Sensors & Transducers, Vol. 23, Special Issue, July 2013, pp. 137-143

www.sensorsportal.com

Sensors & Transducers

http://www.sensorsportal.com

EKF-Based a Novel SOC Estimation Algorithm of Lithium-ion Battery

Xuanju Dang, [*] Bo Chen, Hui Jiang, Xiangwen Zhang, Kai Xu
School of Electronic Engineering and Automation, Guilin University of Electronic Technology, 541004, China
[*] Tel.: 13387736735, fax: 0773-2290806
[*] E-mail: chenboqtech@163.com

Received: 15 April 2013 /Accepted: 20 July 2013 /Published: 30 July 2013

Abstract: State of charge (SOC) is an essential parameter for battery management system (BMS). Accurate estimation of SOC ensures battery work within a reasonable range, which can prevent over-charge or over-discharge damage to extend battery life. The third-order RC equivalent circuit model is established to describe the characteristics of battery, in which the parameters can be identified by the discharge experiment. For the multiple state variables, strong coupling, stochastic noise, and wild values in the battery system, the principle of superposition is used to decompose the measurement equation so that the separately estimating for state variables to eliminate the coupling relationship between them. A novel SOC estimation method based on Extended Kalman Filtering (EKF) is proposed in this paper. The simulation and experimental results show the validity of the established third-order RC equivalent circuit model, SOC estimation has a high accuracy. *Copyright © 2013 IFSA.*

Keywords: Lithium-ion battery, SOC estimation, Third-order RC equivalent circuit, Superimposition, EKF.

1. Introduction

Power battery is a key to the development of new energy vehicles. The nickel-metal battery and lead-acid battery are used as the main power in the field of electric vehicles. However, lithium-ion battery, compared with conventional nickel-cadmium and nickel-metal battery, has the merits of high energy [1], long cycle life, no memory effect, safe and pollution-free, fast charge and discharge, wide operating temperature range, etc., which will be predominant in this field gradually. Thus, the development of using lithium-ion battery as the new energy vehicle power battery has a high practicality.

State of charge (SOC) is necessary parameter for battery management system (BMS) [2] to ensure the battery safety and life. Since the actual SOC is influenced by many factors, such as temperature, cycle of discharge, self-discharge, aging, and others, the complicated nonlinear behaviors result in difficultly estimating for SOC with accurate.

2. SOC Estimation Method

At present, SOC estimation methods mainly include coulomb counting, the open circuit voltage method [3, 4], the impedance method, Kalman filtering, neural network method etc.

Classical Kalman filtering algorithm is only applicable to the linear systems, which cannot be directly used to estimate SOC because of the complex nonlinear nature of the internal chemical characteristics in the battery. Extended Kalman filtering (EKF) is employed to the non-linear system [5], which has a strong correction function for the initial error of SOC. However, the noise statistic characteristics vary with dramatic changes in actual working conditions, which will cause the inaccurate estimation and even the filtering divergence. In this paper, according to the principle of superposition, the decomposition of measurement equation is used to separately estimate the state variables to eliminate the coupling relationship between them. The proposed estimation method based on EKF can accurately estimate SOC.

3. A Novel SOC Estimation Algorithm Based On EKF

3.1. Battery Model

Currently, the main battery models are as follows: electrochemical model [6], neural network model, AC impedance model, equivalent circuit model [7] etc., each model has own advantages [8]. However, the RC network equivalent circuit model with the simple structure and high precision is being widely used in the BMS to describe the operating characteristics of the battery. In this paper, the established third-order RC model is shown in Fig. 1.

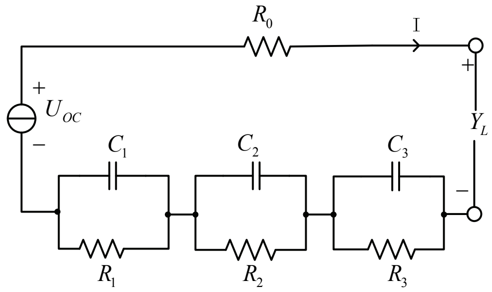

Fig. 1. Third-order RC equivalent circuit model of battery.

Model parameters can refer to [9, 10]. According to Kirchhoff's voltage, Kirchhoff's current theorems and SOC calculation formula, the mathematical model can be presented as follows:

$$\left.\begin{array}{l}\dfrac{dU^1}{dt}=-\dfrac{U^1}{R_1C_1}+\dfrac{I}{C_1}\\ \dfrac{dU^2}{dt}=-\dfrac{U^2}{R_2C_2}+\dfrac{I}{C_2}\\ \dfrac{dU^3}{dt}=-\dfrac{U^3}{R_3C_3}+\dfrac{I}{C_3}\\ Y_L=OCV\left(SOC\right)-IR_0-U^1-U^2-U^3\\ SOC=SOC_{Initial}+\dfrac{1}{C_n}\int\eta Idt\end{array}\right\}, \qquad (1)$$

where η is the coulomb efficiency; $SOC_{Initial}$ is the initial value of SOC; U^1, U^2 and U^3 denote the terminal voltage of capacitor C^1, C^2 and C^3, respectively; Y_L is the battery terminal voltage; C_n is the battery rated capacity.

3.2. Kalman Filtering Principle

Kalman filtering has the advantages of a small amount of calculation, a low storage capacity, and high real-time, and the algorithm block diagram is shown in Fig. 2.

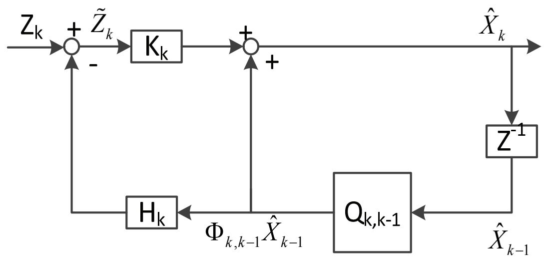

Fig. 2. Kalman algorithm block diagram.

3.3. Novel SOC Estimation Method

EKF is the optimum state estimator, which is widely used for the nonlinear systems. According to the established third-order RC equivalent circuit model, the state variables are selected as follows:

$$X_k=\left[SOC_k\ U_k^1\ U_k^2\ \ U_k^3\right]^T, \qquad (2)$$

where SOC_k is the value of SOC at time index k; U_k^1, U_k^2 and U_k^3 devote the terminal voltage for three RC networks at time index k, respectively.

Combined with equation (1), the state equation and output equation [11] of the above model in discrete space could be described as follows:

$$X_k=\begin{pmatrix}1&0&0&0\\0&e^{-\frac{\Delta t}{\tau_1}}&0&0\\0&0&e^{-\frac{\Delta t}{\tau_2}}&0\\0&0&0&e^{-\frac{\Delta t}{\tau_3}}\end{pmatrix}X_{k-1}+\begin{pmatrix}-\dfrac{\eta\Delta t}{C_n}\\R_1(1-e^{-\frac{\Delta t}{\tau_1}})\\R_2(1-e^{-\frac{\Delta t}{\tau_2}})\\R_3(1-e^{-\frac{\Delta t}{\tau_3}})\end{pmatrix}i_{k-1}+w_{k-1} \qquad (3)$$

$$Y_k=OCV(SOC_k)-i_kR_0-U_k^1-U_k^2-U_k^3+v_k, \qquad (4)$$

where Y_k is the battery terminal voltage at time index k; Δt is the sampling period; i_k is the circuit current at time index k, which is the system control input; $\tau_1=R_1C_1$, $\tau_2=R_2C_2$, $\tau_3=R_3C_3$; w_k and v_k are independent, zero-mean, Gaussian noise processes of covariance matrices Q_k and R_k, respectively; R_0 is the ohmic internal resistance; polarization capacitance C_1, C_2, C_3 and polarization resistance R_1, R_2, R_3 can be identified by the intermittent discharge experiment; $OCV(SOC_k)$ is the nonlinear relationship between open circuit voltage (OCV) and SOC as follows:

$$OCV(SOC_k) = k_1 SOC_k^{\ 8} + k_2 SOC_k^{\ 7} + k_3 SOC_k^{\ 6} + k_4 SOC_k^{\ 5} + k_5 SOC_k^{\ 4} + k_6 SOC_k^{\ 3} + k_7 SOC_k^{\ 2} + k_8 SOC_k + k_9 \tag{5}$$

At different SOC, the battery pack is fully rested, and the terminal voltage can be viewed as open circuit voltage. Based on the obtained OCV and SOC, the undetermined coefficients $k_1 \sim k_9$ can be calculated by using the least squares method.

In the established third-order RC model, the system has multiple state variables. In practical applications, it is necessary to estimate multiple state variables. However, there are certain mutual coupling and influenced relationships each other in this process so that it is difficult to accurately estimate each state variable. Particularly, when random system noise is strong, EKF is directly used for the SOC estimation to result in inaccurate estimation, even is divergent. The proposed novel SOC estimation strategy based on EKF is as follows:

In the measurement equation (4), the terminal voltage of the battery is the linear combination of $OCV(SOC_k)$, U_k^1, U_k^2, U_k^3 and $i_k R_0$, and Y_k is treated as the linear superposition of them. By the superposition principle, the equation (4) can be divided into five independent measurement equation sub-systems, in which each sub-system separately observes corresponding state variables to estimate independently themselves, which eliminating artificially mutual coupling relationship between them and improving estimation accuracy. The method is as follows:

The measurement equation (4) is decomposed as follows:

$$\left.\begin{aligned} Y_{k,x1} &= OCV(SOC_k) - i_k R_0 \\ Y_{k,x2} &= -U_k^1 \\ Y_{k,x3} &= -U_k^2 \\ Y_{k,x4} &= -U_k^3 \end{aligned}\right\} \tag{6}$$

With equation (3), (6), EKF algorithm is used to estimate SOC, and the recursive procedure is as follows:

1) state prediction

$$\hat{X}_{k|k-1,x1} = \psi_{k|k-1} \hat{X}_{k-1|k-1,x1} + \Gamma_{k-1} i_{k-1} , \tag{7}$$

where the state transition matrix:

$$\psi_{k|k-1} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau_1}} & 0 & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{\tau_2}} & 0 \\ 0 & 0 & 0 & e^{-\frac{\Delta t}{\tau_3}} \end{pmatrix} \tag{8}$$

System control input matrix:

$$\Gamma_{k-1} = \left[-\frac{\eta \Delta t}{C_n} \ R_1(1-e^{-\frac{\Delta t}{\tau_1}}) \ R_2(1-e^{-\frac{\Delta t}{\tau_2}}) \ R_3(1-e^{-\frac{\Delta t}{\tau_3}}) \right]^T \tag{9}$$

2) Prediction error variance matrix:

$$P_{k|k-1,x1} = \psi_{k|k-1} P_{k-1|k-1,x1} \psi_{k|k-1}^T + Q_{k-1} \tag{10}$$

3) Filtering gain matrix:

$$K_{k,x1} = P_{k|k-1,x1} H_{k|,x1}^T (H_{k,x1} P_{k|k-1,x1} H_{k,x1}^T + R_k)^{-1} \tag{11}$$

$$\left.\begin{aligned} H_{x1}(k) &= \frac{\partial Y_{k,x1}}{\partial X}\bigg|_{X=\hat{X}_{k,x1}} \\ H_{k,x1} &= [H_{x1}(k) \ 0 \ 0 \ 0] \end{aligned}\right\} , \tag{12}$$

where $H_{k,x1}$ is the observation matrix; $\hat{X}_{k,x1}$ is the data of the prediction matrix $\hat{X}_{k|k-1,x1}$ in the row 1, column k, which is the prediction value for SOC at time index k.

4) State estimation:

$$\hat{X}_{k|k,x1} = \hat{X}_{k|k-1,x1} + K_{k,x1}(Y_{m|k} - \hat{Y}_k) , \tag{13}$$

where $Y_{m|k}$ is the observed value for the terminal voltage of the battery at time index k, disturbed by the measurement noise v_k and measured directly by the experimental equipment; $\hat{Y}_k$ is the corresponding estimation value which can be calculated by the following equation:

$$\left.\begin{aligned} U_k^1 &= U_{k-1}^1 e^{-\frac{\Delta t}{\tau_1}} + R_1(1-e^{-\frac{\Delta t}{\tau_1}}) i_{k-1} \\ U_k^2 &= U_{k-1}^2 e^{-\frac{\Delta t}{\tau_2}} + R_2(1-e^{-\frac{\Delta t}{\tau_2}}) i_{k-1} \\ U_k^3 &= U_{k-1}^3 e^{-\frac{\Delta t}{\tau_3}} + R_3(1-e^{-\frac{\Delta t}{\tau_3}}) i_{k-1} \\ \hat{U}_k^{OCV} &= OCV(\hat{S}OC_{k-1}) \\ \hat{Y}_k &= \hat{U}_k^{OCV} - i_k R_0 - U_k^1 - U_k^2 - U_k^3 \end{aligned}\right\} \tag{14}$$

5) Estimation error covariance matrix:

$$P_{k|k,x1} = (I - K_{k,x1} H_{k,x1}) P_{k|k-1,x1} \tag{15}$$

Steps 1) to 5) are the estimating process for the state variable SOC. Given the initial values of the state estimation matrix $\hat{X}_{k|k,x1}$ and estimation error matrix $P_{k|k,x1}$, the optimal estimation values of SOC are obtained by repeated recursive.

The estimation process for state variables $X_2 \sim X_4$ is similar to SOC.

By comparing recursive process between classical EKF and EKF decomposed measurement equation, the difference is the decomposition of measurement equation, which leads to the change of observation matrix. The theoretical calculations and experimental results show that the correction function of the filtering gain matrix for the EKF decomposed measurement equation, compared with classical EKF, is stronger and more stable.

4. Model Parameters Identification

4.1. Battery Test System

In order to identify [12] parameters in the model, the 60 Ah/72 V power lithium-ion battery pack made by a certain manufacturer is selected in this paper. The intermittent discharge experiments are conducted at room temperature, and the test equipment is Electric Vehicle Test System (EVTS) made by American ARBIN Instruments. The platform is shown in Fig. 3.

4.2. Model Parameters Identification

According to the established third-order RC equivalent circuit model, it is essential to identify the following parameters: ohmic internal resistance R_0; polarization capacitance C_1, C_2 and C_3; polarization resistance R_1, R_2 and R_3. In this paper, the multiple linear regression method is used to identify them.

The intermittent discharge experiments are conducted for the selected battery pack, and the voltage response curves mainly include three stages: firstly, the battery terminal voltage decreases slowly during the constant current discharge; secondly, at the moment of current removal, the voltage has a mutation mainly caused by the ohmic internal resistance [13], and the mutation voltage drop divided by the circuit current is the ohmic internal resistance; thirdly, after the load current is removed, the voltage rises slowly.

According to the experiment voltage data for the falling and rising stages, polarization capacitance C_1, C_2 and C_3, polarization resistance R_1, R_2 and R_3 can be obtained by employing the least squares method. The experimental and the fitted results are shown in Fig. 4, where the blue solid line represents the experimental values, and the red dashed line represents the fitted values. In Fig. 4, the maximum voltage error is about 0.06 V.

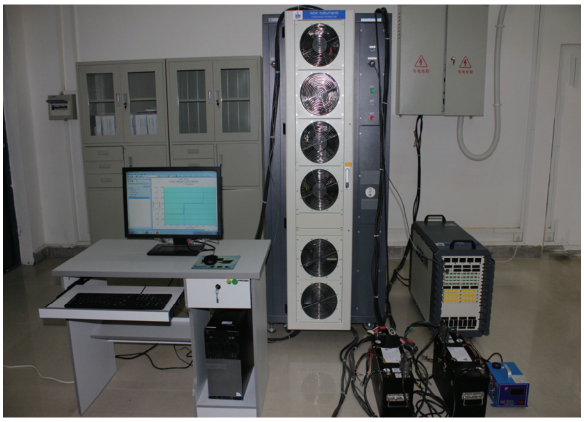

Fig. 3. Battery test platform.

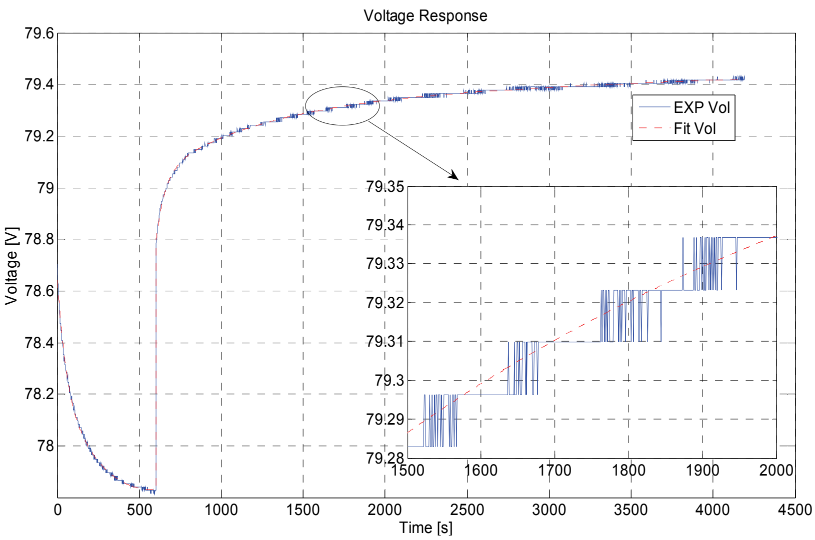

Fig. 4. Experimental voltage and fitted voltage.

5. Simulation and Experiment

5.1. Battery Simulation Model

According to the state and measurement equations of the system, the simulation model built is shown in Fig. 5 in Simulink environment.

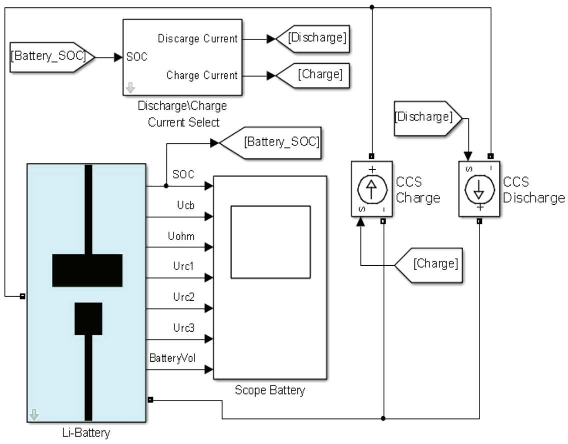

Fig. 5. Battery simulation model.

5.2. Experimental Test Condition

The target of study is to estimate SOC for the 60 Ah/72 V power lithium-ion battery pack made by a certain manufacturer, and the range of working voltage is from 60 V to 86.4 V. The battery pack is discharged with the constant current of 20 A, which is fully charged before starting the experiment.

5.3. Model Validation

Model simulation voltage and the measured voltage results are shown in Fig. 6, where the blue dashed line represents the simulation values, and the red solid line represents the experimental values.

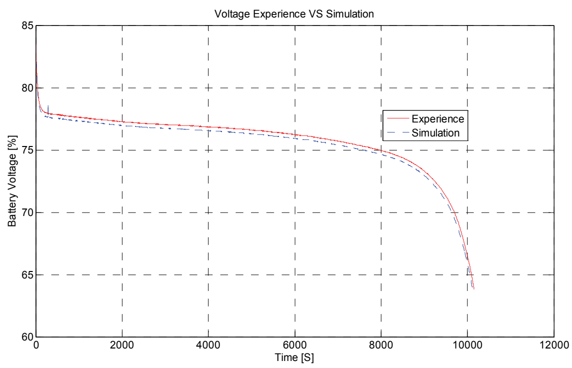

Fig. 6. Simulation and measured voltage.

As show in Fig. 6, the voltage error between the measured and simulation voltage in the whole process, excluding certain point, is about 1.1 V, the others are less than 0.6 V, and the model has a high precision.

5.4. Simulation and Experiment Results

When the current operating conditions change rapidly, and the coupling relationship among multiple state variables is strong, the classical EKF algorithm has been unable to accurately estimate SOC or other state variables. However, the proposed method can be used to accurately estimate each state variable. The SOC estimation results for three methods are shown in Fig. 7 and Fig. 8, Fig. 9, Fig. 10, where the blue dotted line represents the estimated values of the classic EKF, the black dashed line represents the estimated values of the proposed method, and the red solid line represents the experimental values.

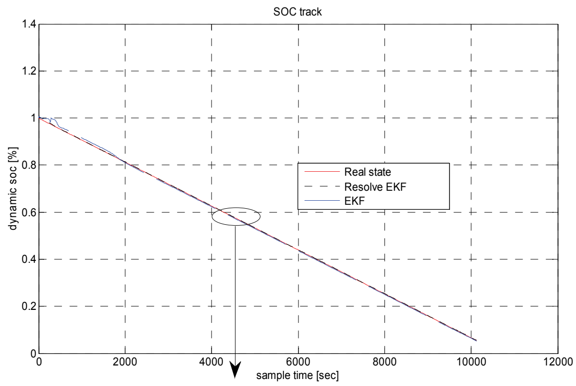

Fig. 7. SOC tracking curve for three methods.

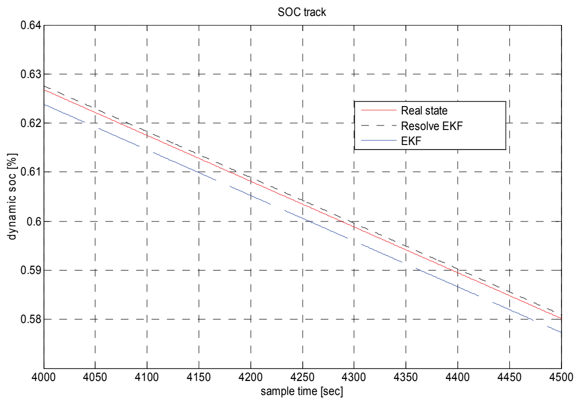

Fig. 8. Larger View of Fig. 7.

The SOC estimation result for classic EKF is shown in Fig. 9, the SOC estimation maximum error is about 3.96 %.

The SOC estimation result for the proposed method is shown in Fig. 10, in the discharge process from 0 to 9680 seconds, the SOC estimation error is less than 1 %, and the maximum error is about 2.05 %.

For the multiple state variables and strong coupling system, the experimental results show that classical EKF algorithm has been unable to accurately estimate SOC and other parameters, even is divergent. However, the proposed method achieves high estimation accuracy for each parameter of battery.

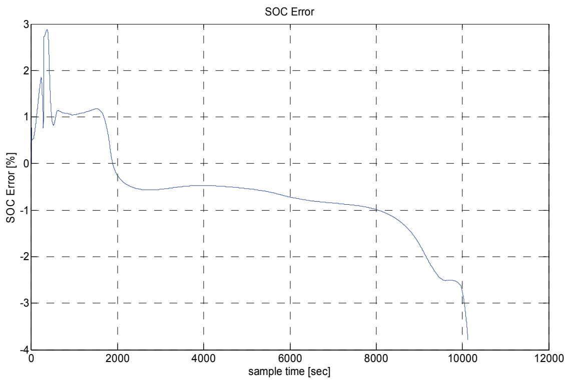

Fig. 9. SOC error for the classical EKF.

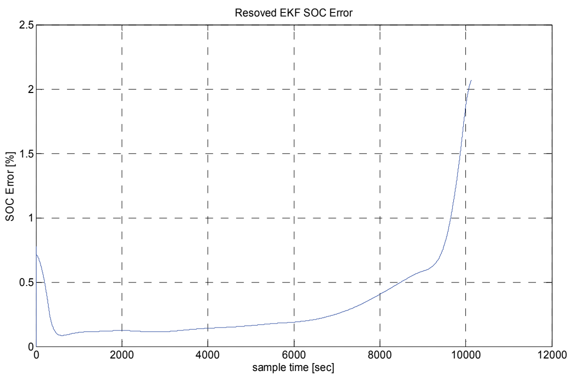

Fig. 10. SOC error for the proposed method.

6. Conclusions

In this paper, the third-order RC equivalent circuit model is established, in which the parameters are obtained through the intermittent discharge experiments. By comparison the simulation and experimental results, the correctness of the model is verified. The simulation and experimental results show that the proposed novel SOC estimation method, for the multiple state variables, the strong coupling and stochastic noise, the wild values in battery system, has a high estimation precision, and is particularly suitable for the SOC estimation under the condition of the current rapidly changing.

However, EKF algorithm relies on the accuracy of the built model. The battery parameters during use will vary with some factors, such as life [14], temperature, self-discharge etc., so the parameters online identification is necessary, which is need to further research.

Acknowledgements

This work has been supported by the National Nature Science Foundation Project (61263013), Scientific Research Project of Guangxi Education Department (201101ZD007) and Guangxi Experiment Center of Information Science, Guilin University of Electronic Technology Project (20130110).

References

[1]. J. Kim, J. Shin, C. Chun and B. H. Cho, Stable Configuration of a Li-Ion Series Battery Pack Based on a Screening Process for Improved Voltage/SOC Balancing, *IEEE Transactions on Power Electronics*, Vol. 27, No. 1, January 2012, pp. 252–292.

[2]. J. H. Kin, G. S. Seo, C. Y. Chun and S. J. Lee, OCV Hysteresis Effect-based SOC Estimation in Extended Kalman Filter Algorithm for a LiFePO4/C Cell, in *Proceedings of the Electric Vehicle Conference (IEVC),* 4-8 March, 2012, pp. 1-5.

[3]. H. X. Song, S. F. Chun, S, F, Chun and Z, Yuan, Online model identification of lithium-ion battery for electric vehicles, *Journal of Central South University of Technology,* Vol. 18, No. 5, October 2011, pp. 209-215.

[4]. J. Lee, O. Nam, and B. H. Cho, Li-ion battery SOC estimation method based on the reduced order extended Kalman filtering, *J. Power Sources*, Vol. 174, No. 1, November 2007, pp. 9–15.

[5]. G. L. Plett, Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Parts 1-3, *J. Power Sources,* Vol. 134, No. 2, August 2004, pp. 252–292.

[6]. N. A. Windarko, J. Choi and G. B. Chung, SOC estimation of LiPB batteries using Extended Kalman Filter based on high accuracy electrical model, in *Proceedings of the 8th International Conference on Power Electronics (ECCE' 2011)*, Shilla Jeju, Korea, May 30-June 3 2011, pp. 2015–2022.

[7]. H. Chaoui and P. Sicard, Accurate State of Charge (SOC) Estimation for Batteries using a Reduced-order Observer, in *Proceedings of the IEEE International Conference on Industrial Technology (ICIT)*, March, 2011, pp. 39 – 43.

[8]. F. X. Yun, S. Z. Chang, A battery model including hysteresis for State-of-Charge estimation in Ni-MH battery, in *Proceedings of the IEEE Vehicle Power and Propulsion Conference (VPPC),* Harbin, China, September 3-5, 2008, pp. 1 – 5.

[9]. L. Y. Wang, L. F. Wang and C. L. Liao, Research on Improved EKF Algorithm Applied on Estimate EV Battery SOC, in *Proceedings of the Power and Energy Engineering Conference (APPEEC)*, Asia-Pacific, March, 2010, pp. 1-4.

[10]. R. C. Kroeze and P. T. Krein, Electrical battery model for use in dynamic electric vehicle simulations, in *Proceedings of the Power Electronics Specialists Conference,* June 2008, pp. 1336-1342.

[11]. D. T. Ting, L. Jun, Z. F. Quan, J. Q. Qian, Analysis on the influence of measurement error on state of charge estimation of LiFePO4 power Battery, in *Proceedings of the International Conference on Materials for Renewable Energy & Environment (ICMREE),* May, 2011, pp. 644-649.

[12]. J. Kim, S. Lee and B. Cho, SOC/Capacity Estimation of a Li-Ion Battery based on Pattern Recognition at Different Temperature, in *Proceedings of the 8th International Conference on Power Electronic (ECCE),* Asia, Shilla Jeju, Korea, May 30-June 3, 2011, pp. 296-303.

[13]. PNGV Battery Test Manual Rev3, *Washington, USA: US Department of Energy,* February, 2001, DOE/ID-10597.

[14]. J. Kim, S. Lee and B. H. Cho, Complementary Cooperation Algorithm Based on DEKF Combined With Pattern Recognition for SOC/Capacity Estimation and SOH Prediction, *IEEE Transactions on Power Electronics,* Vol. 27, No. 1, January, 2012, pp. 436–451.