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SOC EKF Estimation Based on a Second-order LiFePO4 Battery Model

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Abstract

An accurate battery State of Charge (SOC) estimation has great significance in improving battery life and vehicle performance. An improved second-order battery model is proposed in this paper through quantities of LiFePO4 battery experiments. The parameters of the model were acquired by the HPPC composite pulse condition under different temperature, charging and discharging rates, SOC. Based on the model, battery SOC is estimated by Extended Kalman Filter (EKF). Comparison of three different pulse conditions shows that the average error of SOC estimation of this algorithm is about 4.2%. The improved model is able to reflect the dynamic performance of batteries suitably, and the SOC estimation algorithm is provided with higher accuracy and better dynamic adaptability.

Keywords: *state of charge (SOC), extended kalman filter (EKF), LiFePO4 battery*

1. Introduction

In recent years, as the increase of energy crisis and environmental problems, renewable and clean energy sources are attracting more and more attention. LiFePO4 batteries, because of its security, non-pollution property, are widely used in car and backup power supply. Accurate SOC estimation has great significance in extending battery life and improving automotive performance, which makes SOC estimation algorithm be a research hotspot [1-4].

SOC is usually estimated by the external characteristics of the battery, such as battery voltage, current, temperature, internal resistance and other parameters. Furthermore, SOC is also influenced by many other uncertain facts, for example, polarization effect, battery aging, temperature, etc. Consequently, it is difficult to estimate SOC accurately due to the nonlinear and dynamic characters of the battery. Some common methods Current integration method (AH), Open-circuit-voltage (OCV) method, electromotive force (EMF) method and neural network method have been widely applied in SOC estimation. However these methods have too serious disadvantages to act on accurate dynamic estimation. Kalman filter, by contrast, is based on state space model and is fit for state estimation of dynamic system. As far as the theoretical aspect, the Extended Kalman filter (EKF) is the nonlinear version of the Kalman filter with the current mean and covariance linearized. For this reason, the study of SOC estimation based on Extended Kalman filter is carried out in the paper for achieving better dynamic accuracy [5-8].

2. Model and Parameters Acquisition Methods

In order to apply EKF to SOC estimation, an improved second-order battery model of LiFePO4 batteries is proposed in this paper, from which the parameters are acquired in the HPPC composite pulse condition.

2.1. Battery Models

Battery model is used to describe the relationship between external electrical characteristics (voltage, current, temperature, etc.) and internal battery state (resistance, state of charge, etc.). Besides of SOC, the internal state variables of battery could be estimated by

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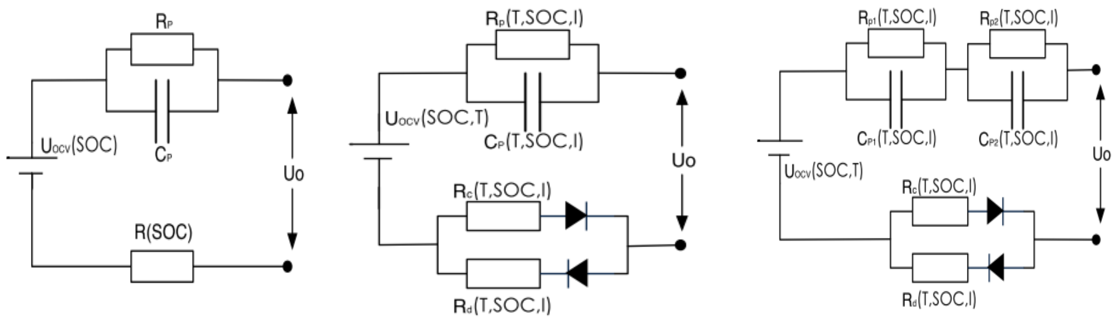
the external variables obtained through test. Battery model develops from simple to complex. The simple one only considers open circuit voltage and battery internal resistance, while the complex one considers the battery self-discharge affects as same as other factors.

Figure 1(a) shows the classical First-order RC model which has been broadly used. However, there are two problems in the application of this model:

1.The battery internal resistance is considered as constant, which does not obey the realistic application;

2.The open circuit voltage is regarded as only related with the current SOC, which neither takes into account the relationship between the open-circuit voltage and the discharge rate, nor considers about the relationship between the open-circuit voltage and temperature.

Regarding the impacts generated by the charge and discharge state for the accuracy of the algorithm, first-ordermodel is improved shown in Figure 1(b). In order to achieve better simulate accuracy and better dynamic characteristics, an improved second-order model is proposed as shown in Figure 1(c). In these models, U_{OCV} is the Battery open circuit voltage, U_0 is the output voltage, I is the battery charge and discharge current, R_0 is the battery ohm resistance, C_p is the polarization capacitance, R_p is the polarization resistance; R_{p1} and R_{p2} are the polarization resistance; C_{p1} and C_{p2} are the polarization capacitance.



(a)First-order RC model (b) First-order RC model (c) Second-order RC model

Figure 1. Battery Models

Table 1. Resistance of Charge Stage

SOC	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
R_0(mΩ)	17	18.1	18.6	18.8	19.1	19.6	19.6	19.5	20	20.4

Table 2. Resistance of Discharge Stage

SOC	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
R_0(mΩ)	17.4	18	18.4	18.6	19.2	19.2	19.4	20	20.1	20.6

Table 3. Parameters of Second-order Model

SOC	U_{ocv} (V)	R_d(Ω)	τ_1(s)	τ_2(s)	R_{p1}(Ω)	C_{p1}(103F)	R_{p2}(Ω)	C_{p2}(104F)
1	3.3480	0.0173	47.0604	788.9944	0.0306	1.5379	0.0155	5.0903
0.9	3.3305	0.0180	38.2906	348.3712	0.0207	1.8498	0.0125	2.7870
0.8	3.3111	0.0184	38.0948	441.3369	0.0234	1.6280	0.0095	4.6457
0.7	3.2909	0.0186	33.9550	317.2752	0.0236	1.4388	0.0081	3.9170
0.6	3.2875	0.0192	32.3484	307.3685	0.0231	1.4004	0.0137	2.2436
0.5	3.2854	0.0192	33.2021	352.3605	0.0276	1.2030	0.0088	4.0041
0.4	3.2714	0.0194	31.7311	375.5209	0.0285	1.1134	0.0176	2.1336
0.3	3.2456	0.0200	30.3255	377.5702	0.0295	1.0280	0.0309	1.2219
0.2	3.2114	0.0201	29.5371	422.7733	0.0319	0.9259	0.0561	0.7536
0.1	3.1505	0.0207	30.5221	626.4187	0.1676	3.7376	0.0331	0.0922

2.2. Parameters Estimation of the Models

Model Parameters testing process adopts HPPC Test method proposed in [9]. Batteries tests were divided into four steps: charging, charging cease, discharging, and discharging cease. The recognition process was divided into two types: charge and discharge, in which excitationresponse analysis method and Least Squares fitting method is used to identify the model parameters under different conditions.

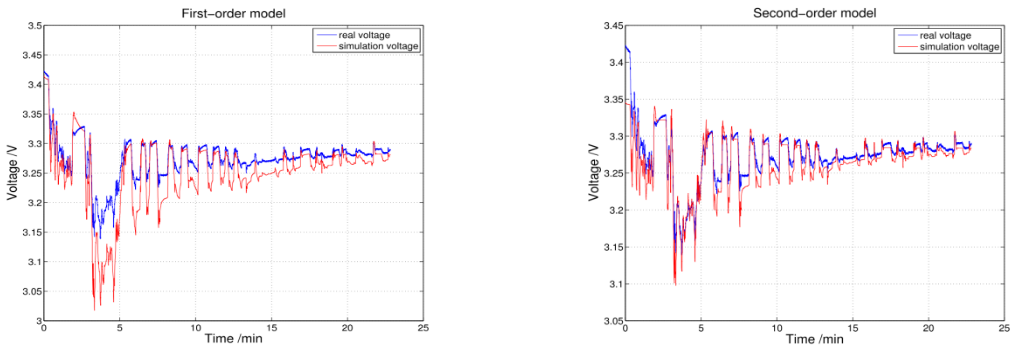
The instantaneous voltage waves were recorded in real time when current is loaded and unloaded, then the battery charge and discharge resistances can be obtained by Ohm's law, which is shown in Table 1 and Table 2.

At the stage of the discharging cease, voltage curve can be regarded as the zero-input response of the RC parallel; the loop equation is illustrated in Equation (1). Least Squares method is applied to solve U_{p1},U_{p2}, $\tau_1$and τ_2. At the discharge stage, the loop equation becomes Equation (2), and R_{p1},R_{p2}, C_{p1} and C_{p2}, can be obtained in the same way. The parameters of Second-order model are shown in Table 3.

$$U_o = U_{ocv}(SOC,T) - \left(U_{p1}\cdot e^{-\frac{t}{\tau_1}} + U_{p2}\cdot e^{-\frac{t}{\tau_2}}\right) \quad (1)$$

$$U_o = U_{ocv}(SOC,T) - \left[I\cdot R_{p1}\cdot\left(1-e^{-\frac{t}{\tau_1}}\right) + I\cdot R_{p2}\cdot\left(1-e^{-\frac{t}{\tau_2}}\right)\right] - I\cdot R_d(SOC,T,I) \quad (2)$$

A first-order and a second-order model simulation model were established, and the corresponding simulated voltage under UDDS dynamics current conditions [10], is shown in Figure 2. As a result, the errors of the first-order model are less than 0.1493V, and the errors of the second-order model are less than 0.0103V, which indicate that the second-order model has a much better dynamic accuracy.



(a) Contrast curve of first-order model (b) Contrast curve of second-order model

Figure 2. Contrast Curve of Real Voltage and Simulation Voltage

3. EKF and SOC Estimation Algorithm

3.1. EKF Theory

For nonlinear model, the Extended Kalman Filter (EKF) method is proposed in paper [11, 12]. A linear model function could be obtained from the nonlinear model by Taylor expansion, and then SOC estimate can be achieved by the basic Kalman filter estimation.

Nonlinear discrete state-space equation is shown in Equation (3).

$$\begin{cases} x_{k+1} = f(x_k,u_k) + w_k \\ y_k = g(x_k,u_k) + v_k \end{cases} \quad (3)$$

Here in, x_k is the system status vector, u_k is the input vector at time *k*, $f(x_k,u_k)$ is the non-linear status transfer function. $g(x_k,u_k)$ is the nonlinear measurement function, w_k and v_k are respectively the system noise and the measurement noise, whose covariance are Q_w and R_v.

$$Q_w = E[w_k \times w_k^T] \quad (4)$$

$$R_w = E[v_k \times v_k^T] \quad (5)$$

By substituting Equation (4) and (5) into the Taylor series A at state estimate$\hat{x}_k$, and neglect the high-order term, then function (6) is obtained. If it is supposed that$A_k = \partial f/\partial \hat{x}_k$ and $C_k = \partial g/\partial \hat{x}_k$, Equation (7) can be derived.

$$x_{k+1} = A_k x_k + [f(\hat{x}_k, u_k) - A_k \hat{x}_k] + w_k \quad (6)$$

$$y_k = C_k x_k + [g(\hat{x}_k, u_k) - C_k \hat{x}_k] + v_k \quad (7)$$

Recursive steps of extended Kalman filter algorithm canbe summarized as following:

1. Initialize the original parameters;

$$\begin{cases} \hat{x}_{0/0} = E[x(0)] \\ P_{0/0} = E\{[x(0) - E[x(0)]]\} \end{cases} \quad (8)$$

2. Predicted state estimate;

$$\hat{x}_{k/k-1} = f\left(\hat{x}_{k-1/k-1}, u_{k-1}\right) \quad (9)$$

3. Updated estimate covariance;

$$P_{k/k-1} = A_{k-1} P_{k-1/k-1} A_{k-1}^T + Q_{k-1} \quad (10)$$

4. Near-Optimal Kalman gain;

$$K_k = P_{k/k-1} C_k^T (C_k P_{k/k-1} C_k^T + R_k)^{-1} \quad (11)$$

5. Updated state estimate;

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k \left(y_k - g\left(\hat{x}_{k/k-1}, u_k\right)\right) \quad (12)$$

6. Predicted estimate covariance;

$$P_{k/k} = (I - K_k C_k) P_{k/k-1} \quad (13)$$

7. Repeat step 1 to step 6, the recursive filter calculation.

3.2. State Space Equation of the Models

Two capacitor voltage and SOC in second-order RC model as the state variables, the circuit equation as the measurement equation, the discrete state equation is establish as Equation (14-15).

$$\begin{pmatrix} SOC_{k+1} \\ U_{p1,k+1} \\ U_{p2,k+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\Delta t/\tau 1} & 0 \\ 0 & 0 & e^{-\Delta t/\tau 2} \end{pmatrix} \times \begin{pmatrix} SOC_k \\ U_{p1,k} \\ U_{p2,k} \end{pmatrix} + \begin{pmatrix} -\eta \Delta t / C_N \\ R_{p1}\left(1 - e^{-\Delta t/\tau 1}\right) \\ R_{p2}\left(1 - e^{-\Delta t/\tau 2}\right) \end{pmatrix} i_k \quad (14)$$

$$U_{o,k} = U_{ocv,k} - R_d i_k - U_{p1,k} - U_{p2,k} \quad (15)$$

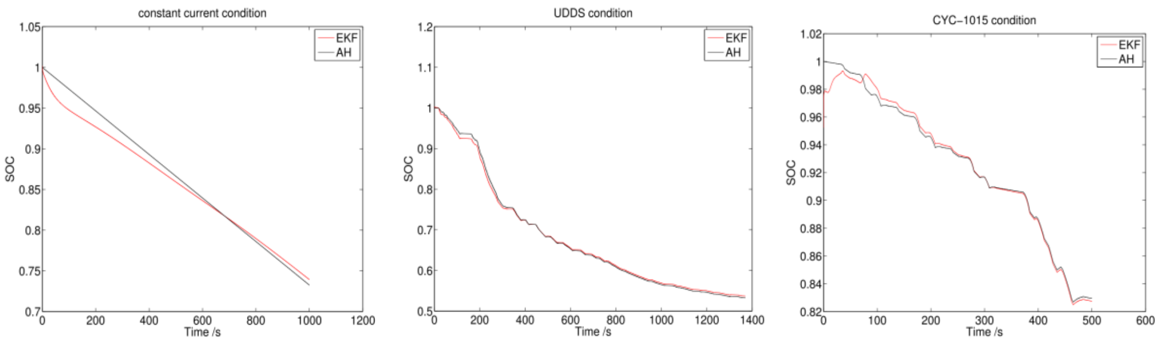
In Equation (13), Δt is the sampling period; $U_{p1,k}$ is the estimated voltage of C_{p1} at the sampling time k; $U_{p2,k}$ is the estimated voltage of C_{p2} at the sampling time k. $\tau 1$ and $\tau 2$ are the time constant of the RC, and their value are respectively defined as $\tau 1 = R_{p1}C_{p1}$, $\tau 2 = R_{p2}C_{p2}$. X_k is the state vector, A_k is the system matrix and C_k is the observed matrix, which could be obtained by the Equation 16-17.

$$X_k = \begin{pmatrix} SOC_k \\ U_{p1,k} \\ U_{p2,k} \end{pmatrix} A_k = \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\Delta t/\tau 1} & 0 \\ 0 & 0 & e^{-\Delta t/\tau 2} \end{pmatrix} \tag{16}$$

$$C_k = \frac{\partial U_o}{\partial X} = \begin{pmatrix} \frac{\partial U_o}{\partial SOC} & \frac{\partial U_o}{\partial U_{p1}} & \frac{\partial U_o}{\partial U_{p2}} \end{pmatrix} = \begin{pmatrix} \frac{\partial (U_{ocv} - R_d i)}{\partial SOC} & -1 & -1 \end{pmatrix} \tag{17}$$

3.3. Verification Experiment

In order to verify the accuracy and the convergence of the algorithm, three conditions (constant current discharge condition, CYC UDDS condition and CYC_1015_prius condition) were selected for the experiment, as shown in Figure 3, and their results will compare with those of AH method, which is regarded as the standard measurement.



(a) Constant current condition (b) CYC UDDS condition (c) CYC_1015_prius condition

Figure 3. Contrast Curve of Verification Experiment

Table 4. Relative Errors of Different Conditions

Conditions	Constantcurrent	UDDS	CYC_1015_prius
Max error	4%	1.38%	2%

Estimated errors of different conditions are shown in Table 4. There are two kinds of principal errors in the calculation: one is the error introduced by Taylor expansion when higher-order terms are omitted. The other comes from parameters calculation of battery circuit model. Especially in Figure 3(a), the error mainly depends on the accuracy of the model parameters. Therefore, further work can be carried out to improve the accuracy of the algorithm based on these two aspects.

4. Conclusion

This paper has dedicated the research to study the LiFePO4 battery modeling method and the SOC estimation algorithm. In view of the impact caused by the external factors, the parameter test method, parameter identification process, an improved first-order and second-order correction model is established and is validated under the UDDS condition. Based on the modified model, Extended Kalman filter estimation algorithm is used to estimate SOC under constant current discharge condition, HPPC condition and UDDS cycle condition. The comparison with AH method demonstrate that the improved model can better reflect the dynamic performance of battery, and can meet the practical needs very well. The state of charge estimation method of battery has the high accuracy, good dynamic adaptability.

Acknowledgments

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