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Charging Optimization of Lithium-ion Batteries Based on Capacity Degradation Speed and Energy Loss

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Abstract

In order to prolong the battery life, a charging optimization in lithium-ion batteries based on capacity degradation speed and energy loss is proposed in this paper. Frist, a first-order equivalent circuit model of the battery is established and the parameters of the model under different SOC and charging rates are identified. Second, the degradation characteristics of the battery life in different SOC cycle intervals are analyzed and a capacity degradation speed model which is related to SOC and charging rate is established. Third, the energy loss is calculated based on the equivalent circuit model and the objective function that aims to reduce the capacity degradation speed and energy loss is established. Finally, the optimal current sequence is obtained by dynamic programming algorithm. Compared with the traditional charging method, the loss of the energy and capacity are reduced under the same average charging rate and the battery cycle life is effectively improved after suffering 300 cycle life verification tests.

Keywords: Lithium-ion battery; charging strategy; SOC intervals ; life characteristics; dynamic programming algorithm

1. Introduction

Lithium-ion batteries have been widely used as power cells because of their advantages of high energy density, low self-discharge rate and no memory. The charging strategy of the battery will affect its charging efficiency, cycle life and safety performance [1]. The constant-current constant-voltage (CCCV) charging method is one of the most widely used charging methods; further, it is simple and easy to control. However, the CV phase takes a long time [2]. Accordingly, a large number of optimized charging strategies have emerged.

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In [3], a pulse charging method was proposed to improve the charging efficiency, which allows lithium ions to diffuse more evenly throughout the battery and thus alleviate polarization. In this scenario, the charging time is realized by changing the amplitude and width of the current, and it is difficult to control effectively. As the charging rate will affect its charging time and cycle life, the multi-stage CC charging strategy is widely used. A multi-stage charging method that considered the charging time and energy loss as optimal objectives was proposed in [4-5], which indirectly controls the cycle life of a battery by controlling energy loss. However, the battery life is not verified at last. In order to realize the online optimization, a charging strategy based on model predictive control was proposed in [6]. It applied system models to predict system responses and to find the best future control sequence by optimizing the user-defined objective function. But the whole process is complex to implement.

In summary, previous battery charging strategy studies mainly concentrated on the optimization of the charging time or polarization. Until now, there has been little work done to improve the cycle life of the battery. As the battery's energy loss during the charging process increases, the corresponding battery capacity degradation will be more serious [7]. Therefore, in order to prolong the cycle life of the battery, the capacity degradation speed and energy loss were taken as two optimal objectives. The cycle life test of the battery at different SOC cycle intervals was used to establish the capacity degradation speed model. In addition, the energy loss was calculated based on the equivalent circuit model of the battery, and the effects of the charging rate and SOC on the model parameters were taken into account. The optimal current sequence was obtained by the dynamic programming algorithm with the average charging rate, maximum charging rate, charging capacity and cut-off voltage as constraints. And a contrast test with the traditional charging method was made.

2. Battery model and parameters identification

The first-order equivalent circuit model was chosen in this paper, as shown in Fig.1. OCV is the open circuit voltage which has a close relationship with SOC. The Ohmic resistance R_Ω represents the internal connection impedance of the battery. The polarization resistance R_P and its parallel capacitance C_P reflect the polarization phenomenon of the battery, mainly including electrochemical polarization and concentration polarization [8]. I_L is the load current (positive for discharge, negative for charge).

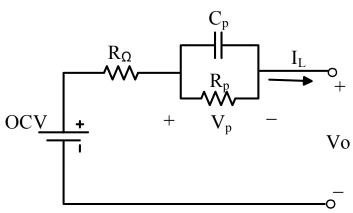


Fig. 1. First-order equivalent circuit model of battery.

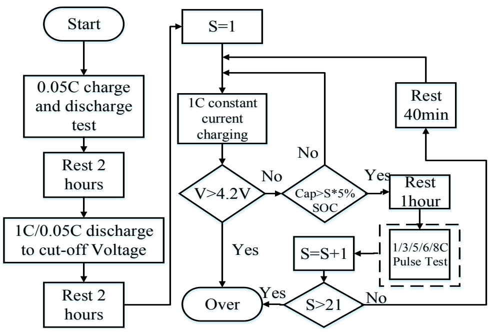


Fig.2. Test flow of battery model parameters.

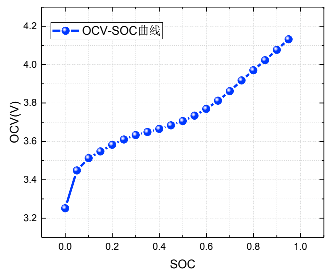


Fig.3. OCV-SOC curve

In this study, the power type battery was selected as the research object. Its positive and negative electrode material is $Li(NiMnCo)O_2$ and graphite respectively, nominal capacity is 8Ah, charging and discharging cut-off voltage is 4.2V and 2.75V respectively, and the maximum charging rate is 15C.

In order to obtain the battery parameters more accurately, the pulse charge-discharge test of the battery at different SOC and charging rates was conducted, as shown in Fig.2. First, a 0.05C charge-discharge test was carried out to obtain the capacity and OCV-SOC curve. Since the polarization is very small with the small charging and discharging rate, the value of OCV is the same as the terminal voltage. The OCV-SOC curve is shown in Fig.3.

Then the battery was tested for internal resistance. The battery has been subjected to a charge process with pulse of 10s for every SOC of 5% which charging rate was 1C, 3C, 5C, 6C, 8C, respectively. The discharging pulse rate was 1C, but it should ensure that the discharging and charging capacity were consistent during the pulse test.

The parameters of internal resistance were identified by the least squares method mentioned. The Ohmic resistance play a role in the moment of adding current and the formula is shown in Formula (1). In addition, the polarization voltage at different SOC points and charging rate in the charging process can be expressed by the battery model through the Formula (2). To make the Equation (2) available for numerical calculation, it should be discretized by Equation (3).

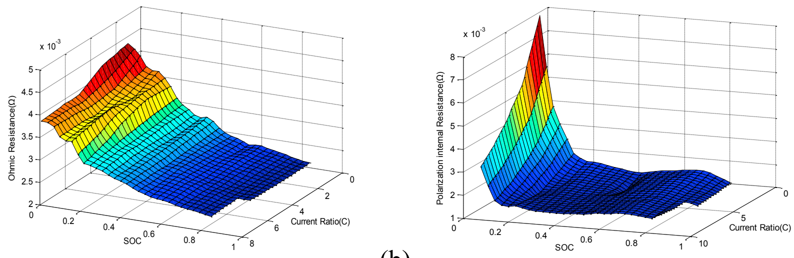
$$R_{\Omega} = \Delta U / \Delta I \tag{1}$$

$$\begin{cases} V_o(SOC, I_c) = OCV(SOC) - I_L R_{\Omega}(SOC, I_c) - V_P(SOC, I_c) \\ \dfrac{dV_P}{dt} = \dfrac{I_L}{C_P} - \dfrac{V_P}{R_P C_P} \end{cases} \tag{2}$$

$$\begin{cases} V_o(K) = OCV(K) - R_{\Omega} I_L(K) - R_p I_p(K) \\ I_p(K) = (1 - \dfrac{1-\exp(-\Delta t/\tau)}{\Delta t/\tau}) I_L(K) + (\dfrac{1-\exp(-\Delta t/\tau)}{\Delta t/\tau} - \exp(-\Delta t/\tau)) I_L(K-1) + \exp(-\Delta t/\tau) I_p(K-1) \end{cases} \tag{3}$$

The identified parameters of R_{Ω} and R_P are plotted in Fig.4 (a) (b). It can be seen from the image that at the same rate, the R_{Ω} and R_P decrease with the increase of SOC and are more stable in the 30%-80%SOC interval. That's because the positive electrode of the battery is in a lithium-rich state at the beginning of charging and it takes more energy to escape. So the polarization is large, resulting in a large internal resistance in the low SOC intervals.

In order to verify the accuracy of the model parameters, the equivalent circuit model of a battery was established under Simulink. The voltage under simulation and actual test with different charging rate are shown in Fig.5. The comparison shows that a little difference between the simulation and test results. The average error is within 0.4%. It can be demonstrated that this result can satisfy the precision of the parameters required in this paper.



(a) (b)

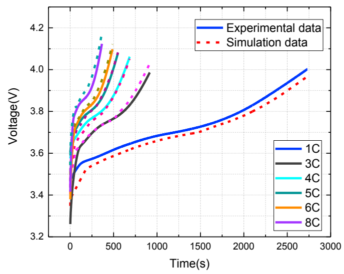


Fig. 4. (a) Ohmic resistance identification results; (b) Polarization resistance identification results. Fig. 5.Voltage curves of simulation and test

3. Formulation of battery charging optimization

3.1. The models of capacity degradation speed

The cycle life test of the battery was carried out in different SOC intervals at 25°C. The SOC was divided into 0%-20%, 20%-40%, 40%-60%, 60%-80%, 80%-100% and 0-100% for a total of 6 intervals for life testing and there are 3 battery samples under each test condition. The charging and discharging rate were 6C (48A). A performance test was conducted every 200 cycles, including 0.05C charge-discharge tests and HPPC tests.

The calculation of capacity degradation is shown in Formula (4). The 1s resistance is regarded as the Ohmic resistance. The difference between the 60s resistance and Ohmic resistance is taken as the polarization resistance. The changes in the capacity degradation, Ohmic and polarization resistance with the number of cycles under different SOC cycle intervals are shown in Fig.6.

$$Capacity_{loss} = 100 \times (1 - Q_{test} / Q_{initial}) \tag{4}$$

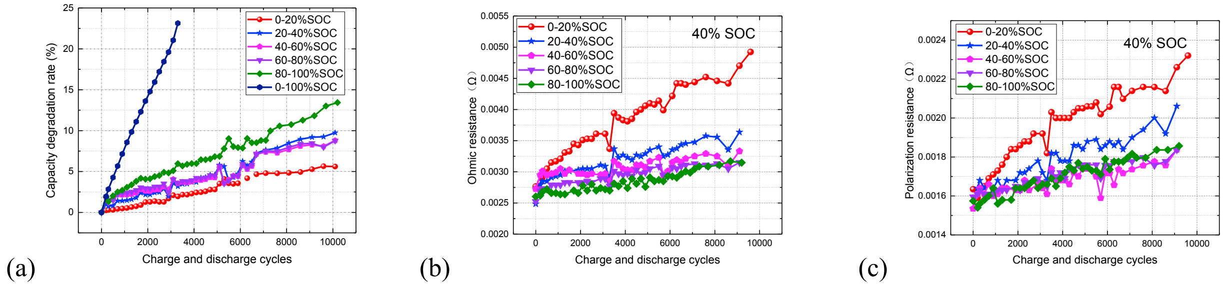


Fig. 6. The changes of (a) Capacity degradation; (b) Ohmic resistance; (c) Polarization resistance with the number of cycles.

The capacity degradation speed model $DS(I_c)$ of the lithium-ion battery with $Li(NiMnCo)O_2$ cathode is shown in Ref. [10]. Since the positive and negative materials of the battery in this paper are the same as those of the literature. Based on this life model, the capacity degradation speed model $DS(SOC,I_c)$ thinking of different charging rates and SOC cycle intervals is shown in Formula (5). The SOC-related parameter K refers to the ratio between the capacity degradation of the each and entire cycle interval. The SOC changes in each charging stage are expressed as Formula (6). η is the Coulomb efficiency and 1 has been taken.

$$DS(soc,I_c)=\sum_{k=1}^{N-1}K(soc)\times\Delta SOC_k\times DS(I_c) \tag{5}$$

$$\Delta SOC=\int_0^{\Delta t_k}\eta\times I_L(t)dt \Big/ 3600\times capacity \tag{6}$$

Fig.6 (a) shows a linear relationship between the capacity degradation and the number of cycles, such as (7). To identify the parameters h and g, the capacity degradation curves under different SOC cycle intervals are fitted by Formula (7). By deriving Formula (7), the capacity degradation speed (DS) is obtained in Formula (8). The parameters g and K under different SOC cycle intervals are shown in Table 1.

$$Capacity_{loss}=h+g\times cycle \tag{7}$$

$$DS=d(Capacity_{loss})\Big/d(cycle)=g \tag{8}$$

Table 1. Values of parameters b and K under different SOC cycle intervals.

	0-20%SOC	20-40%SOC	40-60%SOC	60-80%SOC	80-100%SOC	0-100%SOC
g	0.00304	0.00469	0.00375	0.00375	0.00563	0.00662
K	0.45922	0.70846	0.56647	0.56647	0.85045	1

3.2. Establishment of Optimal Objective Function

This study considers the battery capacity degradation speed and energy loss as the optimal objectives. During the process of formulating this function, the charging process is first divided into N constant current charging stages, and the parameters of the model are constant in each charging stage. The capacity degradation speed can be explained by its model established in the previous section. During the entire charging process, the battery's energy loss can be expressed from the first-order equivalent circuit model as (9).

$$E_{loss}(soc,I_c)=\sum_{k=1}^{N-1}((I_L)^2\times R_\Omega(soc,I_c)+(I_p)^2\times R_p(soc,I_c))\times\Delta t_k \tag{9}$$

In summary, the models of capacity degradation speed and energy loss at different charging rates and SOC cycle intervals were obtained respectively, so that the objective function with them as the optimal objectives is shown in (10). In order to ensure that they have the same order of magnitude, a balance coefficient M is added.

$$J = min\left\{\sum_{k=1}^{N-1} M(K(soc)\times \Delta SOC_k \times DS(I_c)) + ((I_L)^2 \times (R_\Omega(soc, I_c) + R_p(soc, I_c)) \times \Delta t_k\right\} \tag{10}$$

4. Optimal charging current calculation based on DP algorithm

4.1. Current Simulation Results

Dynamic programming is an algorithm for solving multi-stage decision optimal problems [9]. It has the characteristic of global optimization and is divided into five main elements, including the phase, state variable, decision variable, state transfer equation and index function. The principle is shown in Fig7. The decision current I(k) from the previous state SOC(k) to the state SOC(k+1) is pushed in reverse order and the corresponding stage performance index value J(k) is calculated. A similar method is calculated to the initial state. The shortest path to the initial state is determined according to the optimal index function as shown in (11). Then the state variables SOC, the decision variable I and the index function J are determined by forward recurrence.

This paper mainly optimizes the CC charging phase, taking the capacity degradation speed and energy loss as the two optimal objectives. The constraints are shown in (12) and the state transfer equation is shown in (13).

$$\begin{aligned} &min\_J(k-1)+J(k-1)<J(k) \\ &J(k)=min\_J(k-1)+J(k-1) \end{aligned} \tag{11}$$

$$\begin{cases} \bar{I}=6C \\ 2.75V \le V_O(k) \le 4.2V \\ 0 \le Ic(k) \le 10C \\ 80\% \le SOC_{(k=N)} \le 100\% \end{cases} \tag{12}$$

$$SOC_{k+1} = SOC_k + \frac{\int_0^{\Delta t_i} \eta \times I_L(t)dt}{3600 \times capacity} \tag{13}$$

When the balance coefficient M is 0.1, the two optimal objectives have the same order of magnitude. The simulation results of the optimized current and voltage based on the DP algorithm are shown in Fig. 8.

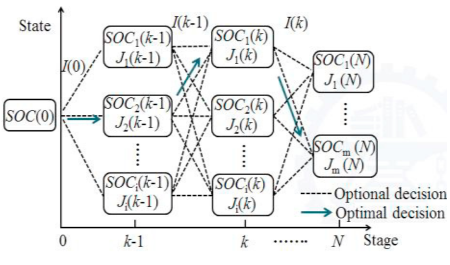


Fig. 7. Schematic diagram of dynamic programming algorithm.

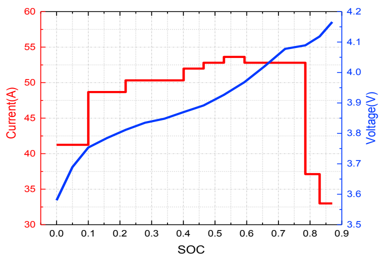


Fig. 8. Simulation results of current and voltage.

4.2. Experimental verification

At 25°C, four batteries of the same batch were selected for comparison between the optimal and traditional charging methods. First, the charge-discharge tests of the four batteries were carried out with the two charging methods. The average charging and discharging was 6C and 1C respectively. The comparison results of the four batteries under the two charging methods are shown in Table 2.

Table2. Capacity and energy loss of the proposed charging method and traditional charging method.

Battery number	Charging capacity (Ah)		Capacity loss (Ah)		Saved (%)	Energy loss (Wh)		Saved (%)
	CC	Optimal	CC	Optimal		CC	Optimal	
#1	7.5912	7.5985	0.4129	0.4034	2.291	3.4746	3.4367	1.092
#2	7.5799	7.5944	0.3415	0.3304	3.223	3.1544	3.1066	1.513
#3	7.5798	7.5945	0.3925	0.3832	2.379	3.2117	3.1240	2.732
#4	7.6000	7.6001	0.4071	0.3949	2.994	3.3998	3.3443	1.633

With the same average charging rate, compared to the CC charging method, the proposed method reduced the average loss of capacity and energy by 3% and 2% respectively, and the charging capacity is slightly increased.

In order to verify the effect of the optimized charging strategy on the battery cycle life, four batteries with little difference were divided into two groups, and the cycle life test was carried out. One group was charged with CC and the other was charged with optimal method. The discharging rate was 1C, and the temperature was also tested. A performance test was conducted every 100 cycles, including capacity and resistance test.

After 300 cycles, the capacity degradation of the traditional and optimal method was about 1.2% and 0.8% respectively. The capacity degradation was reduced by 33.3%, whereas the temperature rise and the average charging rate was almost the same during the cycle process.

5. Conclusions

The charging optimization in lithium-ion batteries based on capacity degradation speed and energy loss is proposed in this paper. The capacity degradation speed model based on the characteristics of the battery life cycle in different SOC intervals is built. By a first-order dynamic equivalent circuit model of the battery, the energy loss is calculated and the optimal objective function is established. The optimal current sequence is obtained by Dynamic programming algorithm. Compared with the traditional charging method, when the balance coefficient M is 0.5, the loss of capacity and energy are reduced by 3% and 2% respectively, whereas the average charging rate is almost the same. In addition, the capacity degradation of the traditional and optimized charging method is 3.85% and 2.64% respectively after 750 cycles, which effectively prolongs the cycle life of the battery.

Acknowledgements

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