PSO-based Optimization for Constant-current Charging Pattern for Li-ion Battery*

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Abstract: A particle swarm optimization algorithm to search for an optimal five-stage constant-current charge pattern is proposed. The goal is to maximize the objective function for the proposed charge pattern based on the charging capacity, time, and energy efficiency, which all share the same weight. Firstly, an equivalent circuit model is built and battery parameters are identified. Then the optimal five-stage constant-current charge pattern is searched using a particle swarm optimization algorithm. At last, comparative experiments using the constant current-constant voltage (CC-CV) method are performed. Although the charging *SOC* of the proposed charging pattern was 2.5% lower than that of the CC-CV strategy, the charging time and charging energy efficiency are improved by 15.6% and 0.47% respectively. In particular, the maximum temperature increase of the battery is approximately 0.8 ℃ lower than that of the CC-CV method, which indicates that the proposed charging pattern is more secure.

Keywords: Li-ion batteries, charging strategy, multi-stage constant current, particle swarm optimization, equivalent circuit model

1 Introduction

With the reduction in fossil fuel energy and increasingly severe environmental problems, electric vehicles (EVs) are a new development milestone due to their advantages of zero emission [1-4]. Li-ion batteries with high energy density and a low self-discharge rate are becoming more and more popular in EVs, and have motivated studies to enhance their charging performance. These issues directly point to the kind of charging strategy that should be adopted. One common charging strategy for Li-ion cells is the traditional constant current-constant voltage (CC-CV) method, but the charging time for the CV mode is too long [5]. Although the efficiency of pulse charging is relatively high, the control method of the charger is too complicated [6].

In order to cut back on the charging time and simplify the charger control method, a multi-stage constant-current (MS-CC) method is proposed with these characteristics [7]. The charging process is often divided into five stages [8], and this is called five-stage constant-current (5SCC) charging. As shown in Fig. 1, pre-charging with a small current is used to prevent damage caused by a large current in Stage 1. When the terminal voltage increases to the desired level of 4.2 V, the charging switches to the next stage, and a new, smaller charging current is used until Stage 5 has completed.

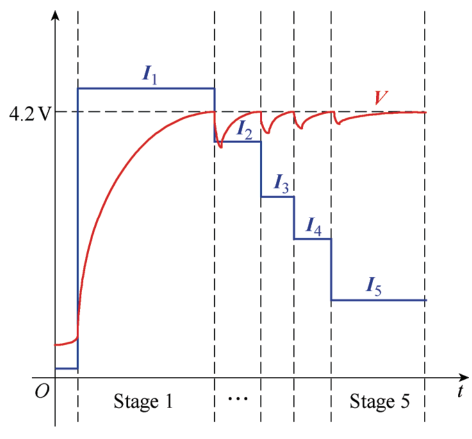

Fig. 1 Five-stage constant-current (5SCC) charge method

A better 5SCC charging strategy would take the charging capacity, energy efficiency, time, and temperature rise into consideration. Due to the performance limitations of the Li-ion battery, these indicators cannot be optimal at the same time. The optimal current pattern in 5SCC charging can be regarded as a multi-objective optimization problem. To select the optimal objects and algorithm in the 5SCC method, several charging approaches have

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been proposed recently [9-15]. Ref. [14] used an equivalent circuit model to optimize charging time and loss. A Taguchi-based algorithm was used in Ref. [15] to achieve multi-objective optimization for the charging capacity and time, which reduced the cost of the experiment.

In this study, the particle swarm optimization (PSO) algorithm is employed to optimize charging capacity, time, and efficiency simultaneously. The obtained 5SCC charge pattern could result in a larger charging capacity and higher charging energy efficiency within a shorter time for Li-ion batteries.

The flowchart of the proposed method is shown in Fig. 2, and the rest of this paper is organized as follows. A second-order equivalent circuit model is built in Section 2. The battery parameters are identified in Section 3. The proposed PSO algorithm for this optimization problem is illustrated in Section 4 in detail. The experiment results are shown in Section 5. Finally, The conclusion is presented in Section 6. A commercially available 18650 Li-ion battery is used in the experiments. The rated capacity of the battery is 2.62 Ah, the maximum allowable charging current is 2 C, and the charging limit voltage is 4.2 V.

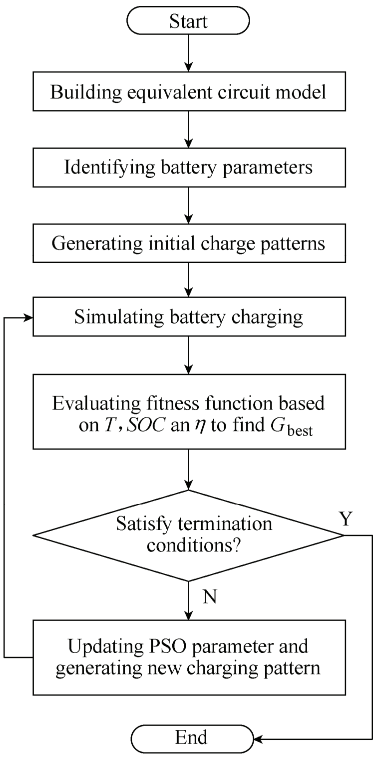

Fig. 2 Flowchart of the proposed method

2 Battery model

To optimize the charging current of the 5SCC charging procedure, a battery model must be formulated. The second-order equivalent circuit of a Li-ion battery is adopted here, as shown in Fig. 3, where OCV is the open circuit voltage; V_t is the terminal voltage; R_0 is the ohmic resistance; R_1 and R_2 are the polarization resistances; and C_1 and C_2 are the polarization capacities.

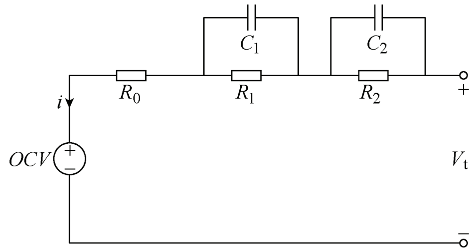

Fig. 3 Equivalent circuit model of Li-ion battery

The equivalent circuit formulations are as follows

$$V_t = OCV + iR_0 + \begin{bmatrix} R_1 & R_2 \end{bmatrix} \begin{bmatrix} i_1 \\ i_2 \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} \dot{i}_1 \\ \dot{i}_2 \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{R_1C_1} & 0 \\ 0 & -\dfrac{1}{R_2C_2} \end{bmatrix} \begin{bmatrix} i_1 \\ i_2 \end{bmatrix} + \begin{bmatrix} \dfrac{1}{R_1C_1} \\ \dfrac{1}{R_2C_2} \end{bmatrix} i \tag{2}$$

where i_1 and i_2 are the currents applied in R_1 and R_2. Solving formulas (1) and (2)

$$\begin{cases} i_1 = \exp\left(-\dfrac{t}{R_1C_1}\right) i_1(0) + \displaystyle\int_0^t \exp\left(-\dfrac{(t-\tau)}{R_1C_1}\right) \dfrac{i(\tau)}{R_1C_1} \mathrm{d}\tau \\ i_2 = \exp\left(-\dfrac{t}{R_2C_2}\right) i_2(0) + \displaystyle\int_0^t \exp\left(-\dfrac{(t-\tau)}{R_2C_2}\right) \dfrac{i(\tau)}{R_2C_2} \mathrm{d}\tau \end{cases} \tag{3}$$

In a recursive discrete-time form, formula (3) is expressed as follows

$$\begin{cases} i_1[k+1] = \exp\left(-\dfrac{\Delta t}{R_1C_1}\right) i_1[k] + \left(1 - \exp\left(-\dfrac{\Delta t}{R_1C_1}\right)\right) i[k] \\ i_2[k+1] = \exp\left(-\dfrac{\Delta t}{R_2C_2}\right) i_2[k] + \left(1 - \exp\left(-\dfrac{\Delta t}{R_2C_2}\right)\right) i[k] \end{cases} \tag{4}$$

The changes in the SOC during the charging process can be expressed as follows

$$SOC = SOC_0 + \frac{1}{Q_{rate}} \int_0^t i(\tau) \mathrm{d}\tau \tag{5}$$

where Q_{rate} is the rated capacity of the battery, which is tested by the 0.05 C (C is the rate that defines the current corresponding to complete charging or discharging of the battery with one hour) current. Discretize the formulation

$$SOC[k+1]=SOC[k]+\frac{1}{Q_{rate}}i(k+1)\Delta t \tag{6}$$

3 Identification of battery parameters

The *OCV* of the battery model should be identified first. Generally, it is assumed that the polarization voltages during charging and discharging at the same current have approximately equal values, but in opposite directions, and the internal resistance of the battery is changeless. The relationships are expressed as follows

$$V_{ch}=OCV+V_R+V_P \tag{7}$$

$$V_{disch}=OCV-V_R-V_P \tag{8}$$

where V_R is the voltage applied in R_0, and V_P is the polarization voltage. As is shown in Fig. 4, the *OCV* is related to the *SOC*, which is obtained by calculating the average of the charge curve and the discharge curve at a low current. Here, the smallest current is taken to be 0.05 C, so the *OCV* can be derived as follows

$$OCV(SOC)=\frac{V_{ch}+V_{disch}}{2} \tag{9}$$

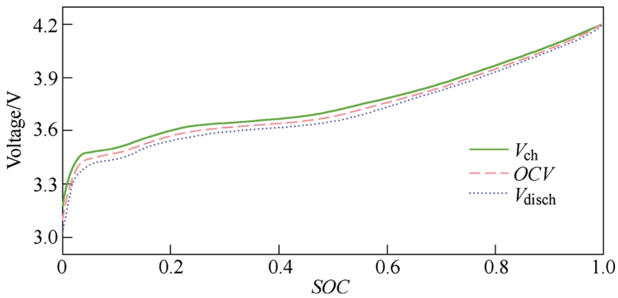

Fig. 4 The curve of *OCV-SOC* for Li-ion battery

The next step is to identify parameters with R_0, R_1, R_2, C_1, and C_2. The specific procedures are as follows:

1) Empty the test battery and let it stand for 2 h to allow the battery to reach a stable state;

2) Perform the constant-current charging operation on the test battery for 90 s, and then allow it to sit for 2 h to obtain voltage data reflecting the relevant polarization effect.

To obtain test data separated by 5% *SOC*, the charging current is 2 C, so the charging time is 90 s. The excitation current and response voltage curves throughout the testing process are shown in Fig. 5. As is shown in Fig. 6, when the charging current drops to zero, the battery voltage drops instantaneously, hence R_0 can be obtained as follows

$$R_0=\frac{V_2-V_1}{I_2-I_1} \tag{10}$$

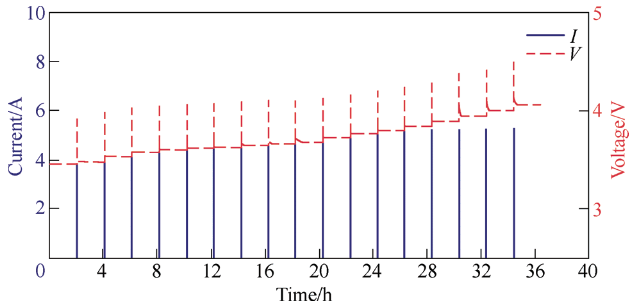

Fig. 5 Overall test curve for Li-ion battery

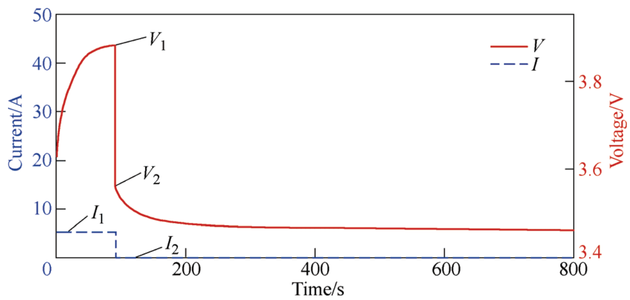

Fig. 6 Local amplification curve for Li-ion battery

Since there is no current input, this process can be regarded as a zero-input response, hence V_t can be defined as follows

$$V_t=OCV+V_{10}\exp(-t/\tau_1)+V_{20}\exp(-t/\tau_2) \tag{11}$$

$$\tau_1=R_1C_1,\quad \tau_2=R_2C_2 \tag{12}$$

where V_{10} and V_{20} are the polarization voltages just before standing. Then the polarization voltage and time parameters can be obtained by least square fitting, so the data for R_1, R_2, C_1, and C_2 can be calculated. Thereby, the battery model parameters separated by 5% *SOC* are identified through the least square algorithm in the MATLAB curve fitting tool (cftool), and the battery model parameters separated by other subtle *SOC* can be acquired by linear interpolation.

The battery model parameters related to the *SOC* are shown in Fig. 7. The dots are the model parameters separated by 5% *SOC*, which are obtained by experiment. The solid lines are acquired by linear interpolation, based on discrete points obtained from the experimental data.

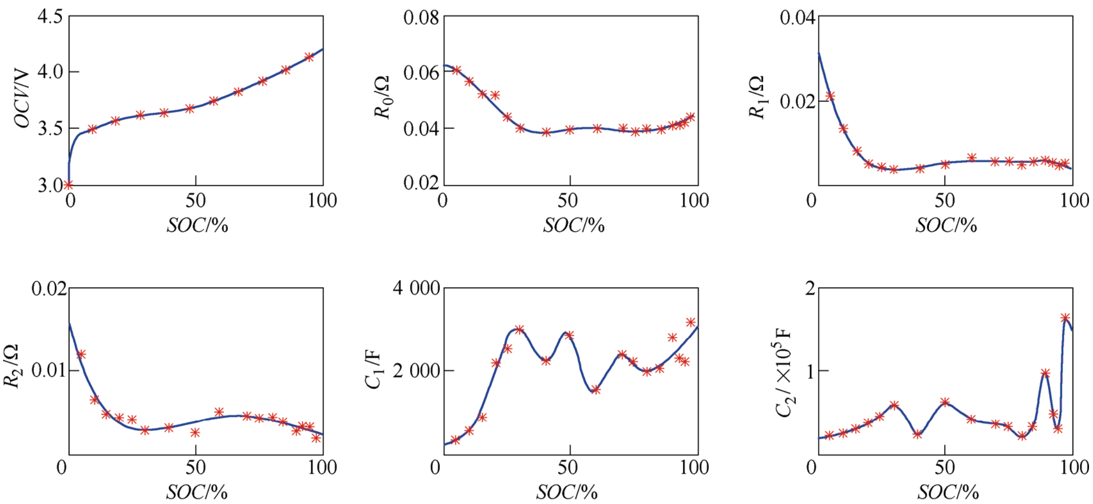

Fig. 7 Battery model parameters

4 PSO-based optimization

4.1 Formulate optimization problem

The charging objective function value is determined by the following three items: charge capacity ratio (SOC), charging time (T), and charging energy efficiency (η), which is derived as follows

$$\eta = 1 - \frac{\int_0^t (i^2 R_0 + i_1^2 R_1 + i_2^2 R_2)\mathrm{d}\tau}{\int_0^t vi\mathrm{d}\tau} \tag{13}$$

where η is the charging energy efficiency when the 5SCC charging process is complete.

Here, assume objective function F_1 is equal to the SOC, and F_2 refers to the charging time that is standardized by the SOC. It can be expressed as follows

$$F_2 = SOC_{\min} + \frac{T_{\max} - T}{T_{\max} - T_{\min}}(SOC_{\max} - SOC_{\min}) \tag{14}$$

where $SOC_{\min}$ and $SOC_{\max}$ are 80% and 100% respectively, and $T_{\min}$ and $T_{\max}$ are 30 min and 90 min respectively. Similarly, the efficiency is standardized by the SOC, and is derived as follows

$$F_3 = SOC_{\min} + \frac{\eta - \eta_{\min}}{\eta_{\max} - \eta_{\min}}(SOC_{\max} - SOC_{\min}) \tag{15}$$

where $\eta_{\min}$ and $\eta_{\max}$ are 90% and 100% respectively. To find an optimal 5SCC charge pattern that results in a larger charging capacity and higher charging energy efficiency within a shorter charging time, the objective function and the constraints are formulated as follows

$$\begin{aligned} \max \quad & F = \alpha \times F_1 + \beta \times F_2 + \gamma \times F_3 \\ \text{s.t.} \quad & 80\% \leqslant SOC \leqslant 100\% \\ & 30\ \text{min} \leqslant T \leqslant 90\ \text{min} \\ & 90\% \leqslant \eta \leqslant 100\% \\ & I_j \geqslant I_k, \text{if } j < k\ (j,\ k = 1,2,3,4,5) \end{aligned} \tag{16}$$

where α, β and γ are the weightings of the charge capacity ratio, charge time, and charge energy efficiency respectively, which are set to 1/3. This means that the importance of the charge capacity ratio, charge time, and charge efficiency are all the same.

4.2 PSO-based optimization

To maximize the objective function based SOC, T, and η, the main operating steps are described as follows:

Step 1) Generation of the initial charge patterns. Based on the battery characteristics, the maximum charge current should be less than 2 C, so the rules established for this study are as shown below:

$$0\ \text{A} \leqslant I_{k+1} \leqslant I_k \leqslant 5.24\ \text{A} (k = 1,2,3,4,5) \tag{17}$$

Assume that the initial population has 100 particles, each of which is uniformly distributed and randomly valued within the definition domain.

Step 2) Battery charging simulation. Based on the equivalent circuit and battery parameters, the charging simulation can be divided into the procedures shown in Tab. 1.

Step 3) P_{best} and G_{best} calculation. For each charge pattern, the fitness function can be evaluated by formula (16). Compare the fitness value with its P_{best} value, and if the fitness value is better than P_{best}, it becomes the new local best value. Compare the P_{best} of all particles to obtain the global best value G_{best}.

Tab. 1 Charging simulation procedures

1. Initialize i_1=i_2=0, *SOC*=0.
2. Input the charging current i, assume i=I_1.
3. Seek the battery model parameters based on the *SOC*.
4. Calculate i_1 and i_2 according to formula (4).
5. Calculate V_t and *SOC* according to formula (1) and formula (6) respectively.
6. Judge whether the charging process is complete according to the returned V_t and *SOC*. If *SOC* reaches the set value or V_t reaches the cut-off voltage, the charge period switches to another stage; otherwise, return to procedure 3.
7. Update i from I_2 to I_5 successively and repeat procedures 3~6.
8. Calculate η according to formula (13).
9. Output *SOC*, *T*, and η.

Step 4) Convergence determination. When the best fitness value G_{best} is no longer updated, the global optimization solution has been found.

Step 5) Updating the particle position to obtain a new charging pattern.The new charging pattern can be acquired by the normal updating formulations of the PSO algorithm, which are shown below

$$\Delta I(k+1)=w(k)\Delta I(k)+c_1r_1(P_{best}-I(k))+c_2r_2(G_{best}-I(k)) \tag{18}$$

$$I(k+1)=I(k)+\Delta I(k+1) \tag{19}$$

$$w(k)=w_{max}-\frac{k}{k_{max}}(w_{max}-w_{min}) \tag{20}$$

where k is the number of iterations, and k_{max} is defined as the maximum number of iterations, which is 200. $\Delta I(k)$ is the mutative current of each of the five stages in the k iteration, and $I(k)$ is the charging current of all stages in the k iteration. $w(k)$ is the inheritance weight in the k iteration, so w_{max} and w_{min} are defined as the maximum and minimum inheritance weight, which are 1 and 0.2 respectively. r_1 and r_2 represent evenly distributed random values that have a variation range of [0,1]. c_1 and c_2 are the self-awareness and population-social factors, which are equal to 1.5 in this study.

5 Results and discussion

5.1 Results of simulation and experiment

As is shown in Fig. 8, the best fitness value G_{best} is no longer updated after 40 iterations, which means the convergence of the PSO algorithm has been reached. It is demonstrated that the proposed searching algorithm can obtain a global optimization solution with fast convergence performance. Similarly, the behavior of the *SOC*, *T*, and η curves in Fig. 9 has similar convergence characteristics. After many algorithm tests, the best 5SCC charging combination is found to be [1.532 C, 0.978 C, 0.668 C, 0.393 C, 0.257 C].

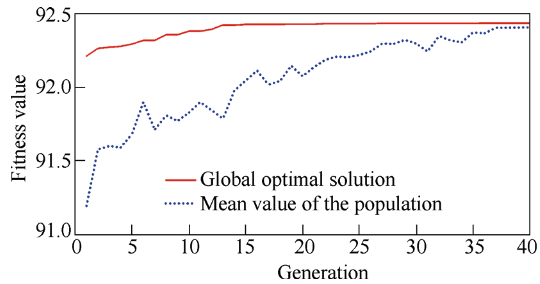

Fig. 8 Evolutionary trends of fitness value

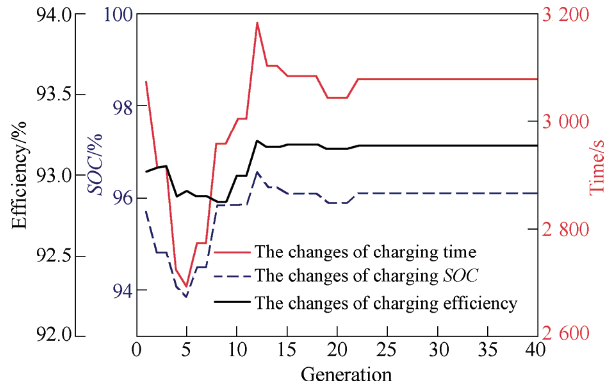

Fig. 9 Optimization results of three objective functions

A real charging experiment is then conducted to verify the correctness of the optimal charging pattern obtained from the simulation. Fig. 10 shows the curves for the voltage, current, and *SOC* obtained by the simulation and the experiment. In Tab. 2, it can be clearly observed that the total charging efficiencies of both simulation and experimental results are quite close to each other, as the difference in their total

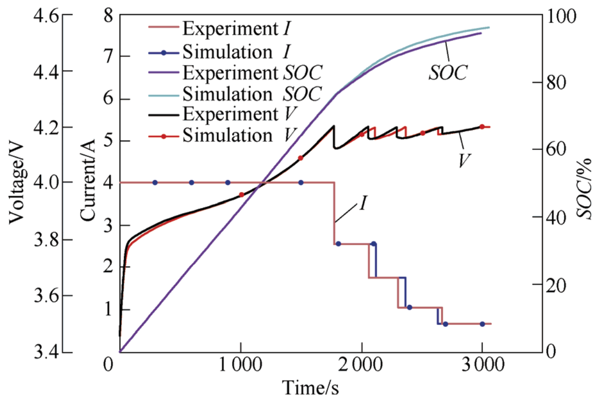

Fig. 10 Comparison curve between simulation and experiment

charge time is about 28 s. The *SOC* values of the experiment and the simulation, which are 94.12% and 94.98% respectively, are approximately the same. It is proved that the equivalent circuit model used in this study is suitable for evaluating the performance of the 5SCC charge method.

Tab. 2 Simulation and experiment comparison

Charging comparison	Charging time/s	Charging *SOC*/%	Charging efficiency/%
Simulation	3024	94.98	93.10
Experiment	2996	94.12	93.01

5.2 Comparative experiment with CC-CV

To evaluate the performance of the obtained charging pattern, a comparative experiment is carried out using the CC-CV method and the obtained charging pattern. In the CC-CV charging process, the current in the CC stage is 1.532 C (i.e., 4.013 A), and the CV stage is complete when the charging current is less than 0.1 C (i.e., 0.262 A).

Fig. 11 shows the waveforms of the battery temperature rise, voltage, and current as a function of time in the comparative test. It is evident that the 5SCC charging strategy can help speed up the charging process and reduce the temperature rise. In the 5SCC method, the temperature rise reaches a maximum at the end of the first stage, at approximately 18 ℃. The results of the comparative experiment are shown in Fig. 12. The charging time of the proposed method is 2 996 s, which is approximately 553 s less than that of the CC-CV strategy, which means the charge speed is improved by 15.6% compared with the traditional CC-CV strategy. Although the charging *SOC* of the proposed charging pattern is 2.5% lower than that of the CC-CV strategy, the temperature rise showes an obvious decrease of 4.3%. It is demonstrated that the 0.47% improvement in charging efficiency is helpful in reducing the temperature rise, which is of great significance to improving charging safety, especially when the battery is implemented in electric cars on a large scale. Therefore, the proposed charging pattern produces the best result for balancing the various functions.

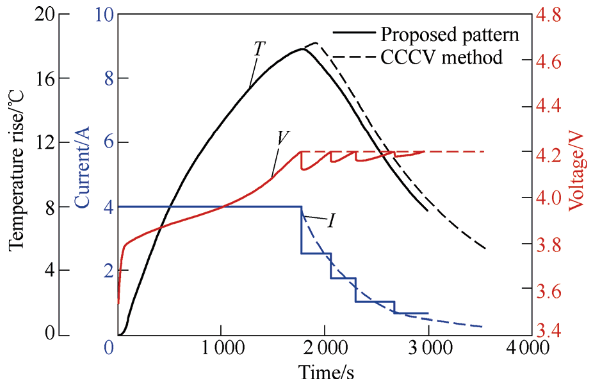

Fig. 11 Waveforms of the battery temperature rise, voltage, and current in the comparative experiment

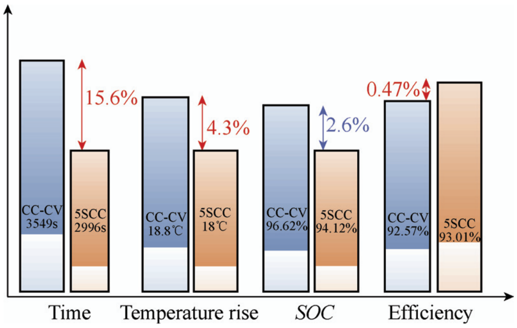

Fig. 12 Results of the comparative experiment

6 Conclusions

A PSO algorithm to search for an optimal 5SCC pattern is proposed in this paper to enable a larger charge capacity within a shorter charging time, and ensure a higher charging energy efficiency. The experimental results verify the correctness of the established battery model and the effectiveness of the obtained charging pattern. Although the charging *SOC* of the proposed charging pattern is 2.5% lower than that of the CC-CV strategy, the charging time and charging energy efficiency is improved by 15.6% and 0.47% respectively. In particular, the temperature rise of the battery was approximately 0.8 ℃ less than that of the CC-CV method, which means that the obtained charging pattern is more secure.

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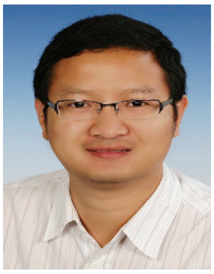

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