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Li-ion battery SOC estimation method based on the reduced order extended Kalman filtering ☆

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Abstract

The extended Kalman filter (EKF) method for SOC estimation has some problems such as the lack of an accurate model, and model errors due to the variation in the parameters of the model due to the nonlinear behavior of a battery. To solve the aforementioned issues, this paper proposes a reduced order EKF including the measurement noise model and data rejection. In order to do so, the model of a battery in the EKF is simplified into the type of reduced order to decrease the calculation time. Additionally, to compensate the model errors caused by the reduced order model and variation in parameters, a measurement noise model and data rejection are implemented because the model accuracy is critical in the EKF algorithm in order to obtain a good estimation. Finally, the proposed algorithm is verified by short and long term experiments.

Keywords: State of charge (SOC); Extended Kalman filter (EKF); Reduced order; Li-ion battery

1. Introduction

In recent years, much research has been done to improve the estimation of the state of charge (SOC), which has increasingly become an important issue in electric/hybrid vehicle applications. Ah counting, which is the most common method of estimating a battery SOC, is easy and reliable. However, it has problems such as the initial value problem, an accumulated error problem from incorrect measurements, and no consideration of the current losses. Open circuit voltage (OCV) for the measure [5,6,7]. However, it requires a sufficient rest period. To deal with these problems for Ah counting and OCV, adaptive methods, such as neural network, fuzzy logic, adaptive observer and extended Kalman filter (EKF) have been employed, based on Ah counting, OCV and other factors [1,4,8].Adaptive methods require an accurate model to obtain good [3,12]. Many states and factors are necessary to develop the accurate model of a battery. In general, if states and input factors increase, the calculation burden also increases. If the number of states in the EKF is n and the dimension of the measurement vector is l, the computational complex is $(l^*(l^2+n^2))$ [9]. Therefore, the number of states and input factors is limited by the processor's calculation capability. The battery pack system in the HEV is composed of many series-connected cells or modules. The BMS (battery management system) in the HEV should measure the voltages of each cell or module, the current of the battery, and the temperatures in the battery pack. Because the charge/discharge current in the HEV can be rapidly fluctuated, the period of the algorithm should be less than 100 ms. Also, SOC estimation algorithm can be applied to each cell or module of the battery pack. Therefore, the states in the EKF should be reduced in order to decrease the calculation time. A trade-off between performance and computational requirements is likely to be made. Also, the parameters of the model vary due to the conditions of the battery. Variations in the parameters of the model cause model errors, which in turn affect the estimation results.

To solve these problems, this paper proposes a reduced order EKF implemented by a simple battery model with a measurement noise model and data rejection. Generally, the battery in the EKF is represented by an equivalent circuit model based on its impedance spectrum. It consists of a series resistance, double layer and charge transfer, and diffusion [2,10,11]. This equivalent circuit model is complex and nonlinear. In the equivalent circuit model, fast dynamic components can be modeled as a resistance and, slow dynamics components can be described as

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a RC ladder circuit. Fast and slow dynamics are separated by the impedance spectrum, where the RC time constant can be determined by the impedance spectrum data. As a result, the battery model is simplified into an open circuit voltage, RC ladder, and series resistance. The infinite series RC ladders of the diffusion are reduced into one or two RC ladder circuits. The double layer and charge transfer are represented by one resistance. The reduced order model can cause an accuracy problem. The errors caused by the model simplification are mainly caused by the fast dynamics of diffusion, charge transfer, and double layer. In addition, the parameters of the equivalent circuit model vary with the SOC, battery current and so on. Variations in the parameters due to the conditions of the battery are an additional cause of the model errors. In order to solve the model accuracy and parameter variation problems, the measurement noise model is used. The noise measurement to compensate the model errors is separately conducted, depending on whether the model is comparatively correct or incorrect, because it has an influence on deciding the Kalman filter gain. The regions are classified by the SOC, battery current, and battery dynamics. The model errors from the fast dynamics of the battery are decreased by data rejection.

Several tests with a 1.3Ah 18650 type Li-ion battery are conducted to verify the proposed algorithm. Short term tests show the effectiveness of each detailed algorithm. Long term tests are performed to guarantee the stability and reliability of the algorithm. As a result of the long term tests, it is shown that the error of SOC estimate is less than 2%.

2. Li-ion battery model

The impedance-based model is used. The equivalent circuit model is reduced to the simple model. The EKF equations of the simple model are also described.

2.1. Impedance-based equivalent circuit model

The electrochemical characteristics of the battery are classified as follows: internal resistance, charge transfer, double layer and diffusion. As shown in Fig. 1, they are described as a resistance, capacitance and constant phase element (CPE) in the impedance-based circuit model [2,10].

The elements of resistance and capacitance are easily realized in the time domain, but the CPE must be realized by a distributed circuit model which consists of infinite RC ladder elements in order to obtain an accurate model. Usually, the diffusion and double layer phenomena in the battery are modeled by the CPE. Fig. 2 shows the RC ladder circuit for diffusion. This series-connected RC ladder circuit for the CPE needs to be simplified, because the increase of the states and parameters is the main cause of the longer EKF calculation time. This simplification is rather critical in reducing the digital processor memory and calculation time, considering the nonlinearity of each parameter (see Fig. 2).

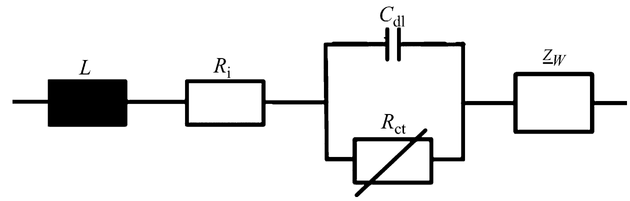

Fig. 1. Circuit model: L (parasitic inductance), R_i (internal resistance), C_{dl} (double layer: CPE), R_{ct} (charge transfer), Z_w (diffusion = Warburg impedance: CPE).

2.2. Model simplification

The electrochemical equivalent circuits can describe the behaviors of the battery and can be separated into three parts, consisting of a series resistance, charge transfer and double layer, and diffusion process, in terms of the frequency components. The slow dynamics of a battery is included in a simple battery model. The fast dynamics is compensated by the measurement noise model and data rejection. The fast and slow dynamics of the battery can be distinguished by the impedance spectrum. The impedance spectra of the battery used in the experiment are plotted in the Nyquist domain, as shown in Fig. 3. The frequency of the series resistance is more than 500 Hz which indicates a very fast dynamics. The frequency of the charge transfer and double layer is in the range between 500 and 0.63 Hz. The calculated R_{ct} and C_{dl} are 27.6 mΩ and 0.5693 F, whose time constant is less than 0.02 [10]. The dynamics of R_{ct} and C_{dl} is relatively fast. The frequency of the diffusion is less than 0.63 Hz. The equivalent circuits of the diffusion are composed of series-connected infinite RC ladder circuits. The time constants of the first and second RC ladder are calculated as about to be 44 and 11, respectively.

The complex equivalent circuit model can be simplified based on the dynamics of the battery. The fast dynamics of a RC ladder circuit can be represented as a resistance. The charge transfer and double layer are modeled as a resistance due to its very fast dynamics. The diffusion is represented by one or two RC ladder

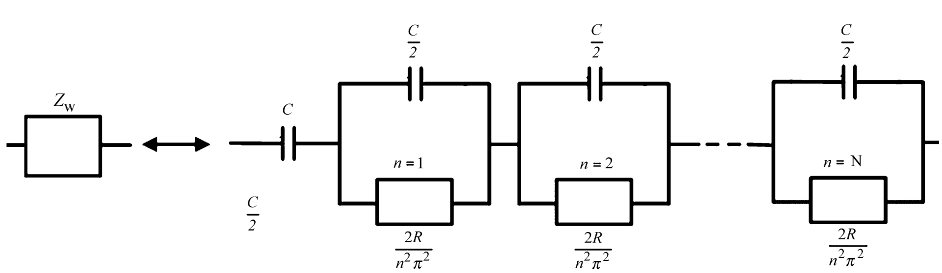

Fig. 2. The infinite numbers of the RC ladder model about diffusion.

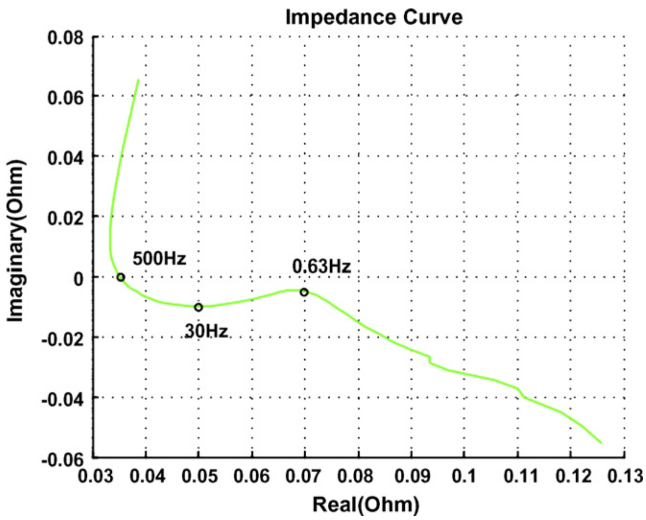

Fig. 3. Nyquist plot of battery used in experiment.

circuits. The first RC ladder is very slow and is included in the model. The second RC ladder is used as a criterion distinguishing the fast and slow dynamics for the diffusion. The dynamics of the other RC ladder circuits, for the diffusion, is fast and negligible.

Finally, the proposed reduced order model of the battery is shown in Fig. 4. The proposed model consists of the OCV, one RC ladder for the diffusion, and, R_D or R_C one resistance for a series resistance and for charge transfer and double layer. It has two states, which are OCV and C_{Diff}.

2.3. Reduced order extended Kalman filter using simple model

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

$$\text{Process model}: \quad x_k = f_{k-1}(x_{k-1}) + g(u_{k-1}) + w_{k-1},$$
$$w_k \sim N(0, Q_k), \qquad \text{Measurement model}:$$
$$z_k = h_k(x_k) + i(u_k) + v_k, \quad v_k \sim N(0, R_k) \tag{1}$$

The equations that decide the Kalman gain are as follows:

$$K_k = P_k H_k^{\mathrm{T}}[H_k P_k H_k^{\mathrm{T}} + R_k]^{-1} \tag{2}$$

$$\hat{x}_k(+) = \hat{x}_k(-) + K_k[Z_k - H_k \hat{x}_k(-)] \tag{3}$$

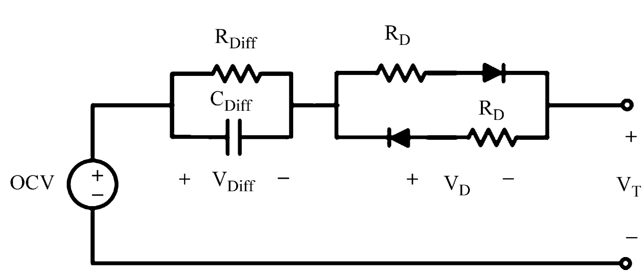

Fig. 4. Simplified model: V_{Diff} (diffusion), V_S (internal resistance and charge transfer).

where X_k is the kth order value of X, $X(-)$ the priori value of X, $X(+)$ the posteriori value of X, x the state x, w the process noise, Q the process noise covariance, v the measurement noise, R the measurement noise covariance, K the Kalman gain, P the covariance matrix of the state estimation uncertainty and H is the measurement sensitivity matrix.

As described in Fig. 4, the model has only two states. With the states incorporated, the process model in the EKF is expressed as follows:

$$\frac{\mathrm{dSOC}}{\mathrm{d}t} = \frac{i}{C_n}, \qquad \mathrm{SOC}_K = \mathrm{SOC}_{K-1} + \frac{\Delta t}{C_n} \cdot i_{K-1} \tag{4}$$

$$\frac{\mathrm{d}V_{\mathrm{Diff}}}{\mathrm{d}t} = \frac{i}{C_{\mathrm{Diff}}} - \frac{V_{\mathrm{Diff}}}{C_{\mathrm{Diff}} \cdot R_{\mathrm{Diff}}},$$
$$V_{\mathrm{Diff\_}K} = \left(1 - \frac{\Delta t}{C_{\mathrm{Diff}} \cdot R_{\mathrm{Diff}}}\right) \cdot V_{\mathrm{Diff\_}K-1} + \frac{\Delta t}{C_{\mathrm{Diff}}} \cdot i_{K-1} \tag{5}$$

$$\begin{bmatrix} \mathrm{SOC}_K \\ V_{\mathrm{Diff\_}K} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \dfrac{\Delta t}{C_{\mathrm{Diff}} \cdot R_{\mathrm{Diff}}} \end{bmatrix} \cdot \begin{bmatrix} \mathrm{SOC}_{K-1} \\ V_{\mathrm{Diff\_}K-1} \end{bmatrix} + \begin{bmatrix} \dfrac{\Delta t}{C_n} \\ \dfrac{\Delta t}{C_{\mathrm{Diff}}} \end{bmatrix} \cdot i_{K-1} \tag{6}$$

The measurement model and the terminal voltage of a battery, are expressed by a nonlinear function as follows:

$$V_T = h_K(\mathrm{OCV}, V_{\mathrm{Diff}}) - V_{\mathrm{S}} = \mathrm{OCV} - V_{\mathrm{Diff}} - V_{\mathrm{S}} \tag{7}$$

$$\frac{\partial h_K}{\partial x_K} = \begin{bmatrix} \dfrac{\partial h_{\mathrm{soc}}(\mathrm{SOC})}{\partial \mathrm{SOC}} & 0 \\ 0 & -1 \end{bmatrix},$$
$$\text{where } \mathrm{OCV} = h_{\mathrm{soc}}(\mathrm{SOC}),\ h_{\mathrm{soc}} = f_{\mathrm{ocv}}^{-1} \tag{8}$$

In this equation, the OCV-SOC table is expressed as an OCV function.

3. Measurement noise model and data rejection

Model errors are the voltage errors between the measured battery voltage and the model output voltage. The model errors are caused by the model simplification and variations in the parameters of the model. The reduced order model involves the slow dynamics of the battery equivalent circuit model, but excludes the fast dynamics. The fast dynamics cause the model errors, which lead to inaccurate estimations. The fast dynamics are mainly composed of the charge transfer and double layer and diffusion. When there is a step change in the battery current, the fast dynamics of the charge transfer and double layer and diffusion are present. The measurement noise model and data rejection are necessary to compensate the model errors caused by the fast dynamics. The parameters of the equivalent circuit model vary with the SOCs, the charge/discharge current rate and so on. Variations in the parameters of the model cause the model errors. The model errors increase when the SOC is in the extreme region or when the charge/discharge current rate is high. In these cases, the model errors should be compensated by the measurement noise model.

The measurement noise model and data rejection are implemented by modifying the measurement noise covariance, R_k. As shown in Eq. (2), the measurement noise covariance, R_k, is an important factor in deciding the Kalman filter gain in the EKF. Since H_k is fixed in the simple model, the measurement noise covariance has a strong influence on the Kalman gain. When R_k is large, an estimate mainly depends on the process model. When R_k is small, the estimate mainly depends on the measurement model. When R_k is infinite, K_k is 0 and the estimate is equal to $\hat{x}_k(+) = f_{k-1}(\hat{x}_{k-1}(+)) + g_{k-1}(u_{k-1})$. When R_k is 0, K_k is H_k^{-1} and the estimate is equal to $\hat{x}_k(+) = K_k Z_k$. Data rejection is achieved when R_k is infinite. By adopting the measurement noise model and data rejection, the Kalman filter becomes robust to the model errors from the model simplification as well as from the variations in the parameters of the model.

3.1. Measurement noise model by dynamics of diffusion

The diffusion in the equivalent circuit model is composed of infinite elements of the RC ladder circuit. However, it can be reduced to one RC ladder circuit through the model simplification. When the battery current changes abruptly, the voltage of the capacitor in the RC ladder is expressed as Eq. (10), and the voltage can be approximated as Eq. (11) after the RC time constant if the current level remains unchanged significantly. When Eq. (11) is applied to the fast dynamic RC ladder circuits in the equivalent circuit model, the measurement voltage at the initial response of the step current does not match the output voltage in the reduced order model and the errors occur. In order to compensate the errors, the measurement noise covariance, R_k, should be determined separately according to whether or not the voltage of the RC ladders can be approximated by Eq. (11).

$$V(t) = RI(1 - \mathrm{e}^{-t/\mathrm{RC}}) + V_{\mathrm{init}}\mathrm{e}^{-t/\mathrm{RC}} \tag{10}$$

$$V \approx RI \tag{11}$$

Because the second, and other RC ladders in the diffusion model described in Fig. 2 have a fast time response, they can be approximated as Eq. (11), and the second RC ladder is selected as a decision ladder. If the voltage in the decision ladder does not satisfy Eq. (12), the errors caused by the dynamics of the diffusion should be compensated.

$$(1-\alpha)\cdot R_n \cdot I < V_n(t) < (1+\alpha)\cdot R_n \cdot I, \quad n = 2, 3, \ldots \tag{12}$$

Where $R_n = 2R_{\mathrm{Diff}}/(n^2\pi^2)$.

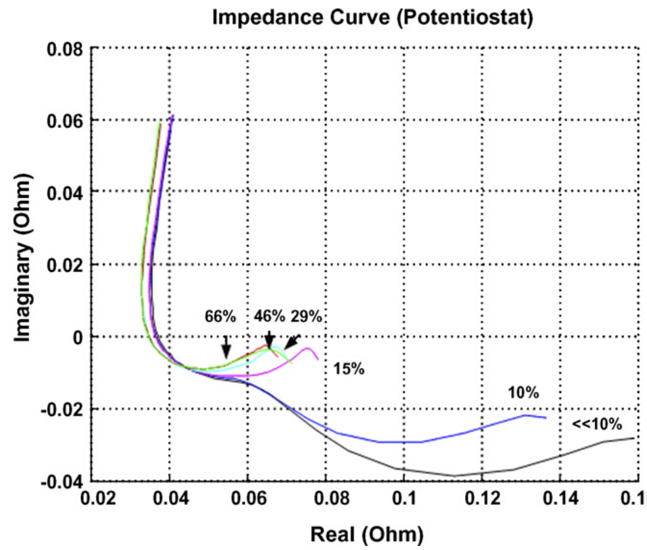

Fig. 5. Impedance curve by SOC regions.

When the condition described in Eq. (12) is not satisfied, the measurement noise model is implemented as follows:

$$R_k = \text{infinite} \quad \text{if } \frac{\Delta I}{T_s} \text{ is greater than a set value}$$
$$R_k = R_k \quad \text{otherwise}$$

Initsteptime can be decided by the second RC ladder's time constant and G_{step} is obtained from trial and error.

3.2. Data rejection caused by the fast dynamics of the charge transfer and double layer

The dynamics of the charge transfer and double layer has a time constant of less than a 100 ms and is modeled as a resistance in this paper. However, when there is a step current, the dynamics of the charge transfer and double layer causes the model errors. Because the errors exist for a short period, data rejection is adapted by the measurement noise covariance, R_k, is set as infinite and the Kalman gain becomes zero. Whether or not to reject data is determined by the step current. If ΔI per sample time is larger than a set value, it is regarded as the step current and the data rejection is carried out.

$$R_k = \text{infinite} \quad \text{if } \frac{\Delta I}{T_s} \text{ is greater than a set value}$$
$$R_k = R_k \quad \text{otherwise}$$

3.3. Measurement noise model by SOCs

The parameters in the circuit model vary with the SOCs. The parameters determined in the middle SOC region are used in the circuit model, because there is little change in this region. However, they vary largely in the extreme SOC region, below 20% and above 90%, as shown in Fig. 5. The impedance curve in the low SOC region is different from that in the middle region. Variations of the parameters in these SOC regions causes the model errors. The measurement noise covariance in the extreme SOC region should be adjusted to compensate the errors.

The measurement noise model is implemented by modifying the R_k according to the SOC regions as follows.

$$R_{k+1} = R_k \text{ for } (0.2 < \mathrm{SOC} < 0.9)$$
$$R_{k+1} = R_k\{1 + G_{\mathrm{soc}1}(0.2 - \mathrm{SOC})\} \quad \text{for extreme SOC } (\mathrm{SOC} < 0.2)$$
$$R_{k+1} = R_k\{1 + G_{\mathrm{soc}2}(\mathrm{SOC} - 0.9)\} \quad \text{for extreme SOC } (\mathrm{SOC} > 0.9)$$
$$G_{\mathrm{soc}1} = G_{\mathrm{soc}2} = 10$$

$G_{\mathrm{soc}1}$ and $G_{\mathrm{soc}2}$ are the optimal values acquired from trial and error.

3.4. Measurement noise model by battery current

The impedance of a battery is generally measured in the stationary condition. However, when the DC current is charged or discharged in a battery, the impedance of the charge transfer and double layer and diffusion varies with the battery current rate [10,11]. The greater the charge/discharge rate increases, the larger the impedance and the parameters of the circuit model become. Also, variations in the parameters caused by the battery current rate contribute to the model errors. The errors are compensated by modifying the measurement noise model. When the battery current is more than a set current, the measurement noise covariance, R_k, is adjusted as follows:

$$R_k = R_k \quad \text{for reliable Current } (|i| < 5)$$
$$R_k = R_k\{1 + G_i(|i| - 5)\} \quad \text{for unreliable Current } (|i| > 5)$$
$$G_i = 2$$

G_i and G_{soc} have the similar roles in adjusting the Kalman filter gain.

3.5. Algorithm of measurement noise model and data rejection

The process model in the EKF algorithm is composed of a reduced order system by omitting the fast dynamics of the equivalent circuit model. Variations in the parameters of the model are caused by the nonlinear characteristics of the battery. Therefore, the model errors in this paper are caused by four factors: dynamics of diffusion, dynamics of charge transfer and double layer, SOC, and battery current rate. The former two factors are caused by the model simplification, while the latter two factors are caused by the nonlinear behavior of the battery. In order to make an accurate estimate, the errors caused by the aforementioned four factors should be compensated. The measurement noise model is implemented by modifying R_k. In the four cases, R_k is adjusted by the above methods. The flow chart of the algorithm is shown in Fig. 6. At an initial stage, initial values are set. In the main loop algorithm, the current and voltage of the battery are measured per sample period. The measurement noise covariance, R_k, for the four error cases is calculated before the EKF algorithm is performed. First, it is determined whether or not to reject data by the fast dynamics of the charge transfer and double layer. After that, the measurement noise model R_k is selected by the three factors. The Kalman filter gain is calculated by using the determined R_k and the states are estimated. In this algorithm, the calculation time is reduced by the simple model, and the model accuracy is obtained from the data rejection and measurement noise model. The error compensation by the four factors is verified through experiments.

3.6. Verification method

The most difficult aspect in the SOC algorithm test is to set a reference SOC to which the estimated values are compared. In this paper, the reference SOC is set by three methods: ampere counting, discharge and OCV method. The reference SOC determined by the ampere counting method is applied to short term dynamics tests. Although the ampere counting method has critical disadvantages such as the initial value and accumulated error problems, it is very correct in a short time test. The reference SOC set by the discharge and OCV methods is generally very accurate. However, the discharge test value by the definition of the SOC cannot be measured in the middle of the dynamic profile test, because the value is acquired after the dynamics tests are finished and the battery is fully discharged. Another method is OCV, but it also has similar problems such as the discharge test value, because it should be measured after some rest time (2 h in these experiments). Therefore, after one profile test, the reference SOC by them is applied for comparison.

4. Experiment result

4.1. Short term dynamic test

Two and three state models with or without the measurement noise model and data rejection are used in a short term dynamic

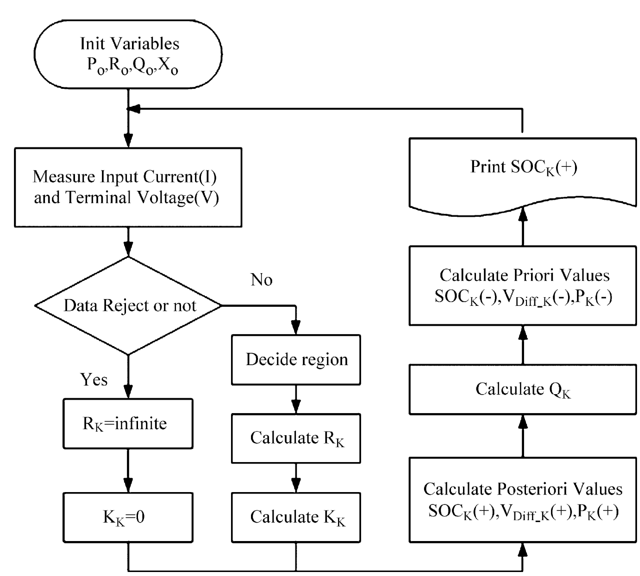

Fig. 6. Flow chart of the algorithm.

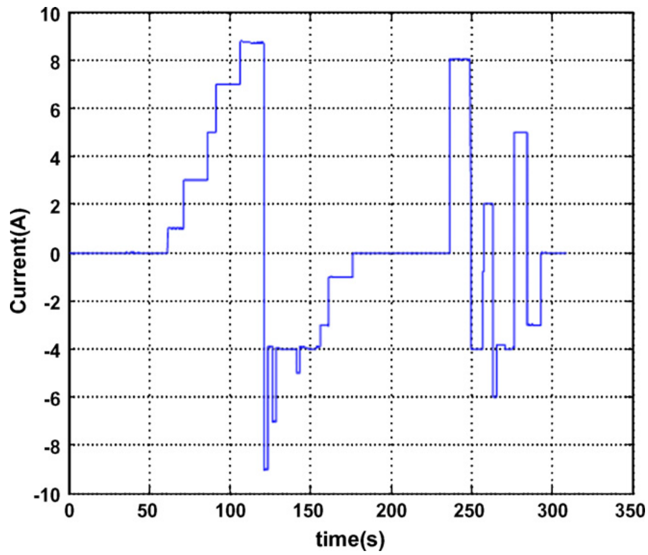

Fig. 7. Short term dynamic test profile.

test to find the proper number of the states. The two state model which consists of the SOC and one RC ladder, is shown in Fig. 4. The three state model consists of a two state model and an additional RC ladder for the diffusion. The reference SOC is set by the ampere count method.

The short term dynamic test, as shown in Fig. 7, was conducted for about 300 s. The results of the SOC error for the two state model with R_k model, the three state model with and without R_k model for the dynamics of the battery current are shown in Fig. 8. The models with the measurement noise model are insensitive to the dynamics of the battery current. In this test, it is shown that the models with the measurement noise model and fast dynamic data rejection for the battery current rate are more effective. Although the three state model has a lower SOC error than the two state model, the latter is proposed in order to reduce the calculation time. The proposed model with two states and measurement noise model are accurate in the SOC estimate.

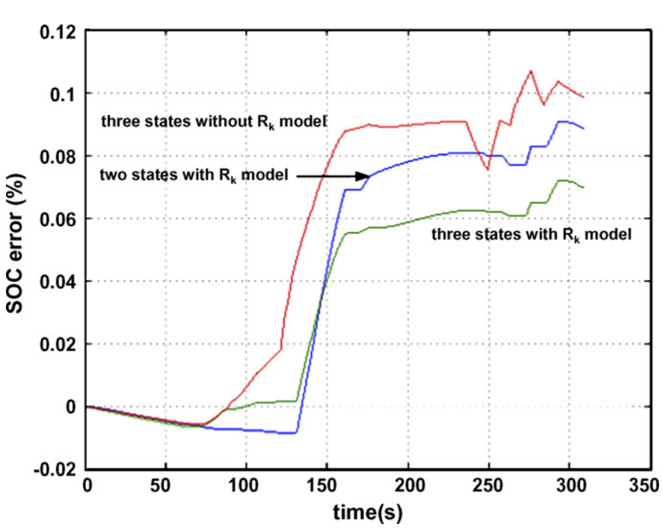

Fig. 8. Simplified short term dynamic test results.

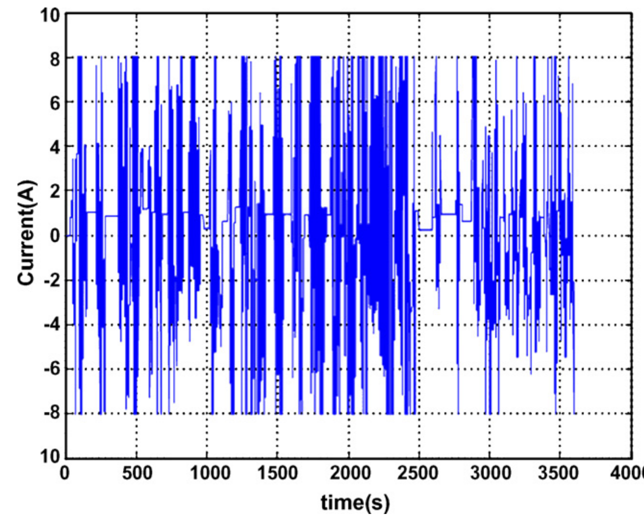

Fig. 9. Automotive profile.

4.2. Automotive profile test

The automotive profile test is necessary to verify whether or not the proposed algorithm is valid in the HEV. The experimental battery is a 1.3Ah 18650 type Li-ion battery, which is not a typical battery for HEV. Therefore, the reference current profile for a driving cycle is scaled down. In this test, it is shown that the diffusion dynamics, the fast dynamics of the charge transfer and double layer, and the battery current rate influences the algorithm. The reference SOC is set by the ampere count method.

Fig. 9 describes the automotive current profile. There are wide variations in the battery charge and discharge current. The reference SOC in this test is shown in Fig. 10. Fig. 11 shows the SOC errors for the EKF without the R_k model, the R_k model caused by the battery current, the R_k model by the diffusion dynamics and fast dynamics of the charge transfer and double layer, and the model with all measurement noise models. The model error by the battery current is small, because the overvolt-

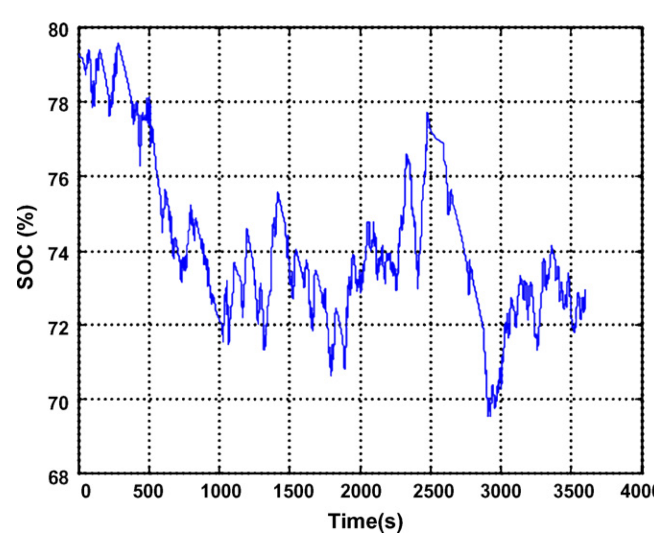

Fig. 10. SOC for automotive profile test.

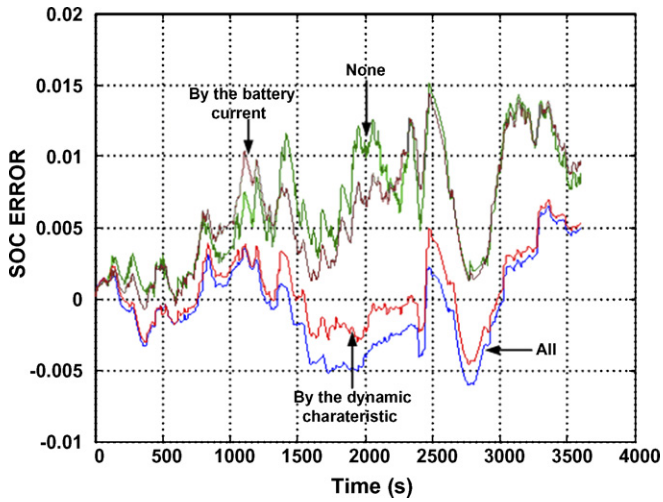

Fig. 11. The result of automotive profile test.

age due to the large battery current is not large. The dynamics of the diffusion and charge transfer and double layer make the model errors large and frequent. Therefore, a G_{step} larger than the G_i is chosen so that the measurement noise model from the dynamic characteristic is more effective than by the input current magnitude.

4.3. Long term test

To guarantee the algorithm's stability in running time and the influence by the SOC, a long term profile experiment is carried out. The long term profile is based on the scale-down automotive profile, described by Fig. 9. The scale-down automotive profile reduces the battery SOC by about 7% in one cycle. Several tests were conducted in order to make comparison for different SOCs. Eight long term profiles lasting 5 days each are applied.

- Test SOC range: 0.35–0.85
- Discharge profile: Fig. 9
- Charge profile: reversed current profile of discharge profile
- 1 Test profile: 9 times discharge profile applied, 8 times charge profile applied.
- 2 Test profile: 9 times discharge profile applied, 7 times charge profile applied.
- ...
- 5 Test profile: 9 times discharge profile applied, 3 times charge profile applied.
- 6 Test profile: 7 times discharge profile applied, 8 times charge profile applied.
- 7 Test profile: 6 times discharge profile applied, 8 times charge profile applied.
- 8 Test profile: 5 times discharge profile applied, 8 times charge profile applied.

The following table is the result of the long term tests. As shown in Table 1, the SOC error is less than 2%. This result has a comparatively smaller error. It is shown that the proposed algorithm (EKF) follows the OCV value well by filtering model errors by using the measurement noise model and data rejection.

Table 1
The result of the long time test

	EKF	OCV	Discharge	Error = EKF − discharge
1	0.7639	0.7617	0.7478	0.0161
2	0.6890	0.6829	0.6707	0.0183
3	0.6125	0.6076	0.5934	0.0191
4	0.5177	0.5137	0.5101	0.0076
5	0.3935	0.3905	0.3763	0.0172
6	0.4595	0.4619	0.4472	0.0123
7	0.5210	0.5287	0.5178	0.0032
8	0.6210	0.6226	0.6152	0.0058

5. Conclusion

An SOC estimation method, based on the reduced order extended Kalman filter with the measurement noise model and the data rejection, is proposed. The method of modeling and simplifying the Li-ion battery is based on the impedance spectrum of the battery and the equivalent circuit model. The calculation time of the EKF method is reduced by the model simplification and the model errors caused by the reduced order model, and variations in the parameters of the model are compensated by the measurement noise model and data rejection. The feasibility and verification of the proposed algorithm and model approach are made through several experiments.

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