Study On SOC Estimation By Coupling Capacity Modified Ampere-Hour Method

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Abstract. When using the Ampere-hour integration (Ah) method to estimate the state of charge (SOC) of battery, the mechanism and working conditions of the battery will have different effects on the battery capacity. When the battery aging and working conditions change, the estimation accuracy of Ah method is challenged. In this paper, the capacity optimization coefficients such as battery aging degree, ambient temperature and discharge rate are added to the Ah method, and the coupling capacity modified Ah method is proposed to correct the capacity deviation in real time, so as to improve the real-time estimation accuracy of SOC. Finally, experiments show that the coupling capacity modified Ah method can effectively correct the battery capacity deviation in real time, reduce the cumulative error, and effectively improve the SOC estimation accuracy of the Ah method.

Keywords:component; Ah method; SOC; optimization coefficient; Lithium-ion battery.

1. Introduction

The low state of charge (SOC) of lithium-ion battery (LIB) is one of the important reasons for the discontinuation of mechanical equipment. SOC is different from physical quantities such as voltage and current that can be directly measured, it is difficult to measure directly and needs to be estimated by voltage value or off-line data[1]. Recently, the SOC estimation methods of LIB have become a research hotspot of scholars at home and abroad. Among them, the Ampere-hour integral (Ah) method is one of the most widely used methods in metallurgical, mining and mechanical engineering[2]. The greater the LIB aging, the greater the fluctuation of charge and discharge current, and lower ambient temperature, affecting estimation accuracy. However, this effect can be reduced by optimizing the Ah method, and the remaining battery power can be obtained more timely and accurately[3]. In addition, SOC estimation of LIB can also be used to monitor other safety issues in battery systems. Therefore, SOC estimation of LIB is of great significance for safe use of mechanical equipments and health monitoring of battery system.

In this paper, in order to enhance the estimation accuracy of the Ah method under varying aging conditions, ambient temperature and current rate, we proposed coupling capacity correction Ah method. The capacity optimization coefficients of different aging states, ambient temperature and discharge rate are calculated through experiments, and fit the coupling capacity correction coefficient. Finally, the experiment shows that the coupling capacity modified Ah method can effectively improve the SOC estimation accuracy.

2. Theoretical Analysis

In order to reduce the SOC estimation error caused by the Ah method in the use stage, it is necessary to consider the battery mechanism and the influence of external conditions on the battery performance. Multiple optimization coefficients are added to the Ah method, and the expression of the coupling modified Ah method is shown in formula (1).

$$SOC_t = SOC_0 - \frac{\eta \int_0^t I_t \, dt}{K \eta_h \eta_t \eta_r Q_0} \tag{1}$$

SOC_t is the battery SOC value at time t. SOC_0 is the initial SOC value of LIB. η is the coulomb efficiency of LIB, it is usually considered constant 1. t is a certain time during battery use. I_t is the current through the battery, and the discharge is positive in this paper. Q_0 is the rated capacity of the battery. η_h is the aging state optimization coefficient. η_t is the temperature optimization coefficient. η_r is the discharge rate optimization coefficient. The respective values of coefficients η_h, η_t and η_r are obtained by experiments. K is the coupling capacity correction coefficient, and it is obtained through a tremendous number of experimental data under different aging conditions, ambient temperature and discharge rate. K is able to prevent the occurrence of excessive correction when the three capacity optimization coefficients simultaneously correct the battery capacity under complex conditions, and it can effectively improve the estimation accuracy of the coupling capacity modified Ah method.

3. Experimental Analysis

The battery experimental platform is built to program and collect the experimental data. The experimental platform used is shown in Figure 1. It can meet the simultaneous collection of the charge and discharge capacity, current, voltage and other data of multiple batteries under different discharge rates, different ambient temperatures and different aging conditions. The detailed specifications of the tested LIB are shown in Table 1.

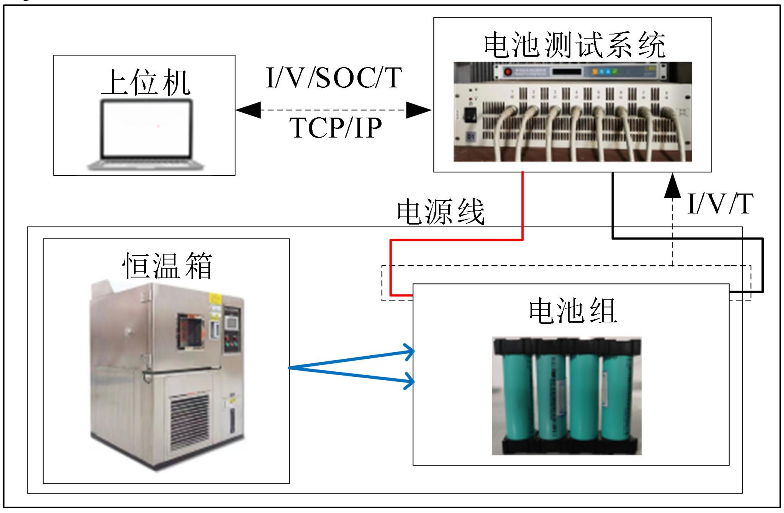

Figure 1. Battery experimental platform.

Table 1. Detailed specifications for tested LIB.

Item	Specification
Nominal capacity	3.0Ah
Nominal voltage	3.6V
Charge voltage	4.2V
Discharge cut-off voltage	2.5V
Standard charge	CCCV, 0.56A, 4.20V, 56mA cut-off
Max continuous discharge	8.4A
Operation Temperature	-20 ℃~60 ℃

4. Acquisition Of SOC-OCV Curve

There is a nonlinear relationship between OCV and SOC in Li-ion batteries. Use the standard Constant Current Constant Voltage (CCCV)charging method to fully charge the battery, and then test the battery terminal voltage value after 1 hour of resting. At this time, the SOC value is 1. With standard constant current discharge, discharge the maximum available capacity of 5 %, and then stand aside for 1 hour to measure the terminal voltage. Cycle this step until the battery reaches the discharge cutoff voltage. At this point, the battery SOC value is 0. The relationship between SOC and OCV can be given by a polynomial fitted function and its can be expressed in (2).

$$U_{oc}(SOC) = a_1 SOC^8 + a_2 SOC^7 + \cdots + a_9 \tag{2}$$

$$\begin{cases} [a_1, a_2, a_3] = [46,7, -171,7, 275,5] \\ [a_4, a_5, a_6] = [-251,2, 126,9, -18,3] \\ [a_7, a_8, a_9] = [-18,3, -13,5, 2,5] \end{cases} \tag{3}$$

The measured data and fitting curves are shown in Figure 2.

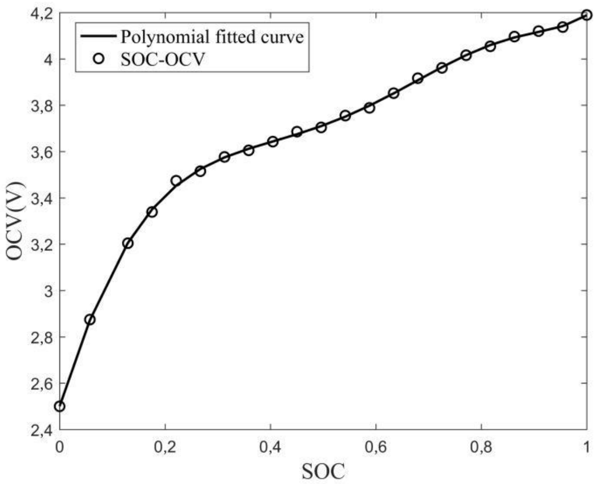

Figure 2. SOC-OCV fitting curve.

To determine the optimization coefficient η_h for various aging states, the battery aging experiment is designed at 25℃ ambient temperature. The battery is charged in the temperature chamber using the standard CCCV method and is discharged using the standard current[4]. η_h is the ratio of battery discharge capacity to rated capacity. The relationship between η_h and charge-discharge times can be fitted by polynomial fitting equation, and its can be expressed in formula (4).

$$\eta_h = b_1 N^4 + b_2 N^3 + b_3 N^2 + b_4 N + b_5 \tag{4}$$

$$\begin{cases} [b_1, b_2] = [7,0, e-12, -5,9e-09] \\ [b_3, b_4, b_5] = [1,2e-04, -4,8e-04, 1,0] \end{cases} \tag{5}$$

N is the number of charge and discharge cycles. The fitting curve of η_h and charge-discharge times is shown in Figure 3.

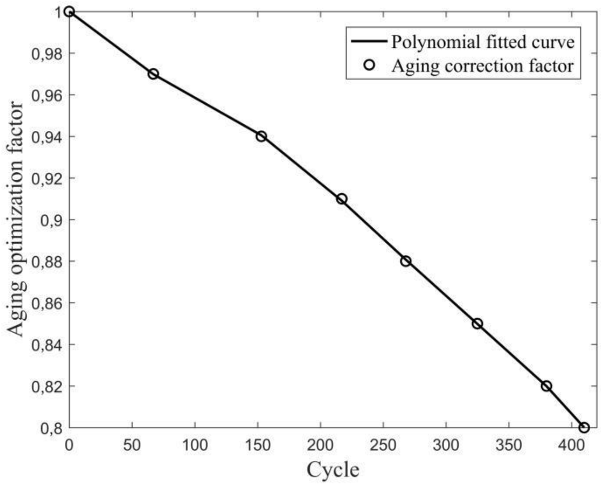

Figure 3. η_t under different aging conditions.

In order to obtain the optimization coefficient η_t at different temperatures, the battery is put in the constant ambient environment of -10 °C, 0 °C, 25 °C and 40 °C respectively for standard CCCV charging and standard discharging experiments. η_t refers to the ratio of the battery's discharge capacity to its rated capacity[5]. The relationship between η_t and ambient temperature can be fitted by polynomial fitting equation, and its can be expressed in formula (6).

$$\eta_t = c_1 T^3 + c_2 T^2 + c_3 T + c_4 \quad (6)$$

$$\begin{cases} [c_1, c_2] = [9{,}81e-07, -1{,}32e-04] \\ [c_3, c_4] = [7{,}58e-03, 0{,}88] \end{cases} \quad (7)$$

T is the ambient temperature. The fitting curve of η_t and temperature is shown in Figure 4.

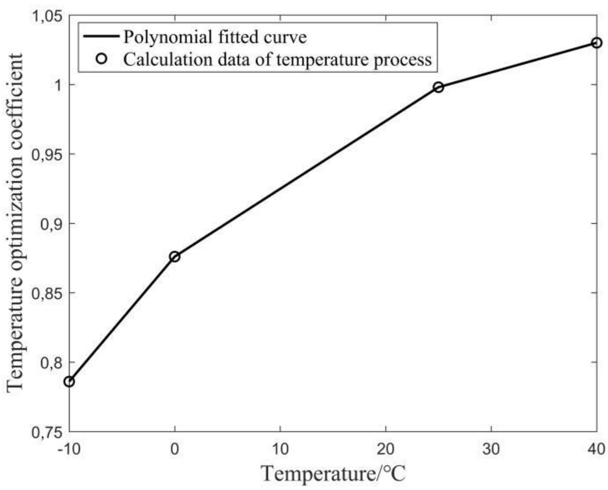

Figure 4. η_t at different ambient temperatures.

In order to obtain the optimization coefficient η_r of different discharge rates. The LIB is fully charged in the standard CCCV method, and discharged at discharge rates of 0.2 C, 0.5 C, 1C, 1.5 C and 2 C, respectively. η_r is the ratio of the battery discharge capacity to the rated capacity. The relationship between η_r and discharge rate can be fitted by polynomial fitting equation, and its can be expressed in formula (8).

$$\eta_r = d_1 r^4 + d_2 r^3 + d_3 r^2 + d_4 r^1 + d_5 \quad (8)$$

$$\begin{cases} [d_1, d_2] = [8,7e-04, -0,002] \\ [d_3, d_4, d_5] = [-2,99e-04, 4,9e-04, 1,0] \end{cases} \quad (9)$$

r is the battery discharge rate. The fitting curve of η_r and discharge rate is shown in Figure 5.

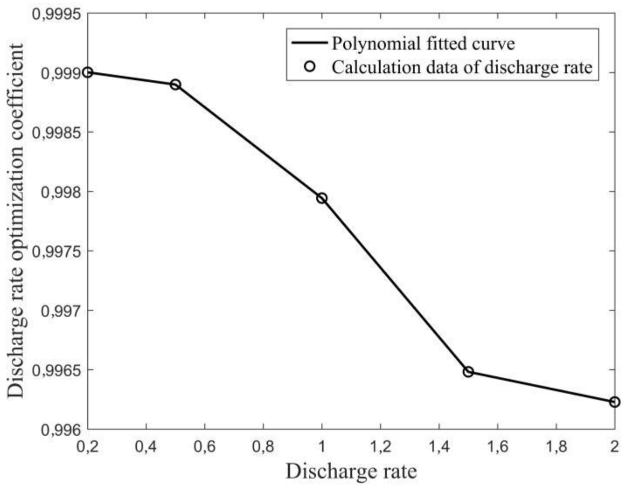

Figure 5. η_r under different discharge rates.

Aging state, ambient temperature and discharge rate have strong time-varying characteristics, which will have different effects on the current capacity of the battery. Therefore, it is necessary to couple the optimization coefficients after obtaining the three optimization coefficients of battery aging, ambient temperature and battery discharge rate, respectively. At this time, we propose to add the coupling capacity correction coefficient K to couple the three capacity optimization coefficients, in order to prevent the excessive capacity correction and the deviation of estimation accuracy. The range of K value is shown in Figure 6.

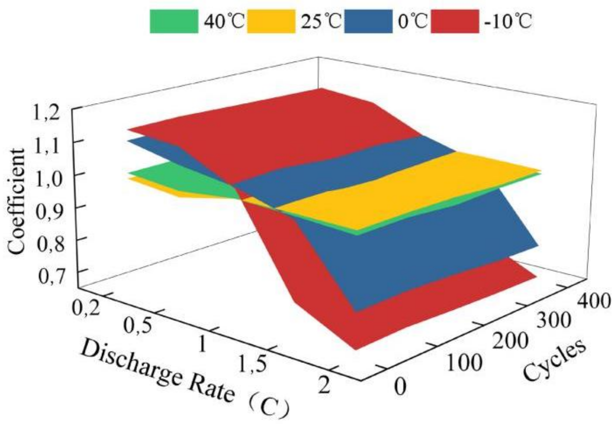

Figure 6. K value range diagram.

5. Experiment And Analysis

The Ah method model and the coupling capacity modified Ah method model are established in Simulink, as shown in Figure 7.

Here, the OCV module refers to the open circuit voltage value. The SOC-OCV module is the fitting curve. The Ah method module is the Ah method. The Current module is the discharge current value. The Cycle module is the battery charging and discharging times. The Temperature module is the ambient temperature. The coefficient K module is the coupling capacity correction coefficient K. The optimized Ah method module is the coupling capacity modified Ah method.

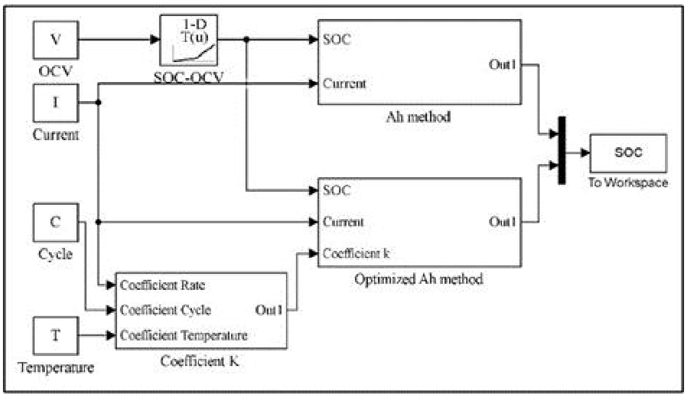

Figure 7. Simulink model diagram.

We adopt Dynamic Stress Test (DST) operation condition to evaluate the SOC estimation accuracy of the coupling capacity modified Ah method. By collecting the current, voltage and other data of the test vehicle under DST condition, they can be used to test the battery[6].

The current characteristics of DST are shown in Figure 8.

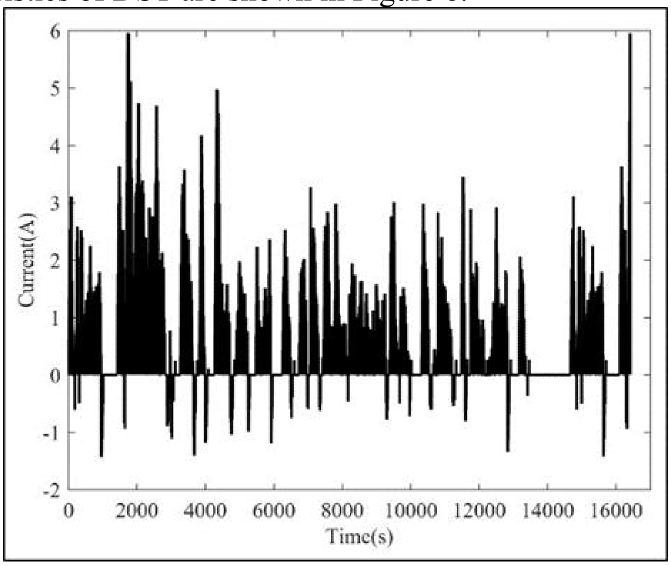

Figure 8. Current characteristics of DST.

The aging battery with 100 cycles of charge-discharge is selected for the experiment. During the discharging process, the ambient temperature rises slowly from -10 ℃ to 10 ℃. Figure 9 illustrates the SOC estimation results obtained through Ah method, coupling capacity modified Ah method, and experimental testing data.

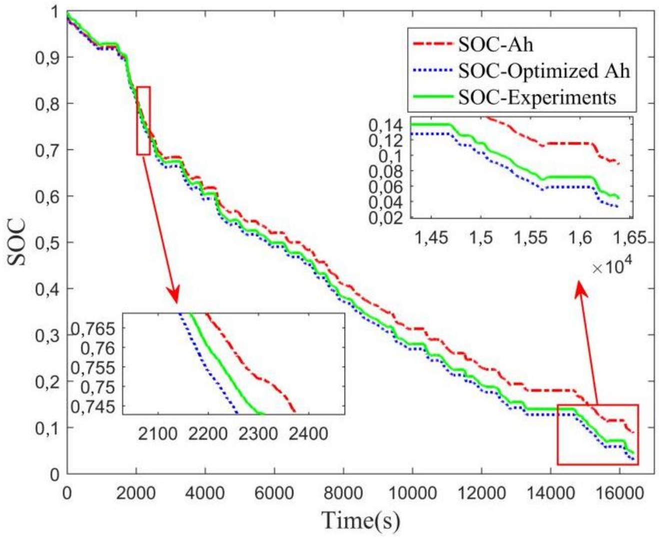

Figure 9. SOC estimation characteristics of UDDS.

It can be seen from Figure 9 that after the battery is used for a short period of time under DST conditions. Compared with Ah method, the SOC estimation value of the coupling capacity modified Ah method began to fit the experimental data value of SOC gradually. It shows that the battery capacity is being corrected according to the changes in working conditions and ambient temperature. During the discharge process's final stage, it is evident that the SOC estimation value obtained from the coupling capacity modified Ah method is closer to the value obtained from the experimental data as compared to the Ah method. The coupling capacity modified Ah method has a lower maximum estimation error than the Ah method when the battery discharges to the cut-off voltage.

To assess the performance of the proposed coupled capacity correction Ah method, we present the maximum errors for state-of-charge (SOC) estimation in Table 2, under different experiments.

Table 2. Maximum SOC estimation errors.

Operation Condition	-10℃~10℃,100 cycle	
DST	Ah method	Proposed Ah method
	4.47%	1.36%

According to the data in Table 2, when aging batteries are used under current fluctuations and ambient temperature changes, the SOC estimation accuracy of the coupled capacity modified Ah method is higher. The maximum estimation error of Ah method is 4,47%. However, under the same experimental conditions, the maximum estimation error of coupled capacity modified Ah method is 1,36%, which is 3,11% lower than the Ah method. The results show that the proposed coupling capacity correction Ah method can effectively reduce the influence of usage conditions on SOC estimation accuracy. At the same time, it is proved that the coupling capacity modified Ah method is feasible and practical in industry.

6. Conclusion

This paper presents the coupling capacity modified Ah method. This paper discusses the influence of battery aging, ambient temperature and current fluctuation on the accuracy of SOC estimation by Ah method. In this paper, aging correction coefficient, temperature correction coefficient, current correction coefficient and coupling capacity correction coefficient are added to the Ah method, and the performance of the coupling capacity modified Ah method in LIB SOC estimation is compared and analyzed through experiments. Experiments show that the coupling capacity modified Ah method can update the changes of battery capacity under different discharge conditions in time, and effectively reduce the cumulative error in the use process. Hence, the

Coupling Capacity Modified Ah method can serve as an effective standard for assessing the accuracy of battery state of charge estimation methods in the industry.

Acknowledgments

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