IOP Conference Series: Earth and Environmental Science

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To cite this article: Yong Tian *et al* 2017 *IOP Conf. Ser.: Earth Environ. Sci.* **94** 012051

Online Estimation of Model Parameters of Lithium-Ion Battery Using the Cubature Kalman Filter

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Abstract. Online estimation of state variables, including state-of-charge (SOC), state-of-energy (SOE) and state-of-health (SOH) is greatly crucial for the operation safety of lithium-ion battery. In order to improve estimation accuracy of these state variables, a precise battery model needs to be established. As the lithium-ion battery is a nonlinear time-varying system, the model parameters significantly vary with many factors, such as ambient temperature, discharge rate and depth of discharge, etc. This paper presents an online estimation method of model parameters for lithium-ion battery based on the cubature Kalman filter. The commonly used first-order resistor-capacitor equivalent circuit model is selected as the battery model, based on which the model parameters are estimated online. Experimental results show that the presented method can accurately track the parameters variation at different scenarios.

1. Introduction

Electric vehicles (EVs) have been rapidly developed in recent years due to their great benefit in easing energy crisis and environmental pollution. Battery plays an important role in EVs because it is the main power source of EVs. Lithium-ion battery is currently used more and more due to the merits of high energy density, long lifespan, and low self-discharge rate [1]. In practice, estimation of state variables, including state-of-charge (SOC) [2-4], state-of-energy (SOE) [5] and state-of-health (SOH) [6] is greatly crucial for the operation safety of lithium-ion battery. In order to improve estimation accuracy of these state variables, a precise battery model needs to be established.

Lithium-ion battery is a strong nonlinear and time-varying system, accordingly some of its characteristics, e.g., internal resistance, available capacity, open-circuit voltage (OCV) are significantly influenced by various factors, such as ambient temperature, discharge rate, depth of discharge and aging, etc. Consequently, these intrinsic parameters of the lithium-ion battery need to be updated online for the purpose of accuracy improvement of battery model. Among them, the internal resistance and OCV are particularly two important parameters, because they are both key factors for SOC estimation, and the internal resistance usually can be used to determine the SOH [7].

In this study, a novel method for online estimation of model parameters of lithium-ion battery is presented. The first-order resistor-capacitor equivalent circuit model is selected to simulate the battery's dynamic characteristics due to its advance in both accuracy and complexity. An online parameters estimator based on the cubature Kalman filter is developed, which can estimate the battery internal resistance and OCV simultaneously. Experimental results are conducted on the INR18650-25R lithium-ion battery at different temperatures to validate the effectiveness of the presented method.

2. Battery Model

A large number of battery models have been developed to simulate static and dynamic characteristics of the battery. Among them, the equivalent circuit models (ECMs) consisting of voltage resource, resistors and capacitors are widely used. Based on the different combination of resistors and capacitors, the ECMs include the Partnership for a New Generation of Vehicle (PNGV) model, Rint model, Thevenin model and resistor-capacitor (RC) models. Generally, the RC models consist of a voltage resource, an ohmic resistor and *n* RC networks, accordingly called as *n*-order RC model. In this study, the first-order RC model is applied due to its advance in both accuracy and complexity. Schematic of the first-order RC model is shown in Figure 1, where V_{oc} stands for the open circuit voltage, R_o is the ohmic resistance, R_p and C_p are the polarization resistance and polarization capacitance respectively, V_t is the terminal voltage, and I_L represents load current, which is assumed to be positive during discharging process and negative during charging process.

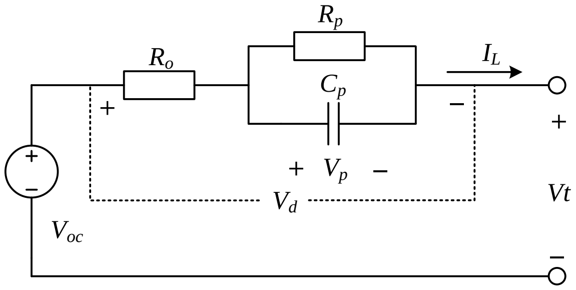


Figure 1. Schematic of the first-order RC model of lithium-ion battery.

By defining $V_d = V_{oc} - V_t$, we can get the transfer function of the first-order RC model as:

$$G(s) = \frac{V_d(s)}{I_L(s)} = \frac{R_p}{1 + R_p C_p s} + R_o \tag{1}$$

Using the bilinear transform rule ($s = \frac{2}{T_s}\frac{1 - z^{-1}}{1 + z^{-1}}$, where T_s is the sampling period), Equation (1) can be discretized as:

$$G(z^{-1}) = \frac{V_d(z^{-1})}{I_L(z^{-1})} = \frac{b_0 + b_1 z^{-1}}{1 + a_1 z^{-1}} \tag{2}$$

where

$$a_1 = \frac{T_s - 2R_p C_p}{T_s + 2R_p C_p},\ b_0 = \frac{R_o T_s + R_p T_s + 2R_0 R_p C_p}{T_s + 2R_p C_p},\ b_1 = \frac{R_o T_s + R_p T_s - 2R_0 R_p C_p}{T_s + 2R_p C_p} \tag{3}$$

Then, the time-domain difference equation of Equation (2) can be obtained as:

$$V_t(k) = V_{oc}(k) + a_1 V_{oc}(k-1) - a_1 V_t(k-1) - b_0 I_L(k) - b_1 I_L(k-1) \tag{4}$$

Assuming V_{oc} is changeless in a sampling interval, i.e., $V_{oc}(k-1) = V_{oc}(k)$, yields:

$$V_t(k) = (1 + a_1)V_{oc}(k) - a_1 V_t(k-1) - b_0 I_L(k) - b_1 I_L(k-1) \tag{5}$$

Then, we can define the state-space function as:

$$\begin{cases} x_k = Ax_{k-1} + Bu_k + w_k \\ y_k = Cx_k + Du_k + v_k \end{cases} \tag{6}$$

where u=0, $x=[(1+a_1)V_{oc},\ a_1,\ b_0,\ b_1]^T$, $y=V_t$, w_k and v_k are system noise and observation noise respectively, A is an identity matrix, $B=D=0$, and $C=[1, -V_t(k\text{-}1), -I_L(k), -I_L(k\text{-}1)]$.

3. Online Estimation for Model Parameters

In order to get an accurate estimation of x, the cubature Kalman filter (CKF) firstly proposed by Arasaratnam and Haykin in 2009 [8] is applied. The CKF is based on the third-degree spherical-radial cubature rule and uses a set of points to approximate the mean and covariance of the states of a nonlinear system with additive Gaussian noise. The process of the CKF algorithm is summarized as follows:

i) Initialization

a. Initial posteriori error covariance: P_0;

b. Initial process noise covariance: $Q_{w,0}$;

c. Initial measurement noise covariance: $R_{v,0}$;

d. Initial mean $\overline{x}_0$ and covariance P_0 with a random state vector x_0 as follows

$$\overline{x}_0 = E[x_0] \tag{7}$$

$$P_0 = E[(x_0 - \overline{x}_0)(x_0 - \overline{x}_0)^T] \tag{8}$$

ii) Time update

a. Factorize the error covariance

$$S_{k-1} = chol(P_{k-1}) \tag{9}$$

where $chol(\cdot)$ represents a Cholesky decomposition of a matrix returning a lower triangular Cholesky factor. That means

$$P_{k-1} = S_{k-1} S_{k-1}^T \tag{10}$$

b. Calculate the cubature points

$$x_{k-1}^{(i)} = S_{k-1}\xi^{(i)} + \hat{x}_{k-1} \quad i = 1,2,\cdots,2n \tag{11}$$

where n is the number of state variables and ξ is the set of standard cubature points given by

$$\xi^{(i)} = \begin{cases} \sqrt{n}[1]^{(i)} & i = 1,2,\cdots n \\ -\sqrt{n}[1]^{(i)} & i = n+1, n+2, \cdots 2n \end{cases} \tag{12}$$

where $[1]^{(i)}$ denotes the i-th column vector of the identity matrix.

c. Propagate the cubature points and calculate the predicted state

$$\chi_{k|k-1} = Ax_{k-1} + Bu_{k-1} \tag{13}$$

$$\overline{x}_{k|k-1} = \frac{1}{2n}\sum_{i=1}^{2n}\chi_{k|k-1}^{(i)} \tag{14}$$

d. Calculate the propagated covariance

$$P_{k|k-1} = \frac{1}{2n}\sum_{i=1}^{2n}(\chi_{k|k-1}^{(i)} - \overline{x}_{k|k-1})(\chi_{k|k-1}^{(i)} - \overline{x}_{k|k-1})^T + Q_{w,k-1} \tag{15}$$

iii) Measurement update

a. Factorize the error covariance

$$S_{k|k-1} = chol(P_{k|k-1}) \tag{16}$$

b. Recalculate the cubature points

$$x_{k|k-1}^{(i)} = S_{k|k-1}\xi^{(i)} + \hat{x}_{k|k-1} \quad i = 1,2,\cdots,2n \tag{17}$$

c. Propagate the cubature points and calculate the predicted measurement

$$y_{k|k-1} = Cx_{k|k-1} + Du_k \tag{18}$$

$$\overline{y}_{k|k-1} = \frac{1}{2n}\sum_{i=1}^{2n} y_{k|k-1}^{(i)} \tag{19}$$

d. Calculate the estimated covariance

$$P_{k|k-1}^{y} = \frac{1}{2n}\sum_{i=1}^{2n}(y_{k|k-1}^{(i)} - \overline{y}_{k|k-1})(y_{k|k-1}^{(i)} - \overline{y}_{k|k-1})^T + R_{v,k-1} \tag{20}$$

$$P_{k|k-1}^{xy} = \frac{1}{2n}\sum_{i=1}^{2n}(x_{k|k-1}^{i} - \overline{x}_{k|k-1})(y_{k|k-1}^{i} - \overline{y}_{k|k-1})^T \tag{21}$$

e. Calculate the Kalman gain

$$K_k = P^{xy}_{k|k-1}(P^{y}_{k|k-1})^{-1} \tag{22}$$

f. Update the predicted state

$$\hat{x}_k = \overline{x}_{k|k-1} + K_k(y_k - \overline{y}_{k|k-1}) \tag{23}$$

g. Update the error covariance

$$P_k = P_{k|k-1} - K_k P^{y}_{k|k-1} K_k^T \tag{24}$$

Using the CKF, state of system in Equation (6) can be estimated online, then battery model parameters, including V_{oc}, R_o, R_p and C_p can be deduced as:

$$V_{oc} = \frac{(1+a_1)V_{oc}}{1+a_1},\ R_o = \frac{b_0 - b_1}{1-a_1},\ R_p = \frac{2(b_1 - a_1 b_0)}{1-a_1^2},\ C_p = \frac{T_s(1-a_1)^2}{4(b_1 - a_1 b_0)} \tag{25}$$

4. Results and Discussion

A battery test bench was established to verify the proposed parameter estimation method. As shown in Figure 2, the test bench consists of a battery cycler (NEWARE BTS4000), a temperature chamber (SANWOOD SMC-80-CC), a monitor, and a tested lithium-ion battery cell (INR18650-25R lithium-ion battery produced by SAMSUNG SDI). The cycler can charge and discharge the battery within a range of voltage 0~5 V and current −6~6A, and the measurement errors of voltage and current are both less than 0.1%. The specifications of the tested lithium-ion battery INR18650-25R mainly include nominal capacity 2500 mAh, nominal voltage 3.6 V, charging end voltage 4.2 V, discharging end voltage 2.5 V and maximum continuous discharging current 20 A.

Figure 2. Test bench.

The commonly used Federal Urban Driving Schedule (FUDS) is applied to assess the proposed method and its current profiles are shown Figure 3. The sampling periods for voltage and current are both 1 second in this paper.

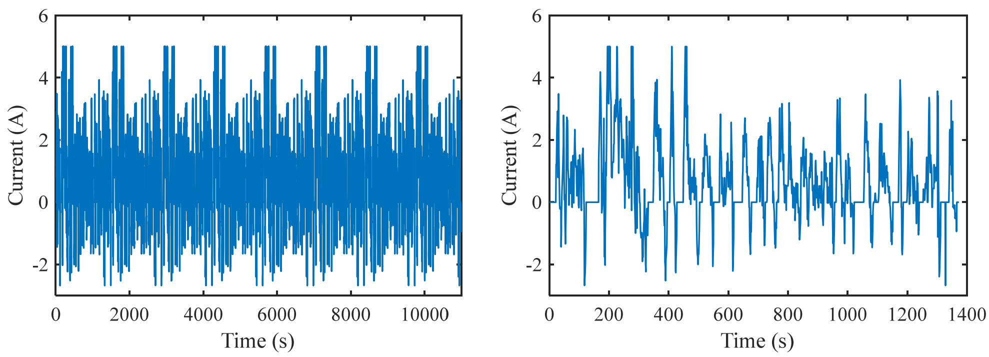
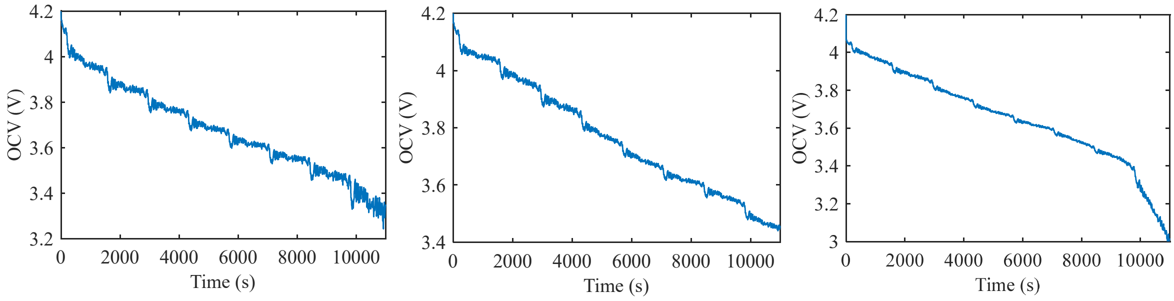


Figure 3. Current profiles under FUDS cycles.

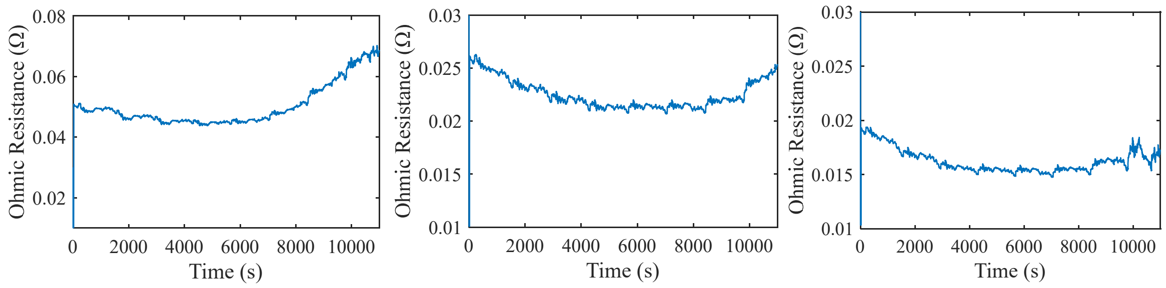
The identified OCV at 0°C, 25°C and 45°C are shown in Figure 4(a), (b) and (c) respectively. It can be seen that the OCV monotonously decreases with increase of depth of discharge (i.e., decrease of SOC). Besides, the relationship curve between OCV and SOC is influenced by temperature.



(a) (b) (c)

Figure 4. Identified OCV at different temperature: (a) 0°C, (b) 25°C, (c) 45°C.

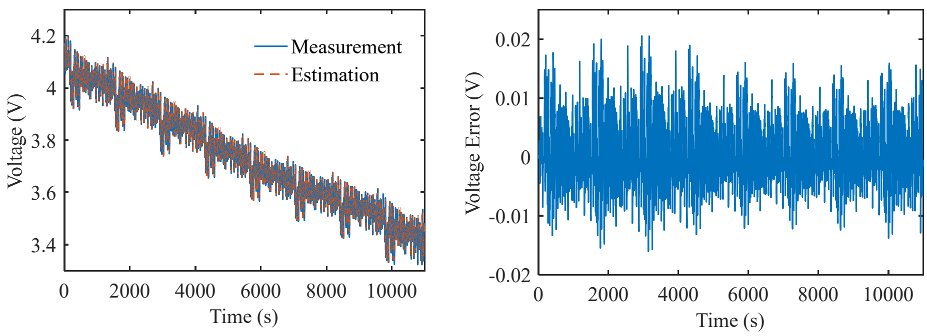
The identified ohmic resistance at 0°C, 25°C and 45°C are shown in Figure 5(a), (b) and (c) respectively. It can be seen that the ohmic resistance fluctuates with the SOC variation, and in general it firstly increases and then decreases with the decrease of SOC (SOC decreases with the time). Additionally, the resistance generally decreases with the increase of temperature, because the higher temperature results in easier internal reaction of the battery.



(a) (b) (c)

Figure 5. Identified ohmic resistance at different temperature: (a) 0°C, (b) 25°C, (c) 45°C.

To evaluate the accuracy of parameters estimation, the model output voltage is compared with the measured voltage. As an example, the case at 25°C is as shown in Figure 6. It can be seen that the battery model with online estimated parameters can well track the voltage variation, and the estimation error is lower than 20 mV.



(a) (b)

Figure 6. Estimated Voltage at 25°C: (a) voltage, (b) voltage error.

5. Conclusions

An online estimation method of model parameters of lithium-ion battery is presented in this paper. Based on the first-order RC equivalent circuit model, the state-space functions for model parameters estimation are deduced. The cubature Kalman filter algorithm is applied to resolve the state-space functions, based on which the model parameters can be further calculated. FUDS cycles are performed on the INR18650-

25R lithium-ion battery at 0°C, 25°C and 45°C, respectively, in order to evaluate performance of the presented method. Experimental results indicate that the presented method can simultaneously estimate the internal resistance and OCV with high precision. Particularly, at 25°C the battery model with online updated parameters can accurately track the battery voltage variation with error less than 20 mV.

Acknowledgments
This work was funded by the Natural Science Foundation of Guangdong Province (No. 2016A030313056), Science and Technology Plan Project of Shenzhen (No. JCYJ20160308092940394), and Natural Science Foundation of Shenzhen University (No. 2016027).

References

[1] Lu L, Han X, Li J, Hua J and Ouyang M, "A review on the key issues for lithium-ion battery management in electric vehicles", *J Power Sources*, no. 266, pp. 272-88.
[2] Tian Y, Li D, Tian J and Xia B, "State of charge estimation of lithium-ion batteries using an optimal adaptive gain nonlinear observer", *Electrochimica Acta*, no. 225, pp. 225-34.
[3] Chen X, Shen W, Cao Z and Kapoor A, "A novel approach for state of charge estimation based on adaptive switching gain sliding mode observer in electric vehicles", *J Power Sources*, no. 246, pp. 667–78.
[4] He H, Xiong R and Peng J, "Real-time estimation of battery state-of-charge with unscented Kalman filter and RTOS μCOS-II platform", *Appl Energy*, no. 162, pp. 1410-18.
[5] Zhang W, Shi W and Ma Z, "Adaptive unscented Kalmanfilter based state of energy and power capability estimation approach for lithium-ion battery", *J Power Sources*, no. 289, pp. 50-62.
[6] Remmlinger J, Buchholz M, Meiler M, Bernreuter P and Dietmayer K, "State-of-health monitoring of lithium-ion batteries in electric vehicles by on-board internal resistance estimation", *J Power Sources*, no. 196, pp. 5357-63.
[7] Chiang Y, SeanW and Ke J, "Online estimation of internal resistance and open-circuit voltage of lithium-ion batteries in electric vehicles", *J Power Sources*, no. 196, pp. 3921-32.
[8] Arasaratnam I and Haykin S, "Cubature Kalman filters", *IEEE Trans. Autom. Control*, no. 54, pp. 1254–69.