The Estimation of the SOC and Capacity for the Lithium-Ion Battery using Kalman Filter

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Abstract

The open circuit voltage (OCV) is widely used to estimate the state of charge (SOC) in many estimation algorithms. However, the relationship between the OCV and SOC can not be exactly same for all batteries. Because the conventional OCV-SOC differs between batteries, there is a problem that the relationship of the OCV-SOC should be measured to accurately estimate the SOC. Therefore, the conventional OCV-SOC is modified to a new relationship in this paper. Thus, problems resulting from the defects of the extended Kalman filter (EKF) can be avoided by preventing the relationship from varying. In this paper, SOC and capacity of the lithium-ion battery are estimated using the dual EKF with the proposed method.

1. Introduction

There are several ways to estimate the SOC of a battery [1]. The ampere-hour counting method is simple and easy to utilize, but it has problems such as an initial value error and accumulated errors. The OCV method is very accurate, but it needs a rest time to estimate the SOC. So it is not possible for an application, such as hybrid electric vehicle (HEV). The extended Kalman filter, which uses the plant model combining the two aforementioned methods, has been presented [2]. This method has been known to be the optimal adaptive algorithm based on recursive estimation. To improve the performance of the estimation, the model parameters should be chosen correctly. However, the parameters of the battery model in the EKF, such as the resistance, capacity and OCV-SOC, are not consistent due to differences of the SOC, temperature and aging.

The relationship of the OCV-SOC differs between batteries. Thus, the use of this varying OCV-SOC data for the SOC estimation algorithm results in unacceptable error. In this work, a methodology of defining the new OCV-SOC relationship which is independent of the battery condition is proposed. However, the battery capacity in the EKF should be estimated because the capacity is changed for the new relationship. Thus, the dual EKF [3, 4] is used to estimate the SOC and the capacity simultaneously. The proposed algorithm is verified through simulations and experiments using an 18650 type lithium-ion battery.

2. The Proposed Approach

2.1 Modification of the OCV-SOC

The conventional relationship of the OCV-SOC is obtained by measuring the open circuit voltage at each SOC. However, the relationship can not be exactly the same for every battery even if the batteries are fabricated with the same materials and structures, as shown in Fig. 1. Therefore, it is difficult to apply the conventional OCV-SOC data to the estimation algorithm. From the viewpoint of the implementation of the algorithm, an equivalent electrical battery model is needed as shown in Fig. 2 and the OCV, as a function of SOC, is utilized as a voltage source. As shown in Fig. 1, the relationships of the OCV-SOC for 9 different batteries are measured for the same conditions, such as temperature and aging. The results show that considerable variations which may cause unacceptable error in the SOC estimation. However, measuring the OCV-SOC of each battery for improvement of the SOC estimation is a very time-consuming process if possible. Therefore, a new OCV-SOC relation must be considered.

In this paper, the new concept of the capacity is defined on the basis of the OCV and the SOC is also modified with respect to the new capacity. To find the proposed OCV-SOC, a cutoff open circuit voltage is chosen arbitrarily. In this case, the cutoff voltage is the set voltage, i.e. 3.6V, as shown in Fig. 3 and the conventional relationship from Fig. 1 is configured using the set voltage as a reference voltage. As can be seen in this figure, a strong consistency can be seen between the OCV-SOC data of each battery. Thus, a single OCV-SOC can be used for all batteries of the same type. However, the estimation using the proposed method causes a change in the capacity. So the capacity must be estimated in addition to the SOC.

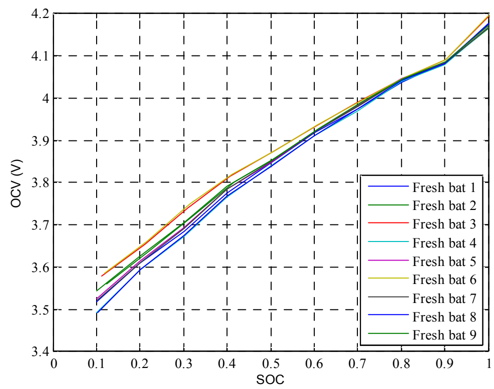

Fig. 1 The conventional relationship of the OCV-SOC

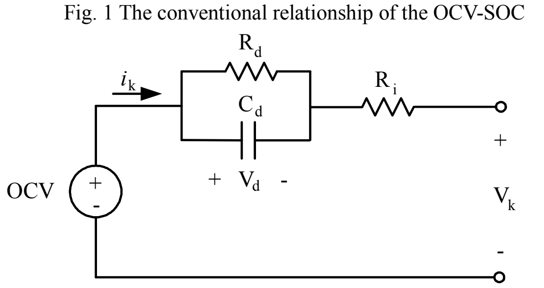

Fig. 2 The simplified equivalent electrical model of the lithium-ion battery

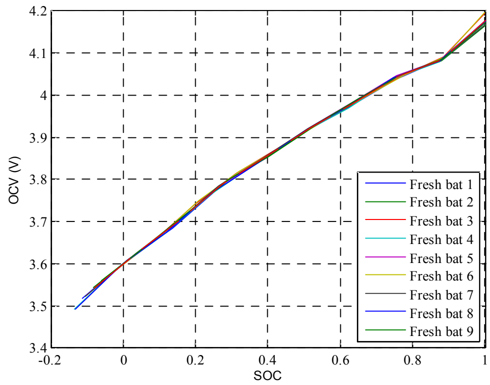

Fig. 3 The proposed relationship of the OCV-SOC

2.2 Implementation of dual extended Kalman filter

The dual EKF is used to estimate the SOC and capacity of lithium-ion battery. This algorithm combines the two EKFs, one of which is the state filter which estimates the SOC, and the other is the weight filter which estimates the capacity. At every time step, the state filter uses a priori value of the weight filter, while the weight filter uses a priori value of the state filter. Therefore the two EKFs are calculated concurrently to estimate the SOC and capacity [4].

To implement the dual EKF, an equivalent electrical model which represents the electrochemical characteristics of the battery is needed. There are several researches that extract the model and its parameters of the battery [5, 6]. In this paper, the current and voltage information of the battery are analyzed to obtain the modeling and parameters as shown in Fig. 2. At first, the open circuit voltage (OCV), which means the equilibrium potential of the battery, is modeled as an equivalent voltage source. Secondly, the parallel circuit consisting of R_d and C_d is used to model the dynamic response of the current reference. Finally, the series resistance, R_i, is used to represent an instantaneous voltage response.

This model can not practically simulate the nonlinear dynamic behavior of the plant. However, the complicated battery modeling increases the order of the system, which makes it difficult to implement the estimation algorithm and to operate in real time. Thus, the measurement noise model can be used in the case that errors between the plant and model exist [2]. Therefore, it can serve to construct the reduced order model and to prevent the dual EKF algorithm from measurement errors caused by inaccurate modeling.

The state-space representation with difference equations of the dual EKF is described (1)-(3). The w_k^x and w_k^θ as the process noise of the state filter and weight filter, respectively, are assumed to be independent, zero-mean, Gaussian noise with the covariance matrices Q_k^x and Q_k^θ. The measurement noise υ_k is assumed to be independent, zero-mean, Gaussian noise with the covariance matrix R_k. In this case, the state-space equation of the battery model is derived as (4)-(6).

$$x_{k+1} = f_x(x_k, u_k, \theta_k) + w_k^x \tag{1}$$

$$\theta_{k+1} = \theta_k + w_k^\theta \tag{2}$$

$$y_k = h_k(x_k, u_k, \theta_k) + \upsilon_k \tag{3}$$

$$x_{k+1} = \begin{bmatrix} SOC_{k+1} \\ V_{d,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \dfrac{\Delta t}{C_d R_d} \end{bmatrix} \begin{bmatrix} SOC_k \\ V_{d,k} \end{bmatrix} + \begin{bmatrix} -\dfrac{\Delta t}{C_{n,k}} \\ \dfrac{\Delta t}{C_d} \end{bmatrix} i_k \tag{4}$$

$$\theta_k = \left[C_{n,k} \right] \tag{5}$$

$$V_k = OCV(SOC_k, C_{n,k}) - V_{d,k} - R_i \cdot i_k \tag{6}$$

The measurement matrix is derived from (7)-(9). In (9), because the first term is irrelevant to the capacity, as shown the Fig. 3, its value is approximately zero. Thus, the realization of the algorithm can be simplified.

$$H_k^{SOC} = \frac{\partial V_t}{\partial SOC} = \frac{\partial OCV}{\partial SOC} \tag{7}$$

$$H_k^{V_d} = \frac{\partial V_t}{\partial V_d} = -1 \tag{8}$$

$$H_k^{C_n} = \frac{dOCV}{dC_n} = \left.\frac{\partial OCV}{\partial C_n}\right|_{C_n^-} + \frac{\partial OCV}{\partial SOC_k^-} \frac{dSOC_k^{-1}}{dC_n} \tag{9}$$

3. Result

Simulations and experiments were carried out to demonstrate the performance of the algorithm with proposed OCV-SOC. The experimental set was comprised of a power supply, electric load, constant temperature and humidity chamber, electrochemical impedance spectroscopy (EIS) and a personal computer (PC). The cycled experimental results, such as the voltage, current, temp., and etc., of the battery were collected through the data acquisition board and they were used as an input of the simulations. The Matlab/Simulink S-function was used for the simulations.

The charge and discharge cycling test of the battery were carried out under the current profile, which was scaled down the HEV automotive profile, from Fig. 4. This profile caused a variation of the SOC for one hour and was used to make a total of eight cycles. Each cycle is different from the time used above profile and the end point of the SOC is varied to verify the estimation results in the 40-80% SOC regions after completing cycles. Because the ampere-hour counting method has critical defects, as mentioned above, the SOC was reset to one to minimize the accumulation error after each cycle in the middle of the cycling profile. Thus, the ampere-hour counting method can be considered to check the general variation trend of the SOC. The performance of the SOC estimation was verified with the discharge test after two hour rest periods between each cycle. The estimation of the capacity was verified with the real capacity during all cycles. The real capacity was newly measured during the SOC reset after each cycle and its values are as shown in Fig 5.

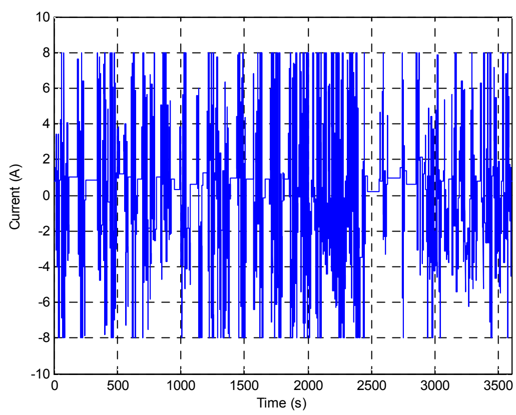

Fig. 4 The charge and discharge cycling profile

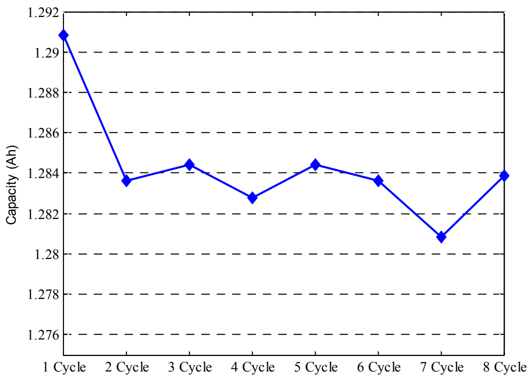

Fig. 5 Capacity variation during cycles

The capacity and SOC measured before cycling are 1.29Ah, and 0.8, respectively. Therefore, the estimated SOC and capacity using the proposed methods are changed to the conventional values, SOC and capacity, from (10)-(11).

$$SOC = 1 - \left(1 - SOC_{new}\right)\left(1 - SOC_{cutoff}\right) \tag{10}$$

$$\text{conventional capacity} = \frac{\text{modified capacity}}{1 - SOC_{cutoff}} \tag{11}$$

where, the SOC_{new}, modified capacity and SOC_{cutoff} denote the modified SOC, capacity and SOC value at the set voltage of the new OCV-SOC, respectively.

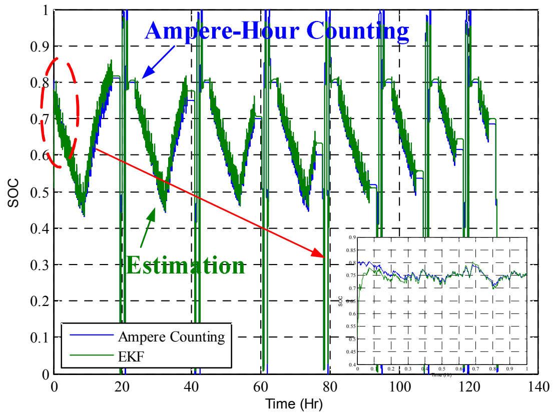

Fig. 6 SOC estimation result of proposed algorithm

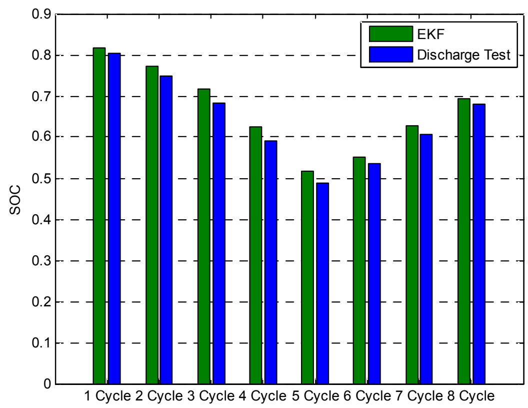

Fig. 7 SOC estimation results at cycles

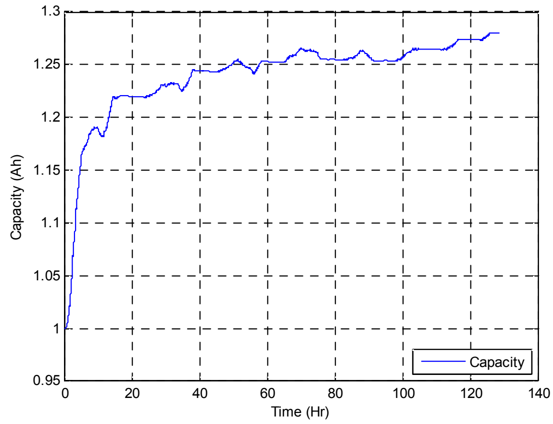

Fig. 8 Capacity estimation result of proposed algorithm

The SOC estimation result accurately tracks the real SOC in spite of an initial value error which is smaller than the real value in Fig. 6. Also, the general trend between ampere-hour counting and estimation is almost the same. The performance results from the discharge test come within the specification of ±5%, as shown in Fig. 7. In Fig. 8, the result of the capacity estimation with an initial value smaller than the real value is shown.

4. Conclusion

In this paper, the estimation method using the dual EKF with the new OCV-SOC is proposed to overcome the variation of the conventional OCV-SOC. The explanation of the OCV-SOC relation and the dual EKF algorithm are given along with experimental results. The estimation results of the dual EKF satisfy the specifications of 5%, and the realization of the dual EKF can be simplified by the proposed method.

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