Chapter 27
State of Charge Estimation Based on a Composite Method for Power Lithium Battery

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Abstract The state of change (SOC) is used to describe the remaining capacity of battery and its accuracy is very important for power battery. In this paper, according to the composite method, the dynamic system model is established, combining with the ampere hour integral method revised by the compensating factor and the equivalent circuit model. After that, the system state equation and observation equation is introduced. At the same time, the Kalman filtering achieves the minimum error of SOC estimation value. The SIMULINK tool is used to establish the mathematical model of dynamic system. The simulation results show that the composite method can monitor the battery SOC in real-time. Its accuracy can keep the error within 4 %, which is good practical value in the estimate of power battery SOC under the complex operating condition.

Keywords SOC · Dynamic system · Kalman filter · Lithium battery

27.1 Introduction

Power lithium battery is a key to the electric vehicle. The state of change (SOC) reflects the remaining capacity of battery. So accurate estimating the SOC value is vital to the battery management system, and it is also one of the important basis for control the EV. Due to the electrochemical properties of battery is very complicated. It shows highly nonlinear in the process of charging and discharging. And

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the influences of current, temperature and charge–discharge cycle make higher difficulty to accurately estimate SOC value. In order to improve the accuracy of estimation, the previous papers took into account the compensation of the charge–discharge efficiency, temperature, aging and other factors in the model algorithm [1]. Nevertheless, a single model to describe the cell dynamic characteristics is rather difficulty and some errors. So the battery SOC estimation has become the difficulty to the battery management system [2].

The traditional SOC estimation methods, such as ampere hour integral method, the open circuit voltage method and impedance method, have their own shortcomings. So the researchers pay more attentions on the new methods to estimate SOC value.

The mathematical method to complex dynamic system model is effective, and also can revise the error in a certain degree. Based on the principle of Kalman filtering [3], it combines with Ah integral method and open circuit voltage method to establish filtering system, so as to realize the composite estimation method.

27.2 The Principle of Composite Method

The composite method of SOC estimation mainly embodied in two aspects: firstly, estimation method relies on the accurate dynamic cell model; secondly, it can be applied to real-time estimation the SOC value. The compound method based on Kalman filtering is appropriate for relative complex condition, and can more fully simulate the power battery operating characteristics. A dynamic model to estimate SOC value is proposed.

27.2.1 Ampere-hour Integral Method

Ah integral method estimates the battery SOC through the accumulation power in charge or discharge. It is one of the most simple and commonly used methods at present. The formula of Ah integral method is:

$$SOC(t) = SOC(t_0) - \int_{t_0}^{t} \eta \frac{i(t)}{C} dt \qquad (27.1)$$

where SOC (t_0) is the battery SOC value of initial state, C is the rated capacity, η is the correction coefficient about the temperature, the discharge rate and the number of cycles.

The ampere-hour method estimates SOC value. It is an easy and stable algorithm. The defect is needed to calibrate SOC initial value; and η is not constant under the different discharge conditions; there has a certain error in high temperature and current fluctuation severe situation [4].

27.2.2 Open Circuit Voltage Method

Open circuit voltage method under a certain condition uses the relationship between the SOC and OCV. The dynamic SOC estimation accuracy depends on the power cell model. To establish the mathematical model of the lithium cell requires identifying the parameters, and then building the relationship of equivalent circuit model. The formula of the OCV is:

$$U_{oc} = K_0 - Ri - K_1 x_k + K_2/x_k + K_3 \ln(x_k) + K_4 \ln(1 - x_k) \tag{27.2}$$

where U_{oc} is the battery terminal voltage of one cell, x_k is value in different conditions of the SOC, and R is the battery internal resistance (differed values in different charging and discharging status and different SOC). K_1 is the polarization effect of equivalent resistance. K_2, K_3 and K_4 is the model matching parameters [5].

This method needs a rest time in measuring the OCV to ensure the SOC value accurately. So it does not apply to real-time estimation for electric vehicle.

27.2.3 The Principle of Kalman Filtering Method

Kalman filtering method is introduced into the system state space model [5, 6]. The State equation describes the state and variation; it gives the mathematical model of the changing of state transition in adjacent time. The measurement equation describes the information of the measurement state, usually containing observation noise.

Kalman filtering problem is to find the optimal estimation of the system state, based on the obtained information from the measurement equation.

For a discrete time process of state variable, the system state equation is:

$$x_k = Ax_{k-1} + Bu_{k-1} + \omega_k \tag{27.3}$$

Definition of system measurement equation is:

$$y_k = Cx_k + v_k \tag{27.4}$$

where the SOC value is the system state variable x_k, the vector u_k is the input, including the factors, such as the power battery current, temperature and discharge ratio. And the vector y_k is the measuring value.

The optimal estimation is the core part of the Kalman filter algorithm, which is revised by the difference between the measured and predicted measurement y_k. So the quantity of state x_k is closer to the real value in this system. And optimal estimate equals to the prior estimation value and algorithm correction [7].

To illustrate this optimal estimation, consider the linear discrete-time system block diagram in Fig. 27.1.
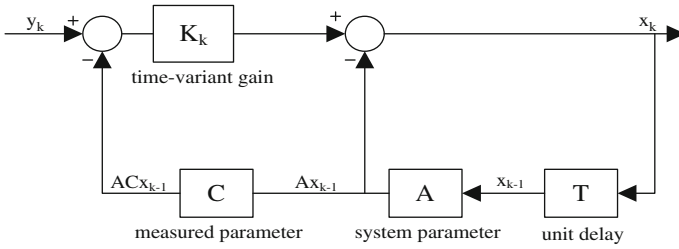
Fig. 27.1 The principle of optimal estimation block diagram

27.3 The Framework of Model

What this work does is taken of Ah integral equation as the system state equation and (27.2) of equivalent circuit equation as measurement equation [8].

1. According to the SOC estimation value at K − 1 time, update the SOC prior estimation at the time K by (27.5);
2. According to the prior estimation of SOC, update the prior voltage estimation at time K by (27.6);
3. The formula (27.7) is equation of the algorithm correction, which is the product of filter gain Kk and prediction error. The prediction error is the difference between the measurement value of terminal voltage and its prior voltage estimation at time K.
4. According to the vectors of formulas (27.5–27.7), updating formula (27.8), it can obtain the SOC estimation value at time K and output this value.

Output value at time K, and take it as the initial estimation at time K + 1, we can get the SOC prior estimate at time K + 1. Through this circle from prediction to update, it can get every moment for SOC filter estimation value [9].

$$x_{k|k-1} = x_{k-1|k-1} - \eta \frac{i(t)}{C} \Delta t \tag{27.5}$$

$$y_{k|k-1} = K_0 - Ri - K_1 x_{k|k-1} + K_2/x_{k|k-1} + K_3 \ln(x_{k|k-1}) + K_4 \ln(1 - x_{k|k-1}) \tag{27.6}$$

$$correct = K_k \times (y_k - y_{k|k-1}) \tag{27.7}$$

$$x_{k|k} = x_{k|k-1} + K_k \times (y_k - y_{k|k-1}) \tag{27.8}$$

where $x_{k-1|k-1}$ is the SOC estimation, $x_{k|k-1}$ is the SOC priori estimation at time K, y_k and $y_{k|k-1}$ are the terminal voltage and the prior voltage estimation at time K, u_{k-1} is the input at time K − 1. w_k and v_k are the incentive noise and observation noise. They are both normal distribution of white noise.

The composite algorithm updates the SOC estimation value, and at the same time, takes the minimum error covariance of the system state as the best standards to correct the SOC estimation value [10].

Formula 27.9 is the Kalman filter gain matrix K_k, whose role is to make the system's estimation error covariance minimum.

$$K_k = \frac{C_k \times P_{k|k-1}}{C_k \times P_{k|k-1} \times C_k^T} \tag{27.9}$$

Formula 27.10 is the measured value matrix:

$$C_k = \frac{\partial y_{k|k-1}}{\partial x} = \frac{K_2}{x_{k|k-1}^2} - K_1 + \frac{K_3}{x_{k|k-1}} - \frac{K_4}{1 - x_{k|k-1}} \tag{27.10}$$

Formula 27.11 is the prior estimation covariance matrix:

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{27.11}$$

Formula 27.12 is the optimal filtering error covariance update:

$$P_{k|k} = P_{k|k-1} \times (1 - C_k K_k) \tag{27.12}$$

27.4 Simulation and Results

The SIMULINK tool is used for the simulation. The mathematical model is established, on the basis of the composite method. The structure diagram of the model is shown in Fig. 27.2. During the simulation, it simulates the process of discharge with 1C pulse rate, and the discharge current waveform is shown in Fig. 27.3.

Figure 27.4 is the voltage of the storage battery varies with time. After 600 s, the battery terminal voltage is stabilized, and fluctuates within a certain range. For the storage battery maintains at a stable voltage state.

Figure 27.5 shows the difference of SOC value between the composite method and the single Ah integral. Comparing the data, it finds that the composite method based on Kalman filtering method is more accurate in real-time estimating cell SOC value.

Figure 27.6 shows the SOC relative error by the composite method. It display the maximum relative error about 4 %. This may be the reason that the relationship between the OCV and SOC is not very clear in discharged interim at that time, and so the error is larger [11].
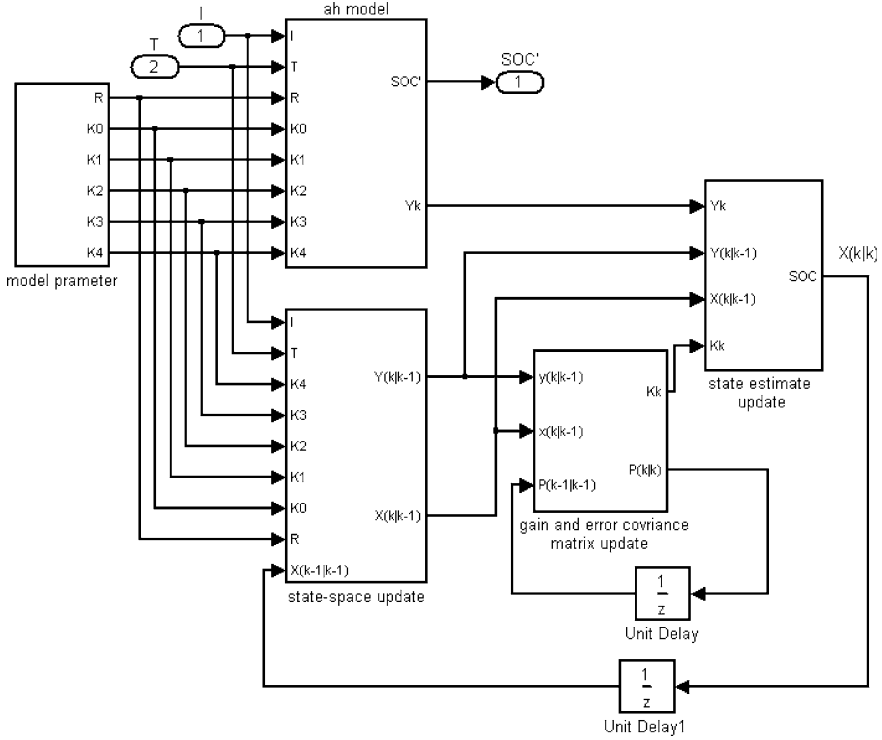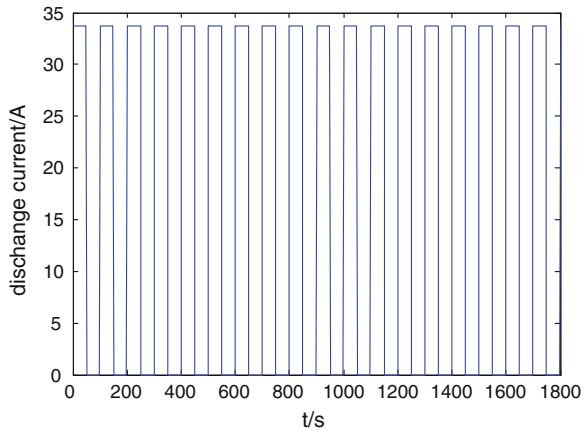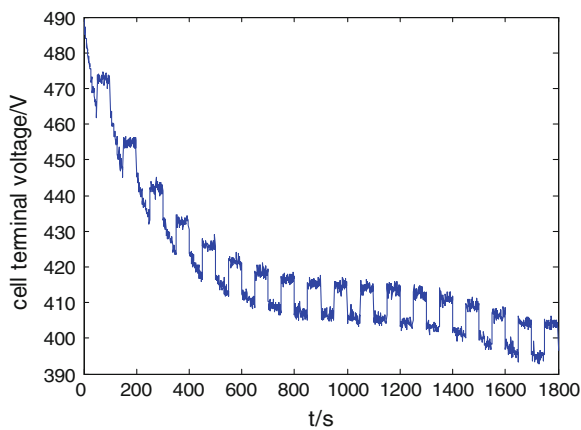
Fig. 27.2 The SOC estimation model based on composite method
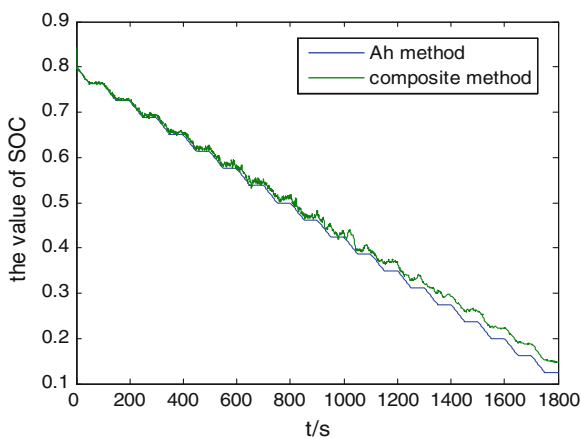
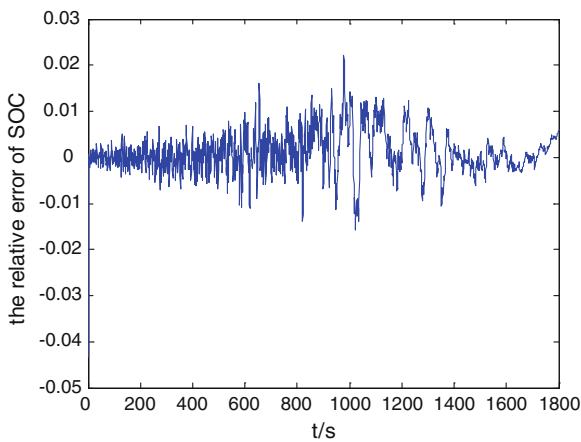**Fig. 27.3** The waveform of discharge current

Fig. 27.4 The terminal
voltage of the cell

Fig. 27.5 The comparison of
the two estimation methods

Fig. 27.6 The relative error
of SOC estimation value

27.5 Conclusion

The paper outlines the composite method used in the SOC estimation of power lithium battery. The temperature and current of cell, as well as theirs correction coefficients are as the system input. The previous moment estimation of SOC is as the system state quantity to estimate SOC value at the next moment. Meanwhile, the terminal voltage of cell is estimated by the open-circuit voltage method. Thus, we make use of the error covariance of the estimated and measured value to revise the SOC estimation. It tests and verifies that the result of simulation experiment is less than 4 % of the estimation error.

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