A Novel Method for Estimating State-of-Charge of Lithium-ion Battery Pack Based on General Open Circuit Voltage

Hao Lei, Xiaokai Chen*, Rui Xiong
National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, PR China

Abstract

The relationship between open-circuit-voltage (OCV) and the state of charge (SOC) has shown a considerable influence on the accuracy of SOC estimation. In this study, in order to deal with the uncertainty and inconsistency of the OCV curve in the battery pack, a novel method for SOC estimation based on the general OCV is proposed. The general OCV unifies the OCV curves of all the cells in the battery pack and can be used to solve the OCV derivative in EKF-based SOC estimation, but it brings model deviation meanwhile. Therefore, the battery model is corrected by the model bias, which is obtained by online identification with other model parameters. The case study results show that the results of SOC estimation is accurate and stable, with the maximum absolute error less than 6% at 0°C, 4% at 25°C and 45°C.

Keywords: state-of-charge estimation, Lithium-ion battery pack, general open-circuit-voltage, model bias, Kalman filter

1. Introduction

Electric vehicles (EVs) have become one of the key development directions for green transportation due to their energy saving and low emissions. The lithium ion battery system as an energy storage is crucial to EVs, and battery management systems (BMSs) are required to monitor SOC in real-time, preventing battery over-charging and over-discharging [1, 2]. Since SOC cannot be measured directly, many methods are proposed for SOC estimation [3]. Among them, model-based methods are widely used for EV applications, especially equivalent circuit model (ECM) based methods.

Open circuit voltage (OCV), which is a function of SOC, is vital for SOC estimation. For example, the KF-based method, which is widely used for SOC estimation and shows good accuracy and stability [4], utilizes OCV-SOC curve to correct the error of the ampere-hour integral method. The studies in Ref. [5] and [6] show that the OCV-SOC curve has a considerable influence on the accuracy of SOC estimation. However, the battery system in an EV is usually composed of hundreds of battery cells in series and parallel, and the inherent inconsistency of the cells will always exist [7]. Different batteries have different OCV curves, and the OCV curves change with temperature and battery aging [8]. Unfortunately, since OCV characterization test is time-consuming, it is impossible to conduct OCV test for every battery cell in EVs. Therefore, the OCV curve is uncertain of a battery that has not been tested, which causes great error for SOC estimation.

In addition, as for a battery with LiFePO4 (LFP) cathode whose OCV curve is flat in a wide SOC region, a small error in OCV will cause a large error in SOC estimation [9]. The SOC estimation error of LFP battery could be much larger than the battery who has a steep OCV curve, e.g. NMC battery. Therefore, the uncertainty of OCV curve has a greater impact on a LFP battery than a NMC battery, especially in pack.

In order to solve the problem above, in this paper, a novel method for SOC estimation of battery pack is proposed, which is based on the general OCV. In this method, the feedback link for SOC estimate is obtained from the general OCV, which is the same for all cells. Therefore, the uncertainty of OCV for each cell is quantified by the model bias, while the model bias is identified online with other model parameters. The proposed method is applicable to variety batteries, including LFP and NMC.

The rest of this paper is organized as follows. Section 2 presents the experimental data used in this paper. Section 3 illustrates the battery model with general OCV and bias, and the online parameter identification method is presented. Section 4 presents
the SOC estimation for battery pack. Finally, conclusions are drawn in Section 5.

2. Experiments

The battery experimental platform used in this study consists of an Arbin battery test machine, a thermal chamber to regulate operation temperature and a computer with Arbin software. Batteries with LiFePO$_4$ (LFP) cathode were used in this study, and their basic specifications are given in Table 1.

Firstly, capacity tests of several battery cells were performed at the temperature of 0°C, 25°C, and 45°C to obtained the average capacity of cells, as shown in Table 2. Secondly, the incremental OCV tests were performed on three cells at 25°C to obtain the OCV-SOC curves of the battery cells, and the OCV were tested at every 5% SOC.

Table 1. Specifications of the tested batteries

<table>
<thead>
<tr>
<th>Material</th>
<th>Nominal capacity (Ah)</th>
<th>Nominal voltage (V)</th>
<th>Lower cut-off voltage (Ah)</th>
<th>Upper cut-off voltage (Ah)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LiFePO$_4$</td>
<td>50 Ah</td>
<td>3.2 V</td>
<td>2.5 V</td>
<td>3.6 V</td>
</tr>
</tbody>
</table>

Table 2. Average capacity at different temperatures

<table>
<thead>
<tr>
<th>Capacity (Ah)</th>
<th>0°C</th>
<th>25°C</th>
<th>45°C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>49.87</td>
<td>52.64</td>
<td>54.34</td>
</tr>
</tbody>
</table>

Thirdly, a battery pack consisting of 12 LFP battery cells connected in series (12S1P) was tested in the platform. The urban dynamometer driving schedule (UDDS) tests were performed at 0°C, 25°C, and 45°C to simulate the actual current excitation of the battery pack in EVs.

3. Lithium-ion battery model

3.1 General open circuit voltage

Inconsistency between different battery cells and environmental variability bring uncertainty in the OCV curve. In order to deal with the uncertainty of OCV curve, the OCV curve is approximated by an artificially constructed monotonically increasing curve. In this paper, the general OCV curve is fitted with a double exponential function from the OCV test results of three cells. As shown in Figure 1, the general OCV is constructed from the OCV tests at 25°C.

\[ U_{OC}(z) = \frac{R_0}{1 + \frac{R_d}{C_d}} + \frac{R_0}{1 + \frac{R_d}{C_d}} \left[ 1 - e^{-\frac{R_0}{C_d}} \right] \]

Figure 1. General OCV curve

The analytical expression of the function is

\[ OCV(z) = \alpha \exp(\beta z) + \gamma \exp(\varepsilon z) \]  

(1)

where \( z \) denotes SOC, and \( \alpha, \beta, \gamma, \varepsilon \) denote the coefficient of the double exponential function. In this study, \( \alpha = 3.243, \beta = 0.03343, \gamma = -0.4421, \varepsilon = -34.77 \).

As can be seen from Figure 2, there is no flat region in the general OCV, but it also brings the difference between the general OCV and actual OCV curve.

3.2 Battery model with general OCV and bias

The 1RC equivalent circuit model (ECM) has shown good balance between the accuracy, stability and computation burden among the various ECMs [10]. In this study, 1RC model is chosen as the basic model. As shown in Figure 2, it consists of three parts: a voltage source \( U_{OC} \) which means the OCV, an ohmic resistance \( R_0 \), and the RC circuit \((R_d \text{ and } C_d)\). \( z \) denotes the SOC, which means the OCV is a function of SOC. \( i \) is the load current, \( U_l \) is the terminal voltage, and \( U_s \) is the voltage of \( C_d \).

\[ z_k = z_{k-1} - \frac{i_{l,k}}{C_d} \Delta t 
\]

\[ U_{l,k} = \text{OCV}(z_k) - U_{d,k} - i_{l,k} R_{o,k} \]

where \( \tau = R_d C_d \) and \( C_0 \) means the maximum available capacity of a battery, and \( k \) denotes the discretization step with a sample interval of \( \Delta t \), \( k = 1, 2, 3, \ldots, n \).
As the OCV has been replaced by the general OCV, the output equation could be expressed as
\[ U_{t,k} = \text{gen OCV}(z_k) + \delta_t - U_{t,k} - R_{t,k} \]
where \( \delta \) denotes the model bias which is used to correct the general OCV.

On the one hand, the model bias represents the difference between the general OCV and the actual OCV at different temperatures. On the other hand, the model bias contains the uncertainty between different battery cells.

### 3.3 Model parameter identification

The recursive least square (RLS) algorithm with forgetting factor exhibits extremely fast convergence and good accuracy and has been widely adopted for parameter identification. For a dynamic system which is represented by
\[ y_k = \phi \theta_k + e_k \]  \hspace{1cm} (4)
where \( y_k \) denotes the output vector, \( \phi \) denotes the data matrix, \( \theta_k \) denotes the parameter vector, and \( e_k \) denotes the zero-mean white Gaussian noise.

The RLS algorithm can be expressed as
\[
\begin{align*}
K_{RLS,k} &= P_{RLS,k-1} \phi_k^T (\phi_k P_{RLS,k-1} \phi_k^T + \mu)^{-1} \\
\hat{\theta}_k &= \hat{\theta}_{k-1} + K_{RLS,k} (y_k - \phi_k \hat{\theta}_{k-1}) \\
P_{RLS,k} &= (I - K_{RLS,k} \phi_k) P_{RLS,k-1}/\mu
\end{align*}
\]  \hspace{1cm} (5)
where \( K_{RLS,k} \) and \( P_{RLS,k} \) denote the gain matrix and error covariance matrix, respectively. \( \mu \) denotes the forgetting factor which is usually set to a value between 0.95 and 1.

In this study, the battery model as Eq. (3) can be expressed as the form of Eq. (4).

\[
\begin{align*}
y_k &= U_{t,k} - \text{gen OCV}(z_k) \\
\phi_k &= \begin{bmatrix} 1 & U_{t,k-1} - \text{gen OCV}(z_{k-1}) & i_{t,k} & i_{t,k-1} \end{bmatrix} \\
\theta_k &= \begin{bmatrix} \theta_{t,k} & \theta_{t,k} & \theta_{t,k} & \theta_{t,k} \end{bmatrix}^T \\
\theta_{t,k} &= \delta_{t,k} - \delta_{t,k-1} \\
\theta_{t,k} &= -\Delta t - 2r_{t,k} \\
\theta_{t,k} &= -\frac{R_{t,k}\Delta t + R_{t,k}\Delta t + 2R_{t,k}\tau_{t,k}}{\Delta t + 2r_{t,k}} \\
\theta_{t,k} &= -\frac{R_{t,k}\Delta t + R_{t,k}\Delta t - 2R_{t,k}\tau_{t,k}}{\Delta t + 2r_{t,k}}
\end{align*}
\]  \hspace{1cm} (6)

As the analytical expression of the function of general OCV has been known, the model bias can be identified with the other parameters. However, the SOC at the 4th moment (\( z_k \)) is unknown, as it should be replaced by the SOC prior estimate, which will be mentioned in Section 4.

### 4. State of charge estimation with bias correction

#### 4.1 SOC estimation based on extend Kalman Filter (EKF)

The EKF have been widely used in SOC estimation and shown good accuracy. The algorithm can be summarized as Table 3.

<table>
<thead>
<tr>
<th>Step 1) Initialization</th>
</tr>
</thead>
<tbody>
<tr>
<td>For ( k = 0 ), set ( \hat{x}_0 = E[x_0] \cdot P_0 = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T] \cdot Q_0 \cdot R_0 )</td>
</tr>
</tbody>
</table>

| Step 2) Prediction: priori estimation |
| State priori estimate: \( \hat{x}_{k|k} = \hat{f}(\hat{x}_{k-1}, u_k) \) |

| Step 3) Update: posterior estimation |
| Measurement residual: \( e_k = y_k - h(\hat{x}_{k|k}, u_k) \) |
| Kalman gain matrix: \( K_k = P_{k|k} H_k^T (H_k P_{k|k} H_k^T + R_k)^{-1} \) |
| State posterior estimate: \( \hat{x}_k = \hat{x}_{k|k} + K_k e_k \) |
| Error covariance posterior estimate: \( P_k = (I - K_k H_k) P_{k|k} \) |

| Step 4) Time update: \( k = k + 1 \); return to Step 2) |

where \( x_0, u_k \) and \( y_k \) denote the system state vector, input vector and output vector at discrete-time index \( k \), \( w_k \) is the unmeasured “process noise” that affects the system state, \( v_k \) is the measurement noise. \( Q \) and \( R \) denote the covariance matrices of independent, zero-mean Gaussian noise of \( w \) and \( v \).

#### 4.2 Battery pack SOC estimation results

In order to evaluate the validity of the proposed method, the experimental data of the 12S1P battery pack at 0°C, 25°C and 45°C was used to estimate the SOC of pack. It is necessary to mention that the battery cells in the pack have not been individually tested, so the exact capacity and actual OCV curve of each cell are unknown. All we know about the cells is the average capacity of the same type of battery in the same batch, and the general OCV curve constructed in Section 3. Therefore, in this paper, the capacity of every cell is set to be the same.

Taking the UDDS test at 0°C as an example, the online identification results of bias are shown in Figure 3, and the SOC estimation errors of cells in pack are shown in Figure 4. The maximum and minimum SOC estimate for the battery pack are shown in Figure 5.
The identification results of model bias in Figure 3 shows that although the constructed general OCV and the actual OCV of the battery cells at 0 °C are different, the model bias can effectively correct these differences.

The results of SOC estimate for cells and the pack in Figure 4 and 5 show that the maximum absolute errors of SOC estimate for all cells are less than 6% at 0°C, and it has also been verified that the maximum absolute errors are less than 4% at 25°C and 45°C. This indicates that the proposed SOC estimation method based on the general OCV can achieve accurate and stable SOC estimation at different temperatures, even if each cell has not been individually tested.

5. Conclusions

In this paper, a novel SOC estimation method is proposed based on general OCV to estimate the SOC of a battery pack without additional testing.

1) The general OCV is obtained from the historical experimental data at 25°C, and it is used to calculate the feedback link for all cells in pack in EKF-based SOC estimation algorithm.

2) In order to correct the difference between the general OCV and the actual OCV, the model is corrected by the bias, which can be identified online with other model parameters.

3) UDDS tests of the 12S1P LFP battery pack at 0°C, 25°C and 45°C are performed, and the proposed method shows good accuracy and stability.

In future study, the inconsistency of the capacity will also be taken into consideration, especially when the consistency significantly deteriorates after the batteries aging.

Acknowledgement

This work was supported by the National Nature Science Foundation of China (Grant No. 51507012 and 51675044). The systematic experiments on batteries were performed by the Advanced Energy Storage and Application (AESA) Group, Beijing Institute of Technology.

Reference


