An Accurate SOC Estimation Method for Lithium-ion Batteries which Considers Thermal Variation

Ryu ISHIZAKI, Lei LIN, and Masahiro FUKUI*

Graduate School of Science and Engineering, Ritsumeikan University, 1-1-1 Noji-higashi, Kusatsu, Shiga 525-8577, Japan
*Corresponding author: mfukui@se.ritsumei.ac.jp

ABSTRACT

This paper discusses an SOC estimation system for lithium ion batteries based on the extended Kalman filter. The accuracy of the estimation is strongly dependent on accuracy of the battery model. We have newly formulated the equivalent circuit model that considers temperature and SOC dependencies. As the result, the error rate of the estimation has been improved significantly. The experimental results show that the new SOC estimation system derives very accurate results for wide range of temperature.

Keywords : Lithium-ion Battery, State of Charge, Karman Filter, Temperature Dependency

1. Introduction

In recent decades, invention of the Li-ion battery has opened a new vista of high energy density storages for smart communities. At the same time, an efficient management system for the Li-ion battery is strongly demanded for longer life time and safety. In order to manage the battery effectively, the characteristics and state of the battery must be grasped definitely. Especially, the charge state of the battery, SOC (State of Charge) is an important parameter. The Extended Kalman Filter, which is one of the recursive filters, was reported as an effective technique as a high precision SOC estimation technique of a lithium ion storage battery. Compared with the conventional techniques, such as OCV, current accumulation method, etc. The Extended Kalman Filter attains higher accuracy. However the accuracy of the algorithm strongly depends on the accuracy of the battery model. The battery model includes the open circuit voltage, OCV, and the internal impedance. Furthermore those model parameters vary depending on the battery states, SOC, temperature and degradation. Thus, it is important to consider the temperature and SOC dependencies of internal impedance for accurate SOC estimation. We consider the dynamic change of temperature and SOC in this paper. Consideration of degradation will also be solved in the future research based on the accurate SOC estimation. We calibrate the internal parameter of the Li-ion battery using the impedance measuring equipment and decide each parameter in the equivalent model of the battery. Then, we have newly formulated the equivalent circuit model that considers temperature and SOC dependencies. Expression for the temperature dependence is made with Arrhenius formula, and the way to find the accurate parameters of the Arrhenius formula is explained. Then, we apply the Extended Karman filter for the accurate model.

2. Experimental

Internal reaction of the Li-ion battery is expressed by resistance and capacitance. Such a reaction can be expressed as an equivalent circuit model as shown in Fig. 1. These circuit parameters changes by the temperature and SOC of the battery. SOC represents the remaining capacity of the battery. For the SOC, 1.0 represents fully charged state, and 0.0 represents the empty state. OCV[V] is open circuit voltage after stabilized, in another word, electromotive force. U[V] is the voltage between the external terminals. 1, 2 is a potential difference of each RC circuit, respectively. i[A] is the current which flows through the battery. The behavior of the two RC circuits is expressed as follows.

\[ \frac{du_1}{dt} + \frac{u_1}{R_1} = i \]  
\[ \frac{du_2}{dt} + \frac{u_2}{R_2} = i \]

The zero-state responses of the RC combination are given by:

\[ u_1 = iR_1 \left(1 - e^{-\frac{t}{\tau}}\right) \]  
\[ u_2 = iR_2 \left(1 - e^{-\frac{t}{\tau}}\right) \]

The SOC dependence of U(L) is expressed by the next expression.

\[ U_L = OCV(SOC) + iR_0 + u_1 + u_2 \]

It is necessary to understand the dependence of the internal parameters on the SOC and temperature in the equivalent circuit model described in Chapter II. Therefore, we perform an experiment to measure the AC impedance by changing the environmental temperature from 0°C to 45°C. The Li-ion battery used for the experiment is 18650 type new one. At first, we perform the AC impedance measurement of the battery with SOC1.0 over the frequency range from 3 kHz to 0.08 Hz at each environmental condition.
temperature. The SOC is reduced by 0.1, then the battery is left for 3 hours in order to wait for the voltage recovery. Then, the AC impedance measurement is performed again. This process is repeated until the lowest voltage. An example of the measurement result at each temperature is shown in Fig. 2. This is called the Nyquist plot. The horizontal axis represents the resistance, and the vertical axis represents the reactance. The internal parameter follows the Arrhenius Law: $A \times e^{-B/RT}$. $R$ is the gas constant, $T$ is absolute temperature. $A$ is constant for temperature, thus, SOC dependency is represented by this parameter. $B$ is constant for SOC. First, for each SOC, coefficients $A$ and $B$ are fitted to the measured values by the least-squares method. Then, average of $B$ is selected as the representative value. Then, $A$ is fitted again by the least-square method for the fixed value $B$. The approximated functions of the coefficients $A$ and $B$ are shown in Table 1.

As mentioned above, $R_2C_2$ is difficult to measure by using the AC impedance measuring device. However, $R_2C_2$ are assumed to follow the Arrhenius law. Thus, we find the coefficients $A$ and $B$ so that the error is reduced by SOC simulation at each temperature. Then, the value of the ideal $R_2C_2$ calculated by using the $A$ and $B$ is summarized in tables. These values in the tables are assumed to be read from the point in which the reactance is zero. $R_0$ in the equivalent circuit can be read from the diameter of the semicircle depicted. The capacity $C$ is determined by the least-square method for the fitted to the measured values by the least-squares method. Then, the value of the ideal $R_2C_2$ is difficult to read and is not able to obtain the definite measured value.

The Kalman filter is the technique to estimate the optimal internal states of a system by iterative observation of signal with noise. The Kalman filter needs a system model consisting of two equations. One is the state equation that connects the current state and the one step future state of the system. The other is the observation equation that connects the current state and the observed output. Equation (6) is the state equation, and (7) is the observation equation.

$$x(k + 1) = f(x(k), u(k)) + w(k)$$  \hspace{1cm} (6)

$$y(k) = h(x(k), u(k)) + v(k)$$  \hspace{1cm} (7)

$f(x(k), u(k))$ is the functional relationship of the state vector $x(k)$ and the next sample time $x(k+1)$. $h(x(k), u(k))$ is the functional relationship of the state vector $x(k)$ and observation vector $y(k)$. $u(k)$ is the system noise, $v(k)$ is the observation noise. When (6) and (7) are adapted to the equivalent circuit model of the battery, they become (8) and (9). Electric current $i(k)$ is selected as $u(k)$, and terminal voltage $U_L(k)$ is selected as $y(k)$. The system noise $w(k)$ is caused by battery characteristics fluctuation, and observation noise is caused by external noise. Each noise is normal noise which mean value is 0.

$$x(k + 1) = \begin{bmatrix} \text{SOC}(k + 1) \\ u_1(k + 1) \\ u_2(k + 1) \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 - \frac{\Delta t}{R_1C_1} & 0 & 0 \\ 0 & 0 & 1 - \frac{\Delta t}{R_2C_2} & 0 \end{bmatrix} \times \begin{bmatrix} \text{SOC}(k) \\ U_1(k) \\ U_2(k) \end{bmatrix} + \begin{bmatrix} \frac{\Delta t}{C_1} \\ \frac{\Delta t}{C_2} \end{bmatrix} \times i(k) + w(k)$$  \hspace{1cm} (8)

$$y(k) = U_L(k)$$

$$= \text{OCV(SOC)} + i(k)R_0\text{(SOC,T)}$$

$$+ U_1(k) + U_2(k) + v(k)$$  \hspace{1cm} (9)

Internal parameters of $R_0$ and $R_1C_1$ and $R_2C_2$ in Eqs. (8) and (9) are dependent on temperature and SOC, and the value is updated by those changes. In the filtering process, it estimates the next state by calculating state model and observation model. The error between the estimated value and the observed value is calculated, and adds the value to the next step. At the same time covariance of error is also updated. The Kalman filter minimizes the covariance of estimation error in each step. Sample time is set 1 second, and practically accurate results are obtained.

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**Table 1.** Fitting result ($R_0$ and $R_1C_1$).

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_0$</td>
<td>$-0.80 \times \text{SOC} + 9.84$</td>
<td>$-2110$</td>
</tr>
<tr>
<td>$R_1$</td>
<td>$7.38E-09 \times \text{SOC}^2 - 1.17E-08 \times \text{SOC} + 7.66E-09$</td>
<td>$-54800$</td>
</tr>
<tr>
<td>$C_1$</td>
<td>$-1.19E-05 \times \text{SOC}^3 + 3.06E-05 \times \text{SOC}^2 - 2.53E-05 \times \text{SOC} + 8.58E-06$</td>
<td>$-14000$</td>
</tr>
</tbody>
</table>

**Table 2.** Fitting result ($R_2C_2$).

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_2$</td>
<td>$0.54 \times \text{SOC}^2 + -0.86 \times \text{SOC} + 0.56$</td>
<td>$-1520$</td>
</tr>
<tr>
<td>$C_2$</td>
<td>$-7.53E-12 \times \text{SOC}^3 + 1.93E-11 \times \text{SOC}^2 - 1.60E-11 \times \text{SOC} + 5.42E-12$</td>
<td>$-5070$</td>
</tr>
</tbody>
</table>
3. Results and Discussion

We performed the SOC simulation using MATLAB. Temperature is changed from 15°C to 45°C. As the input, we have evaluated by simple current load and several patterns of random current. Because the SOC estimation is more difficult for the random current, and it is more general in practical situation, thus we discuss error evaluation by the random current as shown in Fig. 3. The SOC predicted value which the simulation at that time outputted is compared with the value of SOC which a charge/discharge machine measures. The average error rate for each temperature is shown in Fig. 4. It is comparing as what nothing is taking into consideration (No consideration), the thing in consideration of three parameters of $R_0$ and $R_1C_1$ (Partial consideration) and the thing in consideration of all the parameters included to $R_2C_2$ (All consideration). As is seen in Fig. 4, “Partial consideration” is accurate compared with “No consideration.” However, “No consideration” has better precision than “Partial consideration” at 25°C. The reason is that the value of the internal parameter used for “No consideration” is directly due to the use of a value measured at 25°C. The result of “All consideration” shows the SOC estimation result having very high precision. However, we have not obtained satisfied result for 5°C, the error was 5%. It is supposed that the internal reaction of battery is greatly different in low temperature. It is necessary for us to establish a different model for low temperature to be improved. Especially, more accurate method to grasp the $R_2C_2$ is expected. However, we have not obtained satisfied result for 5°C, the error was 5%. It is supposed that the internal reaction of battery is greatly different in low temperature. For example, the initial internal impedance is very high but it is reduced rapidly by joule heat. Consequently, it is hard to fit by Arrhenius law.

4. Conclusions

The internal impedance of the storage battery was measured. The temperature dependency was well formulated by Arrhenius’ equation. The Extended Kalman filter was applied to the SOC estimation for the above model. Compared with the conventional techniques, accuracy improvement is significant, and the error rate brought less than 1.0% of highly precise result in temperature range of 15°C–45°C. Since this technique can also be applied to the Li-ion battery temperature change of charge and discharge, it can obtain a more precise SOC estimation result by combining with the Li-ion battery internal temperature estimation method. For future work, we plan to improve the formulation of diffusion impedance $R_2$, $C_2$, especially in case of low temperature.

References