Li-Ion Battery SOC Estimation Method based on the Reduced Order Extended Kalman Filtering

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The Extended Kalman Filter (EKF) method has some problems for SOC estimation such as a long calculation time and high sensitivity to parameter errors and disturbance. This paper proposes a reduced order EKF including an observation noise model and data rejection. To reduce calculation time, the battery model is simplified and the EKF is built as a reduced order type. To solve the model accuracy and parameter sensitivity problem caused by the simplification, the observation noise is measured separately in regions where the model is comparatively correct or incorrect. The sensitivity problem due to disturbance is decreased by the data rejection. This paper explains not only the observation noise model and the data rejection, but also the method of building and simplifying the Li-Ion battery model.

Nomenclature

\[
\begin{align*}
SOC &= \text{State-Of-Charge} \\
OCV &= \text{open circuit voltage} \\
EKF &= \text{the Extended Kalman Filter} \\
X_k &= \text{the kth order value of } X \\
X(-) &= \text{priori value of } X \\
X(+) &= \text{priori value of } X \\
x &= \text{state } x \\
w &= \text{the process noise} \\
Q &= \text{the process noise covariance} \\
v &= \text{the observer noise} \\
R &= \text{the observer noise covariance} \\
K &= \text{the Kalman gain} \\
P &= \text{the covariance matrix of the state estimation uncertainty} \\
H &= \text{the measurement sensitivity matrix} \\
dt &= \text{time step} \\
diff &= \text{diffusion} \\
ct &= \text{charge transfer} \\
Z_w &= \text{Warburg Impedance}
\end{align*}
\]

I. Introduction

The ampere counting method for the battery state-of-charge (SOC) estimation can be easily realized, but it has an initial value problem and an accumulated error problem, due to the open loop state estimation characteristics. On the contrary, the numerical methods such as the neural and fuzzy methods can deal successfully with these problems. However, the estimated value may fluctuate very widely, because these methods are very sensitive to the

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model error and disturbance. The method of utilizing the advantages of both types is the Extended Kalman Filter (EKF). Additionally, the EKF has the advantage of the use of probability, which is the best way to estimate the highly nonlinear internal states.  

Although the EKF method has the above-mentioned advantages, a number of problems exist for applications. The first problem is caused by the digital processor’s physical limitation. In general, the more states the model has, the more accurate it can be. However, the number of the states is limited by the processor’s calculation ability, because the number of the states critically increases the EKF calculation time. Furthermore, a model with such limitations has a significant accuracy problem. The second problem is that the EKF is still sensitive to parameter error and disturbance. Although the problem is comparatively smaller than the traditional numerical methods, it is still an important point in the model’s robustness and accuracy.

To solve these problems, this paper proposes the reduced order EKF including the observation noise model and the data rejection. To save calculation time, the battery model is simplified and the EKF is built as a reduced order type. To solve the model accuracy and parameter sensitivity problem caused by the model simplification, the observation noise is measured separately in regions where the model is comparatively correct or incorrect, and the measured observation noise is used to compensate the model error. The sensitivity problem caused by disturbance is decreased by data rejection.  

This paper explains not only the observation noise model and the data rejection, but also the method of building and simplifying the Li-Ion battery model. The proposed algorithm is verified by experiments with a 1.3Ah 18650 type Li-Ion battery.

II. Li-Ion Battery Model

The impedance-based model is used in this paper, where the reliable and unreliable region of the simplified model can be easily classified by the battery input current characteristics.

A. Impedance-based circuit model

The electrochemical characteristics of the battery are classified as follows: internal resistance, charge transfer, double layer and diffusion, and, as shown in Fig. 1, they correspond to resistance, capacitance and the constant phase element (CPE) in the impedance-based circuit model.

![Circuit Model: L(parastic inductance), R_i(internal resistance), C_{dl}(double layer:CPE), R_{ct}(charge transfer), Z_w(diffusion:CPE)](image)

The resistance and capacitance elements can be easily realized in the time domain, but the CPE must be realized by infinite numbers of the RC ladder in order to obtain an accurate model. Usually, the diffusion and double layer phenomenon in the battery is modeled by the CPE. This complex RC ladder model for the CPE should be simplified, because each capacitance of the RC ladders is represented by the state and thus increasing the EKF calculation time.

In addition to the RC ladder simplification, the highly nonlinear parameters of each should be also simplified to save the digital processor memory and calculation time.
B. Model simplification

Firstly, to simplify the complex RC ladder model, the RC ladder are classified by three cases. The first case is where the time constant of the RC ladder is faster than the arbitrarily set value. The second case is where the time constant is slower than the set value, but negligible, and the third case is where the time constant is not negligible. The following simplification strategies used in this paper are based on these three cases.

The strategy in the first case is to ignore the capacitance in the RC ladder. The RC ladder is realized only by the resistance element. In the lithium-ion battery used in this paper, the part guessed as double layer or SEI is only modeled by one resistance, because its time constant is faster than the set value. The strategy in the second case is to use the resistance of the RC ladder for the model, and to include the effect of the ignored capacitance in the observation noise model. This strategy is used to compensate the model error caused by the reduced states with the observation noise model.

In the third case, the RC ladder is modeled completely without simplifying. Of the infinite number of RC ladders regarding diffusion, some RC ladders next to the first one are simplified using the second strategy, and the other ladders next to them are simplified by the first strategy. Only the first RC ladder is modeled correctly. The time constants of each element can be identified by the Nyquist plot, which is measured by electrochemical impedance spectroscopy (EIS).

Secondly, to simplify the nonlinear parameters, the strategy that obtains the parameters of the model in the middle region of the SOC which is quite linear except for the extreme SOC region is used. This allows the model error in the extreme SOC region to be included in the observation noise.

C. The reduced order Extended Kalman Filter model

As described in Fig. 3, the model has only two states. With these two states, the dynamic model in the EKF is expressed as follows:

\[
\begin{align*}
Z_w & = \frac{C}{T} \\
C & = \frac{2R}{n^2 \pi^2} \\
R & = \frac{2R}{n^2 \pi^2} \\
\end{align*}
\]
\[
\frac{dSOC}{dt} = \frac{i}{Cn} \quad SOC_k = SOC_{k-1} + \frac{\Delta t}{Cn} \cdot i_{k-1}
\]

\[
\frac{dV_{diff}}{dt} = \frac{i}{C_{diff}} - \frac{V_{diff}}{C_{diff} \cdot R_{diff}} ... V_{diff \_k} = (1 - \frac{\Delta t}{C_{diff} \cdot R_{diff}}) \cdot V_{diff \_k-1} + \frac{\Delta t}{C_{diff}} \cdot i_{k-1}
\]

\[
\begin{bmatrix}
SOC_k \\
V_{diff \_k-1}
\end{bmatrix} = \begin{bmatrix}
1 & 0 \\
0 & 1 - \frac{\Delta t}{C_{diff} \cdot R_{diff}}
\end{bmatrix} \cdot \begin{bmatrix}
SOC_{k-1} \\
V_{diff \_k-1}
\end{bmatrix} + \begin{bmatrix}
\Delta t \\
\frac{\Delta t}{C_{diff}}
\end{bmatrix} \cdot i_{k-1}
\]

And the measurement model is expressed by a non-linear function as follows:

\[
V_T = h_K(OCV, V_{diff}) - V_S = OCV - V_{diff1} - V_S
\]

\[
\frac{\partial h_K}{\partial x} = \begin{bmatrix}
hsoc(SOC) \\
SOC
\end{bmatrix} \begin{bmatrix}
OCV = hsoc(SOC), hsoc = f_{ocv^{-1}}
\end{bmatrix}
\]

In this equation, the OCV-SOC table can express the OCV function.

### III. Observation noise model and data rejection

#### D. Observation Noise

In general, the models used in the EKF are as follows:

**Dynamic model:**

\[
x_k = f_{k-1}(x_{k-1}) + g(u_{k-1}) + w_{k-1}, \quad w_k \sim N(0, Q_k)
\]

**Measurement model:**

\[
z_k = h_k(x_k) + v_k, \quad v_k \sim N(0, R_k)
\]

The equations that decide the Kalman gain are as follows:

\[
K_k = P_k H_k^T \left( H_k P_k H_k^T + R_k \right)^{-1}
\]

\[
x_k(+) = F_k x_k(\(-) + G_k u_k + K_k [Z_k - H_k x_k(\(-))]
\]

As shown in equation (7), \( R_k \) is an important variable in deciding the Kalman gain in the EKF. In fact, since \( H_k \) is fixed in the time of modeling, the observation noise model is the same as the Kalman gain model. The object of the observation noise model is to protect the state from the model error by reducing the Kalman gain in the incorrect region of the model.

#### E. Observation noise model by regions

Since the observation noise is regarded as white noise and it is difficult to divide the region for noise measurement, the observation noise is generally measured as one value through the entire region. However, the observation noise of this case includes not only random white noise, but also the model error caused by the model.
simplification. Therefore, the observation noise value should be measured separately in regions in order to compensate the model error.

A model designer who makes the simplification process from the complete model can classify the model as a reliable region and an unreliable region, while considering the effect of the simplification. For example, if the designer receives a parameter in the middle region of the SOC, the model is unreliable in the extreme SOC region. This process is applicable for all of the strategies introduced in B. Model simplification.

F. By SOC regions

The Li-ion battery has complex characteristics in the extreme SOC region. As can be seen in Fig. 5, impedance curves in the region of less than 20% SOC are apparently different from others. Therefore, the battery should be modeled differently in the extreme SOC region. However, since this process increases model complexity and calculation time, it is better to find model parameters in the middle of the SOC region and to include the model error in the extreme SOC region in the observation noise model. The example values used in this paper are follows:

- Extreme SOC (SOC < 0.2, SOC > 0.9)
- \( R_k = R_k \{1 + G_{soc}(0.2 - SOC)\} \)
- \( R_k = R_k \{1 + G_{soc}(SOC - 0.9)\} \)
- \( G_{soc} = 10 \)

\( G_{soc} \) is the optimal value acquired from trial and error. If it is desired to make the effect of the Kalman gain much smaller in the extreme SOC region, this can be achieved by increasing the value of \( G_{soc} \).

G. By input current magnitude

The model’s accuracy is varied by the input current magnitude. This is originated mainly by incorrect measurements of the parameters and the battery’s non-linear characteristic.

\[ \Delta V = I \cdot \Delta R \]

As can be seen in equation (9), high current can amplify a small parameter error. In addition, the battery has a non-linear characteristic from the input current magnitude. Fig. 5 describes the total impedance decreases from the input current increase.

This study uses a parameter in low current and the model error from high current is included in the observation noise model.

- Reliable Current (\(|i| < 5\))
- \( R_k = R_k \{1 + G_i(i - 5)\} \)
- \( G_i = 2 \)

\( G_i \) has a similar role to \( G_{soc} \) in adjusting the Kalman gain.

H. By dynamic characteristic

For this method, it is assumed that the battery is operated either in the constant power (CP) or in the constant current (CC) mode. The assumption is valid in an electric vehicle, because the power converter connected to the

Figure 5 Impedance Curve by SOC regions

Figure 6 Total impedance vs SOC by input current magnitude
battery should be operated in the current control mode. Thus, it can be assumed that the battery input current has a step or a similar shape for a short or long time. In such cases, the voltage of the capacitor of the RC ladder is calculated as in equation (10), and the voltage approximates to equation (11) after some time passes unless the current level changes significantly. Thus, if the model uses the value of equation (11) for the purpose of simplification, the early response of the step input current will not match with the value. This method is to measure the observation noise separately according to the voltage of the RC ladders whether or not it can be approximated by equation (11).

\[
V(t) = R \cdot I \cdot \left(1 - e^{-\frac{t}{RC}}\right) + V_{\text{init}} \cdot e^{-\frac{t}{RC}}
\]  

\[
V \approx R \cdot I
\]  

In the diffusion model described in Fig. 2, if one RC ladder with a fast time constant is approximated as in equation (11), the following RC ladders also can be approximated in the same way. Therefore, just a few preceding RC ladders can be selected as the decision ladders, and if they satisfy expression (12), then all of the following RC ladders can be assumed to satisfy expression (12).

\[
(1 - \alpha) \cdot R \cdot I < V_a(t) < (1 + \alpha) \cdot R \cdot I, \ n = 1, 2, 3, \ldots
\]  

The condition described in expression (12) means that the system has a high possibility of satisfying equation (11) based on the assumed condition, but expression (12) does not always satisfy equation (11). In this paper, the following rule is applied.

- \(R_k = R_k \{1 + G_{\text{step}} \cdot (\text{Initsteptime} - \text{Passedtime})\}\)
- \(G_{\text{step}} = 0.1\)
- \(\text{Initsteptime} = 10\)

Initsteptime can be decided by the RC ladder’s time constant and \(G_{\text{step}}\) is a similar value to \(G_{\text{soc}}\).

I. Fast dynamic data rejection

The effect of the film like solid electrolyte inter-phase (SEI) or double layer may load to a time constant of less than a few hundred milliseconds. If the capacitance of these parts are not included in the model, extreme the fast dynamics such as a step current input causes an unexpected error. Thus, it is better to reject data in this region in order to keep estimating the SOC robustly. In order to decide whether or not to reject data or not, differentiation of the input current is used. If it is larger than the set value, it can be regarded as a step input and the data should be rejected for a few milliseconds after such a step current input. In this paper, \(R_k\) is set to an infinite value in the data rejection case. As shown in equation (7) and (8), if \(R_k\) is infinite, the Kalman gain becomes zero and the measurement does not affect equation (8) as if the data is rejected.
IV. Experiment Result

J. Reference values

The most difficult aspect in the SOC algorithm test is to obtain reference values for the comparison with the estimated values. The discharge test value by the definition of the SOC is the most valid reference. However, it cannot be measured in the middle of the dynamic profile test and the value at only the final moment can be acquired. Another value is the OCV, but it also has similar problems to the discharge test value, because it can only be measured after some rest time.

The reference value compared in the middle of the dynamic profile test is the ampere counting value. Although the ampere counting method has critical disadvantages in the aspect of the initial value estimation and the accumulated error, it is comparatively correct in the short time test.

As a result, it is better to use the discharge test value or the OCV value in long time experiments to test the stability of the SOC algorithm. On the other hand, it is better to determine the reference of the ampere counting value in short time experiments in order to verify the dynamic characteristic of the SOC algorithm.

K. Dynamic test for the observer noise model and the data rejection

A simple shape profile as shown in Fig. 8 for 300 seconds is applied to the dynamic test. Three types of algorithms are compared. Figure 9 describes the result in the case that each algorithm is applied. In the figure, the SOC error is the difference between the ampere counting value and the estimated value using the EKF. The ampere counting value is used as the reference value, since the experiment time is short.

As it can be seen, the algorithms including the observer noise (R_e) model create flat outputs. This means the algorithms are more robust against current variation than the other. In this test, the observation noise model by the current dynamic characteristic and the fast dynamic data rejection algorithm reduce the effect of the model error, which occurs in large current changes, such as at 120s and 240s in Fig. 9.

L. Observation noise model by input current magnitude and dynamic characteristic

The algorithm is tested separately by the method dividing the regions. Figure 10 and 11 describe the current and the SOC profile used in the experiment. The profile is scaled down from the automotive profile to test the Li-Ion battery’s performance.

Figure 12 shows that the estimated state error is improved by the observer noise model and the data rejection. However, in the Fig. 12, the observation noise model from the dynamic characteristic is more effective than from the input current magnitude. This can be explained by the gain value, G_i and G_step. In this case, G_step is comparatively larger than the G_i. If these values are adjusted, different result can be obtained.
M. Long time test

To test the algorithm’s stability in running time and to get exact error values at a certain point, a long time profile is applied. The long time profile is based on the scale-downed automotive profile, described by Fig. 10. The scale-downed automotive profile reduces the battery SOC by about 7% in running time. By repeating this profile, one can get any battery test profile that is finished at different SOC region, such as at 80%, 70%, etc. During a period of 5 days, 8 long time profiles were applied.

- Test SOC range : 0.35-0.85
- Discharge profile : figure 10, 11
- Charge profile : reversed current profile of discharge profile
- 1 Test profile : discharge profile applied 9 times, charge profile applied 8 times.
- 2 Test profile : discharge profile applied 9 times, charge profile applied 6 times.
- ……
- 5 Test profile : discharge profile applied 9 times, charge profile applied 0 times.
- 6 Test profile : discharge profile applied 7 times.
- …..
8 Test profile: discharge profile applied 3 times.

The following table is the result of the long time test. As it can be seen, the error is less than 2%. This result has a comparatively smaller error than that of other researches. This is explained by the following reasons. First, the algorithm (EKF) follows the value of OCV well by filtering the model error using the observation noise model and the data rejection. Second, the scale-downed profile is used. If the original profile, which is five times bigger than the scale-downed profile, is used, the error may be larger than this one. This will be presented in future works.

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<th>EKF</th>
<th>OCV</th>
<th>Discharge</th>
<th>Error = EKF – Discharge</th>
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<td>1</td>
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V. Conclusion

The SOC estimation method, based on the reduced order Extended Kalman Filter with the observation noise model and the data rejection is proposed. The method of modeling and simplifying the Li-Ion battery is also introduced. The calculation time of the EKF method can be reduced by the simplified model and the error caused by the model simplification can be compensated by the observation noise model and the data rejection. This method can be applied to a general battery SOC estimation system. The feasibility of the proposed algorithm and model approach is verified by experiments.

Acknowledgments

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