of OCV-SOC function on SOC estimation

The fitted OCV-SOC curve is a crucial element of SOC estimation, since accurate OCV-SOC curve is critical to improve the SOC estimation accuracy. In this paper, the impact of the order of fitted OCV-SOC curve on SOC estimation is investigated and its influence on SOC estimation results is analyzed. The corresponding SOC and measured OCV values are acquired according to the experiments described in Section 2. Then, the different ordered polynomial fitting methods are used to match the OCV-SOC curve. In order to compare the accuracy of different OCV-SOC curves, the RMSE of SOC estimation is employed. The results are shown in Fig. 7. It can be seen that the sixth-order of fitted OCV-SOC curve has the best SOC estimation accuracy, and the RMSE of SOC estimation is about 0.52%. This conclusion is meaningful on the online SOC estimation which can improve the estimation accuracy. Besides, the CKF has higher SOC estimation accuracy than the EKF.

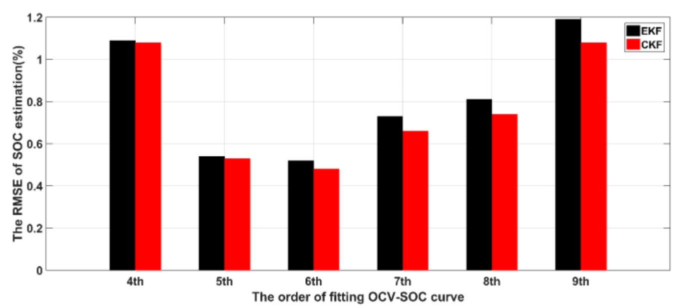

Fig 7 Relationship between the order of fitted OCV-SOC curve and SOC-RMSE.

4.3 Influence of measurement noises on SOC estimation

For a practical BMS system, it is inevitable that current sensors and voltage sensors are disturbed by noises as acquiring the battery current and voltage. In this section, we analyze the impacts of the current and voltage errors on SOC estimation. Generated white Gaussian noise sequences as measurement noises are added to current and voltage data to emulate the actual measurement noises. Herein, a normal distribution random number series with mean 0 and variance 1 is added to the measured current and voltage data respectively as current and voltage noises. The results are shown in Fig. 8. It is indicated that the voltage error has bigger influence on the SOC estimation accuracy than the current error. Thus, it can be concluded that high-precision voltage measurement is usually more important than current measurement referring to the improvement of SOC estimation accuracy.

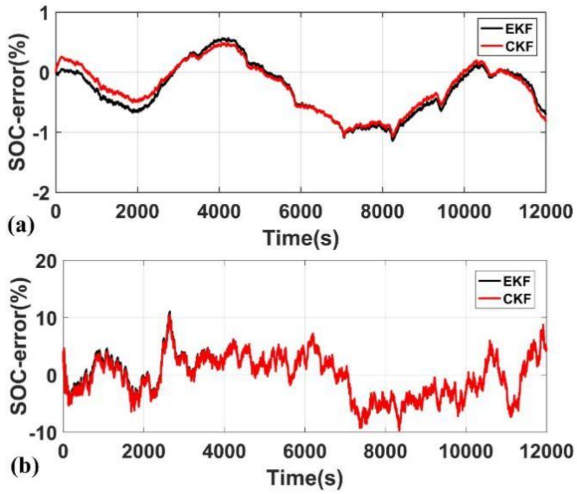

Fig 8 RMSE of SOC estimation with measurement noises: (a) current noise; (b) voltage noise.

5. CONCLUSIONS

Effects of parameters of the battery model, including RC parameters, OCV-SOC function, and measurement noise on the SOC estimation have been systematically investigated in this paper. The second-order RC equivalent circuit model was selected due to its balance between the accuracy and complexity. Some results have been obtained as follows:

(1) As for the RC parameters of the battery model, the polarization capacitor C_{p1} and C_{p2} have not obvious influence on SOC estimation accuracy, but the Ohmic resistance, R_o, greatly affects the SOC estimation. This will be meaningful to reduce the calculation time of the algorithm by implementing offline identification rather than online identification for these parameters which slightly affect the SOC estimation.

(2) The impact of the order of fitting OCV-SOC curve on SOC estimation was investigated and its influence on SOC estimation results was analyzed. It can be seen that the five-order and six-order polynomials significantly perform better than the others in simulating the OCV-SOC curve. Therefore, it is important to select a proper function to simulate the relationship between the OCV and SOC for improving the accuracy of SOC estimation. In addition, the CKF has higher SOC estimation accuracy than the EKF with the same OCV-SOC function.

(3) The voltage measurement error has greater influence on the SOC estimation than the current measurement error. Thus, high-precision voltage measurement is usually more important than current measurement referring to the improvement of SOC estimation accuracy.

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