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
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-order model 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.

![First-order RC model](image1)

![First-order RC model](image2)

![Second-order RC model](image3)

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

Table 1. Resistance of Charge Stage

<table>
<thead>
<tr>
<th>SOC</th>
<th>1</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
<th>0.4</th>
<th>0.3</th>
<th>0.2</th>
<th>0.1</th>
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</thead>
<tbody>
<tr>
<td>R_0(mΩ)</td>
<td>17</td>
<td>18.1</td>
<td>18.6</td>
<td>18.8</td>
<td>19.1</td>
<td>19.6</td>
<td>19.5</td>
<td>20</td>
<td>20.4</td>
<td></td>
</tr>
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</table>

Table 2. Resistance of Discharge Stage

<table>
<thead>
<tr>
<th>SOC</th>
<th>1</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
<th>0.4</th>
<th>0.3</th>
<th>0.2</th>
<th>0.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>R_0(mΩ)</td>
<td>17.4</td>
<td>18</td>
<td>18.4</td>
<td>18.6</td>
<td>19.2</td>
<td>19.2</td>
<td>19.4</td>
<td>20</td>
<td>20.1</td>
<td>20.6</td>
</tr>
</tbody>
</table>

Table 3. Parameters of Second-order Model

<table>
<thead>
<tr>
<th>SOC</th>
<th>$U_{OCV}$(V)</th>
<th>R_0(Ω)</th>
<th>r_1(s)</th>
<th>r_2(s)</th>
<th>R_{p1}(Ω)</th>
<th>C_{p1}(10^3F)</th>
<th>R_{p2}(Ω)</th>
<th>C_{p2}(10^4F)</th>
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<tr>
<td>1</td>
<td>3.3480</td>
<td>0.0173</td>
<td>47.0604</td>
<td>788.9944</td>
<td>0.0306</td>
<td>1.5379</td>
<td>0.0155</td>
<td>5.0903</td>
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<tr>
<td>0.9</td>
<td>3.3305</td>
<td>0.0180</td>
<td>38.2906</td>
<td>348.3712</td>
<td>0.0207</td>
<td>1.8498</td>
<td>0.0125</td>
<td>2.7870</td>
</tr>
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<td>0.8</td>
<td>3.3111</td>
<td>0.0184</td>
<td>38.0948</td>
<td>441.3369</td>
<td>0.0234</td>
<td>1.6280</td>
<td>0.0095</td>
<td>4.6457</td>
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<tr>
<td>0.7</td>
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<td>0.6</td>
<td>3.2875</td>
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<td>307.3685</td>
<td>0.0231</td>
<td>1.4004</td>
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<td>2.2436</td>
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<td>0.5</td>
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<td>0.0192</td>
<td>33.2021</td>
<td>352.3605</td>
<td>0.0276</td>
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</tr>
<tr>
<td>0.4</td>
<td>3.2714</td>
<td>0.0194</td>
<td>31.7311</td>
<td>375.5209</td>
<td>0.0285</td>
<td>1.1134</td>
<td>0.0176</td>
<td>2.1336</td>
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<tr>
<td>0.3</td>
<td>3.2456</td>
<td>0.0200</td>
<td>30.3255</td>
<td>377.5702</td>
<td>0.0295</td>
<td>1.0280</td>
<td>0.0309</td>
<td>1.2219</td>
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<tr>
<td>0.2</td>
<td>3.2114</td>
<td>0.0201</td>
<td>29.5371</td>
<td>422.7733</td>
<td>0.0319</td>
<td>0.9259</td>
<td>0.0561</td>
<td>0.7536</td>
</tr>
<tr>
<td>0.1</td>
<td>3.1505</td>
<td>0.0207</td>
<td>30.5221</td>
<td>626.4187</td>
<td>0.1676</td>
<td>3.7376</td>
<td>0.0331</td>
<td>0.0922</td>
</tr>
</tbody>
</table>
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 $\tau_2$. 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.

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

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

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.

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 nonlinear 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 $R_v$. 
\[ Q_w = E[w_k \times w_k^T] \]  \hspace{1cm} (4)

\[ R_w = E[v_k \times v_k^T] \]  \hspace{1cm} (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 \( A_k = \frac{\partial f}{\partial \hat{x}_k} \) and \( C_k = \frac{\partial g}{\partial \hat{x}_k} \), Equation (7) can be derived.

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

\[ y_k = C_k x_k + [g(\hat{x}_k, u_k) - C_k \hat{x}_k] + v_k \]  \hspace{1cm} (7)

Recursive steps of extended Kalman filter algorithm can be summarized as following:

1. Initialize the original parameters;
\[
\begin{align*}
\hat{x}_{0/0} &= E[x(0)] \\
\text{P}_{0/0} &= E[(x(0) - E[x(0)])]
\end{align*}
\]  \hspace{1cm} (8)

2. Predicted state estimate;
\[ \hat{x}_{k/k-1} = f(\hat{x}_{k-1/k-1}, u_{k-1}) \]  \hspace{1cm} (9)

3. Updated estimate covariance;
\[ P_{k/k-1} = A_{k-1} P_{k-1/k-1} A_{k-1}^T + Q_{k-1} \]  \hspace{1cm} (10)

4. Near-Optimal Kalman gain;
\[ K_k = P_{k/k-1} C_k^T (C_k P_{k/k-1} C_k^T + R_k)^{-1} \]  \hspace{1cm} (11)

5. Updated state estimate;
\[ \hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k (y_k - g(\hat{x}_{k/k-1}, u_k)) \]  \hspace{1cm} (12)

6. Predicted estimate covariance;
\[ P_{k/k} = (I - K_k C_k) P_{k/k-1} \]  \hspace{1cm} (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).

\[
\begin{pmatrix}
SOC_{k+1} \\
U_{p1,k+1} \\
U_{p2,k+1}
\end{pmatrix} =
\begin{pmatrix}
1 & 0 & 0 \\
0 & e^{-\Delta t/\tau_1} & 0 \\
0 & 0 & e^{-\Delta t/\tau_2}
\end{pmatrix}
\begin{pmatrix}
SOC_k \\
U_{p1,k} \\
U_{p2,k}
\end{pmatrix}
+ \begin{pmatrix}
-\eta \Delta t / C_N \\
R p1 \left(1 - e^{-\Delta t / \tau_1}\right) \\
R p2 \left(1 - e^{-\Delta t / \tau_2}\right)
\end{pmatrix} i_k
\]  \hspace{1cm} (14)

\[ U_{o,k} = U_{occ,k} - R_d i_k - U_{p1,k} - U_{p2,k} \]  \hspace{1cm} (15)
In Equation (13), \(\Delta t\) 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.

\[
X_k = \begin{pmatrix}
SOC_k \\
U_{p1,k} \\
U_{p2,k}
\end{pmatrix}
A_k = \begin{pmatrix}
1 & 0 & 0 \\
0 & e^{-\Delta t/\tau_1} & 0 \\
0 & 0 & e^{-\Delta t/\tau_2}
\end{pmatrix}
\]

\[
C_k = \begin{pmatrix}
\frac{\partial U_0}{\partial \text{SOC}} \\
\frac{\partial U_0}{\partial U_{p1}} \\
\frac{\partial U_0}{\partial U_{p2}}
\end{pmatrix} = \begin{pmatrix}
\frac{\partial (U_{oc0} - R_d(\text{SOC}))}{\partial \text{SOC}} \\
-1 \\
-1
\end{pmatrix}
\]

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.

![Figure 3. Contrast Curve of Verification Experiment](image)

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

<table>
<thead>
<tr>
<th>Table 4. Relative Errors of Different Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditions</td>
</tr>
<tr>
<td>----------------------------</td>
</tr>
<tr>
<td>Max error</td>
</tr>
</tbody>
</table>

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
This work was supported by the project of "SOC Estimation of Lithium Ion Battery
Manage System" funded by ZTEHoldings Co., LTD. It was also sponsored by National Natural
Science Foundation of China (NSFC, Grant No. 61171183) and the Fundamental Research
Funds for the Central Universities (Grant No. HIT. NSRIF. 201146).

References
[1] Long Xu, Junping Wang, Quanshi Chen. Kalman filtering state of charge estimation for battery
management system based on a stochastic fuzzy neural network battery model. Energy Conversion
2011; 33: 472–476.
6699–6708.
modeling and systematic parameterization for a lithium-ion battery cell. Journal of Power Sources.
modeling of li-ion battery designed for an electric scooter. Journal of Power Sources. 2006; 158: 673–
678.
[10] Pong battery test manual. United States Idaho National Engineering & Environmental Laboratory,
lithium-ion batteries. Journal of Power Sources. 2004; 130: 266–274.
[12] Gregory L Plett. Extended kalman filtering for battery management systems of lipb-based hev battery