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Model-based State-of-energy Estimation of Lithium-ion Batteries in Electric Vehicles

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Abstract

With the increasing application of lithium-ion batteries, the function of battery management system (BMS) comes to be more sophisticated. The state-of-energy (SOE) of lithium-ion batteries is a critical index for energy optimization and management in electric vehicles. The conventional power integral methods are easy to cause accumulated error due to current or voltage drift of sensors. Therefore the EKF method is employed in this study. A data-driven model is established to describe the relationship between the open-circuit voltage (OCV) and SOE based on the experimental data of a $Li(Ni_{1/3}Co_{1/3}Mn_{1/3})O_2$ battery. The dynamic urban driving schedule of Wuhui city in China has been conducted on the lithium-ion battery to verify the accuracy of the proposed method. The results show that accurate SOE estimation results can be obtained by the proposed method.

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Keywords: Electric vehicle; Battery modeling; State-of-energy; EKF.

1. Introduction

With the growing concerns on the depletion of energy resources and global warming problems caused by conventional internal combustion engine vehicles, electric vehicles have drawn more and more attentions. The battery is the key to the development of electric vehicles. Lithium-ion batteries as featured by high energy density, low self-discharge rate, long cycle life and environmental friendliness have found wide applications in the area of electric vehicle power supply system [1]. The lithium-ion battery is a strong nonlinear and time variability system for its complicated electrochemical process. The estimation

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of cell state parameters, such as the open-circuit voltage (OCV), state-of-charge (SOC) and available energy, plays an important role in ensuring vehicle stability and reliability.

In recent years, studies in estimation of residual energy have increased in literatures [2-5], among which the most direct algorithm is the power integral method. However through the integral methods, the estimation error increases conspicuously due to the accumulated error introduced by current or voltage drift of sensors. Therefore model-based estimation methods have been developed.

The battery models used in electric vehicles can be divided into three types, the electrochemical models, the neural network models and the equivalent circuit models. The electrochemical model based on the electrochemical mechanism of the battery can accurately reflect the characteristics of the battery. The neural network model can simulate the high nonlinearity of lithium-ion batteries, but requires a large number of training samples. Based on the dynamic characteristics and working principles of the battery, the equivalent circuit model is developed by using resistors, capacitors, and voltage sources to form a circuit network.

This paper proposes a method for SOE estimation of lithium-ion battery based on EKF. Since there is still not an accepted model for SOE, A data-driven model is established to describe the relationship between the open-circuit voltage (OCV) and SOE based on the experimental data. The paper is organized as follows: In Section 2, the definition of SOE is first introduced. Then a data-driven model for SOE estimation is proposed based on the real data of a lithium-ion cell. At last, the EKF implementation is presented. In Section 3, we first introduced the battery test bench, then experiments under dynamic current conditions are conducted to verify the accuracy of the proposed method. The results show that accurate SOE estimation results can be obtained by the proposed method. Finally, the conclusions of the study are given in Section 4.

2. Model Based SOE Estimation

2.1. Definition of SOE

Real-time estimation of the available energy of the battery is a crucial need in the growing fields of electric vehicles applications. The SOE reflects the residual energy of a battery, and is defined as the ratio of the remaining energy to the total energy. The SOE can be expressed as the following equation:

$$SOE(t) = SOE(t_0) + \frac{\int_{t_0}^{t} P(\tau)\mathrm{d}\tau}{\mathrm{E_N}} \tag{1}$$

where $SOE(t)$ is the SOE value at time t, $SOE(t_0)$ is the SOE value at initial time t_0, $\mathrm{E_N}$ represents the nominal energy which can be obtained by the measurement average of multiple battery tests, $P(\tau)$ represents the power at time τ.

2.2. Model for SOE estimation

The equivalent circuit model has been widely used in various types of modeling and simulation for its high accuracy. Depending on different applications and the required accuracy, different types of cell models have been developed in literatures. Among which, the Thevenin equivalent circuit model is an effective model to represent the battery's dynamics.

As shown in Fig.1, the Thevenin equivalent circuit model includes an open-circuit voltage U_{ocv} which is used to represent the voltage source and describe the static character of the cell, a serial resistance R_i

which is used to describe the cell ohmic internal resistance, a RC network which describes the cell polarization effect is composed by a polarization resistance R_p and a polarization capacitance C_p.

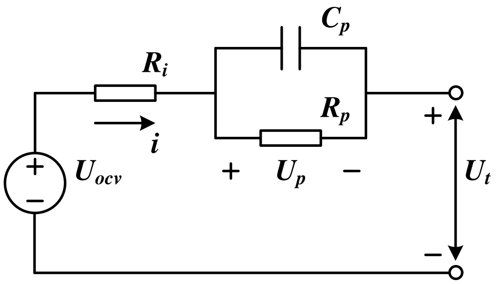

Figure 1 Battery model

Based on the electric circuit analysis, the electrical behavior of the cell model can be expressed as:

$$\begin{cases} \dot{U}_p = -U_p / C_p R_p + i / C_p \\ U_t = U_{ocv} - U_p - iR_i \end{cases} \tag{2}$$

where i represents the load current (negative for charge, positive for discharge), U_{ocv} represents the open-circuit voltage, U_t represents the terminal voltage, U_p represents the polarization voltage over the RC network, R_i represents the ohmic internal resistance, R_p and C_p represent the polarization resistance and polarization capacitance, respectively.

The electrical behavior of Thevenin model in Eq. (2) can be rewritten in the frequency domain as follows:

$$U_t(s) = U_{ocv}(s) - i(s)(R_i + R_p / (1 + R_p C_p s)) \tag{3}$$

The transfer function G(s) of Eq. (3) can be written as follows:

$$G(s) = -(R_i + \frac{R_p}{1 + R_p C_p s}) = -\frac{R_i + R_p + R_p C_p s}{1 + R_p C_p s} \tag{4}$$

A bilinear transformation method shown in Eq. (5) is employed for the discretization calculation of G(s) and the result is shown in Eq. (6):

$$s = \frac{2}{T_s} \frac{1 - z^{-1}}{1 + z^{-1}} \tag{5}$$

where z is the discretization operator and T_s is the sample interval. Herein, T_s is 1 s.

$$G(z^{-1}) = -\frac{a_2 + a_3 z^{-1}}{1 - a_1 z^{-1}} \tag{6}$$

where

$$\begin{cases} a_1 = -\dfrac{1 - 2R_p C_p}{1 + 2R_p C_p} \\ a_2 = -\dfrac{R_0 + R_p + 2R_0 R_p C_p}{1 + 2R_p C_p} \\ a_3 = -\dfrac{R_0 + R_p - 2R_0 R_p C_p}{1 + 2R_p C_p} \end{cases} \tag{7}$$

Then the discretization equation can be written as follows:

$$U_{t,k} = (1-a_1)U_{ocv,k} + a_1 U_{t,k-1} + a_2 i_k + a_3 i_{k-1} \tag{8}$$

where a_1 , a_2 and a_3 are the coefficient.

The static relationship between U_{ocv} and the SOE in Eq. (8) is nonlinear which influences the complexity of the estimator. Since there is still not an accepted model for SOE, a data-driven model is established to describe the relationship between U_{ocv} and SOE. Considering the U_{ocv}-SOE curve of a $Li(Ni_{1/3}Co_{1/3}Mn_{1/3})O_2$ battery from the experimental datas shown in Fig.2, the data-driven model can be expressed as Eq. (9):

$$\begin{aligned} U_{ocv}(t) &= \beta_0 + \beta_1 SOE(t) + \beta_2 SOE^2(t) \\ &+ \beta_3 SOE^3(t) + \beta_4 / SOE(t) \\ &+ \beta_5 \ln(SOE(t)) + \beta_6 \ln(1-SOE(t)) \end{aligned} \tag{9}$$

where U_{ocv} represents the open-circuit voltage at time t, $SOE(t)$ represent the SOE at time t and β_i (i = 0, 1, 2, 3, 4, 5, 6) are model coefficients which can be identified by the least-square method.

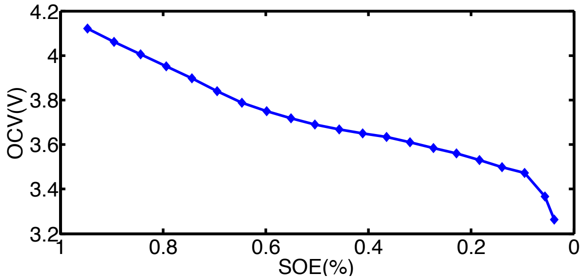

Figure 2 Uocv-SOE curve of a $Li(Ni_{1/3}Co_{1/3}Mn_{1/3})O_2$ battery

2.3. EKF based SOE estimation

The system model in a state-space form can be written as:

$$\begin{cases} \mathbf{X}_k = \mathbf{A}\mathbf{X}_{k-1} + \mathbf{B}\mathbf{u}_{1,k-1} + w_k \\ \mathbf{Y}_k = \mathbf{C}\mathbf{X}_k + \mathbf{D}\mathbf{u}_{2,k} + v_k \end{cases} \tag{10}$$

where

$$\begin{aligned} &\mathbf{X}_k = \begin{bmatrix} U_{p,k} \\ x_k \end{bmatrix}, \mathbf{Y}_k = U_{t,k}, \mathbf{u}_{1,k-1} = \begin{bmatrix} i_{k-1} \\ P_{k-1} \end{bmatrix}, \mathbf{u}_{2,k} = i_k \\ &\mathbf{A} = \begin{bmatrix} \exp(-\Delta t / C_p R_p) & 0 \\ 0 & 1 \end{bmatrix} \\ &\mathbf{B} = \begin{bmatrix} (1-\exp(-\Delta t / C_p R_p))R_p & 0 \\ 0 & \eta \Delta t / C_N \end{bmatrix} \\ &\mathbf{C} = \begin{bmatrix} -1 \\ \partial U_{ocv} / \partial x \end{bmatrix}, \mathbf{D} = -R_i \end{aligned} \tag{11}$$

Then the EKF algorithm can be applied for the state estimation.

3. Experiment and Analysis

3.1. Test bench

In order to sample the measurement data such as current, voltage, temperature, charge/discharge Amp-hours (Ah) and Watt-hours (Wh) etc., the battery test bench is built in laboratory, as shown in Figure. 3, which consists of an UTEK battery test system UBTS60KW500V120A for loading the battery with a programmable current, a BMS for protection of circuits and a host computer for data recording. The measured data is transmitted to the host computer through TCP/IP.

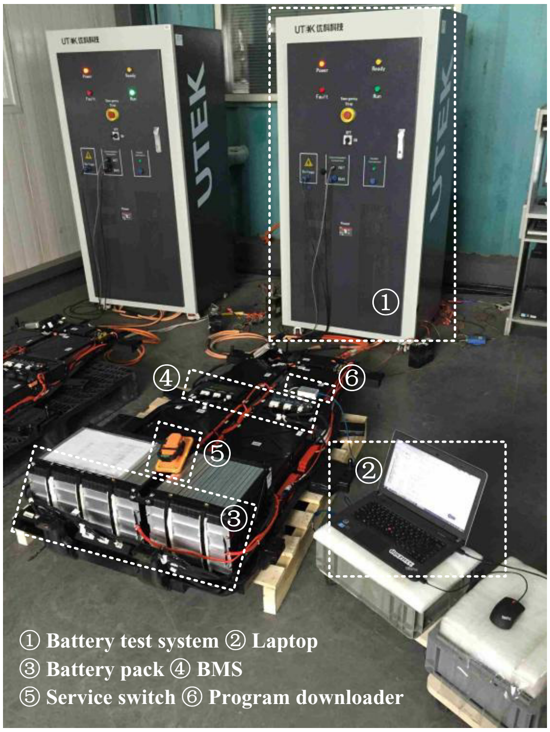

Figure 3 Laboratory battery test bench

3.2. Experiments Analysis

In order to verify the applicability of the estimating algorithm based on EKF, a battery electric vehicle produced by Chery Automobile Co., Ltd. is tested in the experiment. The nominal capacity and the nominal energy of the battery system are 76 Ah and 320 Wh. The cut-off voltage of charge and discharge are 4.2 V and 3.0 V, respectively. Fig.4 (a) shows the dynamic urban driving schedule in Wuhui, China. Fig.4 (b) shows the Comparison of model and measured voltage of a cell in pack. As can be seen in the figure, the general shape of the model and measured voltage are almost the same.

The SOE estimation result and the SOE estimation error are shown in Fig.5 (a) and Fig.5 (b), respectively. The root-mean square error and maximum absolute estimation error are calculated to assess and the estimated performance of the proposed algorithm. The results show that the proposed EKF based SOE estimation approach has a maximum absolute estimation error of 0.8119% and a root-mean square error of 0.4629%.

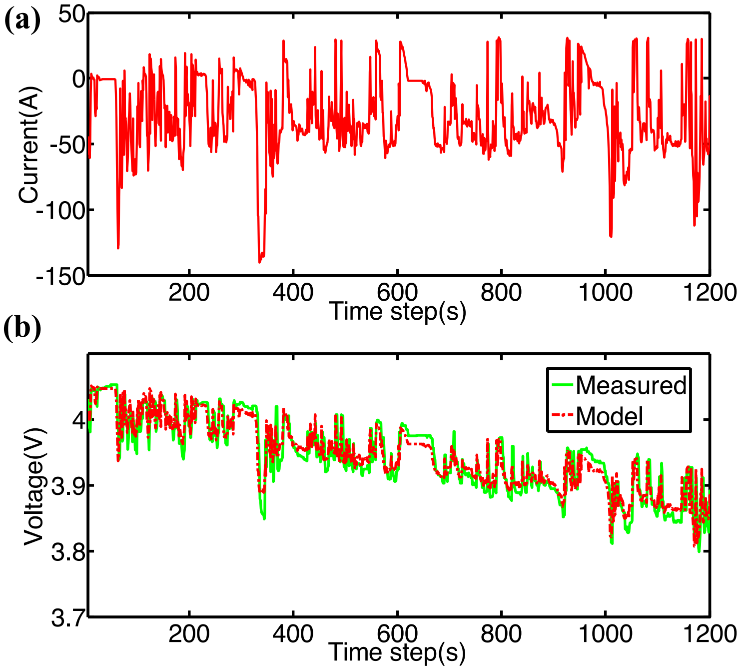

Figure 4 (a). Dynamic urban driving schedule of Wuhui city in China. (b). Comparison of model and measured voltage of a cell in pack.

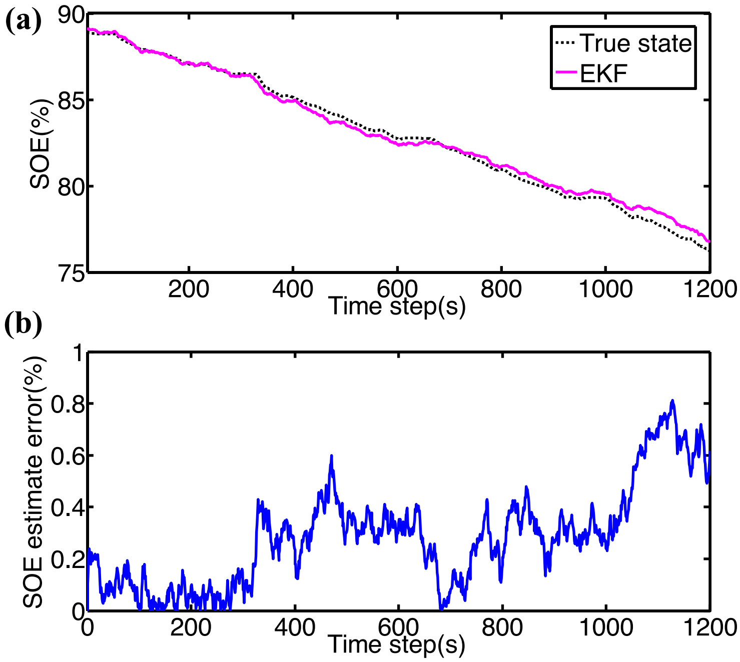

Figure 5 (a). SOE estimation result. (b). SOE estimation error.

4. Conclusion

The SOE of lithium-ion batteries is a critical index for energy optimization and management in electric vehicles. This paper proposes a SOE estimation method for lithium-ion battery based on EKF with a data-driven model developed by the the real experimental data of a $Li(Ni_{1/3}Co_{1/3}Mn_{1/3})O_2$ battery. The dynamic urban driving schedule is used for verifying the accuracy of the proposed method. The experiment results show that accurate SOE estimation results can be obtained by the proposed method.

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