Optimal charging strategy design for lithium-ion batteries considering minimization of temperature rise and energy loss

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Summary
Battery charging techniques are critical to enhance battery operation performance. Charging temperature rise, energy loss, and charging time are three key indicators to evaluate charging performance. It is imperative to decrease temperature rise and energy loss without extending the charging time during the charging process. To this end, an equivalent circuit electrical model, a power loss model, and a thermal model are built in this study for lithium-ion batteries. Then, an integrated objective function is formulated to minimize energy loss and temperature increment during battery charging. To further validate the generality and feasibility of the proposed charging strategy, experiments are conducted with respect to different current, operating temperatures, battery types, and aging status. Comparison results demonstrate that the devised charging strategy is capable of achieving the intended effect under any operating temperature and with different aging status.

KEYWORDS
battery charging, closed-form expression, Lagrange multiplier, minimization, thermal model

1 INTRODUCTION

Nowadays, the development of electric vehicles (EVs) cannot be independent of advanced battery technologies, and lithium-ion batteries seem to be the most competitive candidate due to their reasonable power and energy density, long life cycle, and memoryless effect. To ensure safe and healthy battery operation and to extend battery life to the greatest extent, a variety of research has been carried out to estimate internal battery status, eg, state of charge (SOC), state of energy (SOE), state of power (SOP), and state of health (SOH). In addition, balancing techniques used for cells, thermal management, and...
charging strategies\textsuperscript{18,19} are also critical to ensure battery operation with high performance. In particular, the charge control is one of the most important factors and can affect the charging speed, efficiency, temperature rise, and even battery lifespan.

Currently, a variety of lithium-ion battery charging strategies have been proposed, such as the typical constant current (CC), constant voltage (CV), pulse current (PC), and intelligent charging strategies.\textsuperscript{20,21} The CC strategy charges a battery with a constant current until the battery voltage attains a preset level. Various algorithms have been proposed to improve its efficiency,\textsuperscript{22-27} but most of them were tested within a narrow temperature range, meaning the temperature effect was not fully taken into account. For the CV charging strategy, the battery terminal voltage is kept unchanged at a preset value, and the charging current gradually decreases to a cutoff value. The CV method can avoid overcharge and prevent irreversible internal reactions of the battery, which may lead to undesired degradation of the battery lifetime.\textsuperscript{26} In practice, the combined CC-CV charging strategy is widely employed, in which the CV charging stage is imposed after the battery terminal voltage increases to a predetermined maximum value under the CC mode.\textsuperscript{26} In this manner, the advantages of the CC and CV strategies can both be exploited. However, with the increase of charging-depletion cycles, battery polarization becomes increasingly inevitable.\textsuperscript{29} To mitigate its influence, the PC mode is proposed, in which the charging current is intermittently applied with a preset value and a predetermined frequency. During the charging process, there exists a certain interval of rest or reverse discharging current between two pulses, by which the polarization effect can be eliminated to some extent, and the charging speed can thus be improved.\textsuperscript{30} That said, a faster charging speed may result in the generation of enormous heat due to the internal resistance of the battery and thus lead to temperature rise and possible capacity degradation acceleration.\textsuperscript{31} Intelligent charging strategies are favorable as they are capable of increasing charging speed while controlling the temperature rise. Under such strategies, batteries are charged in a short period until the terminal voltage attains a preset threshold, and then the charging current is adapted dynamically according to the variation of battery SOC and SOH.\textsuperscript{10,32,33} These kinds of strategies only aim at increasing charging speed\textsuperscript{34} and do not consider the charging energy loss.

Most importantly, the aforementioned charging strategies do not fully take heat generation into account and rarely discuss its effect on battery parameters.\textsuperscript{35} In terms of most existing strategies, the relationship among internal resistance, polarization resistance, open circuit voltage (OCV), and SOC is solely considered under a certain temperature, and these strategies are widely employed without considering the observed thermal effect in practice.\textsuperscript{35} In reality, a significant change in temperature is inevitable in EVs, and the corresponding change in battery parameter variation can and should be found.\textsuperscript{36} The lithium ion in a battery is active, and energy can be efficaciously generated during reactions under a high-temperature condition; however, when the battery temperature exceeds a threshold value, the cathode crystal lattice of the battery becomes unstable, thereby leading to a potential safety hazard. When the battery temperature rises above 90°C, the solid electrolyte interface (SEI) film will experience exothermic decomposition, and thus battery performance will certainly decrease. On the contrary, under a low-temperature condition, the lithium-ion activity noticeably decreases, leading to a decrease in polarization voltage and battery discharge capacity. According to existing literature and operation requirements, the optimal charging/discharging temperature range for lithium-ion batteries is usually confined to within 0°C and 40°C to avoid rapid degradation.\textsuperscript{37} In a poorly designed thermal management system, heat accumulation can lead to overheating, possibly producing a safety hazard and resulting in battery explosion in some extreme cases.\textsuperscript{38} Moreover, improperly charging a battery, or allowing the battery surface and internal temperatures to go beyond the operating window, can possibly destroy its inner electro-chemical structure and thus reduce charging efficiency and shorten the battery's lifespan.\textsuperscript{39}

To overcome these problems, a comprehensive charging strategy needs to be designed that fully addresses the thermal effect, namely, by minimizing temperature increment during the charging process. This is the main motivation of this study. In this paper, we focus on optimal and reliable battery charging strategy design to minimize the temperature rise and shorten the charging time while considering the parameters' variation at different temperatures. To summarize, the major contributions of this study can be attributed to the following three aspects: first, we analyze the battery charging temperature variation principle and establish the battery thermal model based on which two different cost functions are considered in one objective function. One cost function is the charging energy loss, and the other one is the charging temperature increment. Second, in terms of the thermal effect on battery charging performance, different penalty factors are set in the objective function according to the low, high, and optimal temperature, respectively. Third, the objective function is solved with a closed-form expression, ie, the Lagrange multiplier method, which intuitively reveals...
the relationship among the optimal charging current, internal resistance, and polarization resistance.

Focusing on the charging optimization, this paper proposes a novel and applicable battery charging strategy to optimize the charging temperature rise and energy loss. First, an equivalent circuit model (ECM), a power loss model, and a battery thermal model are established, and the genetic algorithm (GA) is introduced to estimate the model parameters considering the thermal effect. Then, different penalty factors are set in the objective function according to temperature constraints. The objective function is solved by a closed-form expression, which intuitively reveals the relationship between the optimal charging current, internal resistance, and polarization resistance. Experimental results demonstrate that the proposed optimal charging strategy can shorten the charging time, lower the battery charging temperature rise, and reduce energy loss effectively.

The rest of the article is structured as follows. Section 2 demonstrates the battery test schedule, modeling, and its parameters identification at different temperatures. Section 3 formulates the optimal charging objective function and constraints and solves the objective function with a closed-form expression, followed by experimental validation in Section 4. Finally, the main conclusions are drawn in Section 5.

2 | BATTERY TESTING AND MODELING

2.1 | Battery test

A 26650-type cylindrical lithium iron phosphate (LiFePO₄) battery is tested in the experimental setup. The nominal capacity and voltage of the test battery are 3.3 Ah and 3.2 V, respectively. During the test, the voltage, current, and temperature of the battery are monitored with a sampling frequency of 1 Hz. The test flow chart is illustrated in Figure 1. According to the battery specifications, the suitable operating temperature range that we tested is from 10°C to 50°C, and the interval is set to 10°C. Before conducting the experiment, the battery is placed in a thermal-controlled chamber to stabilize its internal/operating temperature. In each temperature stage, the experiment proceeds sequentially as follows: a CC discharge of 1C current, a 2-hour rest, a capacity test, a CC-CV charge test, a 2-hour rest, and a hybrid pulse power characterization (HPPC) test followed by a rest of 3 hours. Here C is the battery capacity value with unit Ampere-hour. The intention of the capacity test is to measure the battery discharge capacity under each temperature with different current rates. Here, the discharge rates are imposed to be 0.3C, 0.6C, 1C, and 1.5C,
respectively. During the test, a thermocouple is attached to the battery surface to monitor the temperature variation. Figure 2A exhibits the discharging profiles of the battery terminal voltage at 20°C. As can be clearly observed, the duration of the terminal voltage platform decreases as the discharge rate increases. Figure 2B presents the voltage variation rate with the discharge capacity under a 1C discharge rate at different temperatures, and it can be found that the maximum discharge capacity increases with the operating temperature.

The HPPC test is conducted to identify the model parameters, as shown in Figure 3. Detailed information can be found in our previous publication. During the experiment, the upper and lower voltage threshold and the current cutoff value are set to 3.65 V, 2 V, and 0.05C, respectively.

2.2 | Battery modeling

In this paper, minimization of both the battery charging power loss and charging temperature increase is considered as one optimization target. Given this objective, the battery ECM, battery thermal model, and power loss model are built simultaneously and analyzed in depth.

2.2.1 | Battery equivalent circuit model

In this study, a one-order resistance-capacitance (RC) ECM is built considering computational complexity and model precision, as shown in Figure 4. The one-order RC ECM includes an RC network, an OCV source, and a resistor connected in series topology. According to the battery ECM, we can formulate the following equations to simulate voltage responses across the OCV source, the voltage drop on $V_p$, and $R_0$. Note that $I$ is negative for discharging and positive for charging in this paper.

$$
\begin{align*}
\frac{dV_p}{dt} &= I - \frac{V_p}{C_p} - \frac{V_p}{R_pC_p} \\
V_t &= R_0I + V_p + V_{OCV}
\end{align*}
$$

(1)
The discrete SOC calculation can be expressed as

\[
    s(t) = s(t-1) + \left( \frac{I(t-1)T_s}{C_b} \right)
    = s(0) + \left( \sum_{j=0}^{t-1} I(j) \right) / C_b,
\]

(2)

where \( s(0) \) is defined as the initial SOC value, \( C_b \) represents the battery nominal capacity, and \( T_s \) is the sampling interval time, ie, 1 second in this study.

Based on (1) and (2), the discrete equation of this system can be presented as

\[
\begin{align*}
    V_p(k+1) &= aV_p(k) + bI_p(k) \\
    V_t(k+1) &= R_0I_p(k) + V_p(k) + V_{OCV}(k) + V_{p}(k) \\
    s(k+1) &= s(k) + Ts/C_bI_p(k)
\end{align*}
\]

(3)

where \( a = \exp(-T_s/\tau), \ b = R_p \cdot (1-a), \) and \( \tau \) is the time constant, which can be calculated by \( R_pC_p \).

### 2.2.2 Battery power loss model

Based on the established ECM shown in Figure 4, the charging power loss model can be calculated. Power loss during the charging process is divided into two parts, ie, the internal resistance loss and the polarization resistance loss, which can be calculated as

\[
\begin{align*}
    P_{R_0} &= I^2R_0 \\
    P_{p} &= \frac{V^2}{R_p}
\end{align*}
\]

(4)

Hence, the instantaneous power loss can be expressed as

\[
P_{\text{loss}} = P_{R_0} + P_{p} = I^2R_0 + V^2/R_p.
\]

(5)

### 2.2.3 Battery thermal model

The thermal energy of a battery is mainly comprised of four sources, ie, reversible heat, polarization heat, Joule thermal, and transferred heat.\(^{18,42,43}\) For simplification, we assume that the battery’s surface temperature is uniformly distributed; thus, the battery can be considered as a particle. Consequently, the battery thermal model behavior can be expressed as

\[
C_h \frac{dT}{dt} = Q_r + Q_p + Q_j - Q_t,
\]

(6)

where \( C_h \) represents the battery thermal capacity, \( T \) expresses the battery temperature, and \( Q_p \) and \( Q_j \) denote the polarized thermal power and the Joule thermal power, as shown in (4). \( Q_r \) and \( Q_t \) are the reversible thermal power induced by entropy change and the thermal power transferred to the surroundings, respectively, which can be calculated as

\[
\begin{align*}
    Q_r &= T\Delta S \frac{I}{eF} \\
    Q_t &= hA(T - T_{\text{ope}})
\end{align*}
\]

(7)

where \( \Delta S \) represents the entropy change, as expressed in (8), \( e \) describes the charging number of electrons per reaction, \( F \) is the Faraday constant, \( A \) means the battery surface area, \( T_{\text{ope}} \) expresses the operating temperature controlled by the thermal chamber, and \( h \) represents the heat transfer coefficient. Thus, we attain

\[
\Delta S = eF \frac{\partial E}{\partial T}.
\]

(8)

In which \( E \) is the open circuit potential. By discretizing (4) and (6) to (8), we can attain

\[
T(t+1) = T(t) + \frac{I^2R_0 + V^2/R_p + T(t)\frac{\partial E}{\partial T} - Ah(T(t) - T_{\text{ope}})}{mC_h},
\]

(9)

where \( m \) is the weight of the battery. Here, we assume that \( T(0) = T_{\text{ope}} \).

### 2.3 Parameter identification

In this study, the temperature effect is taken into account when identifying the battery model parameters. Figure 5 shows the capacity comparison with different discharge rates and temperatures [Colour figure can be viewed at wileyonlinelibrary.com]
shows the capacity test results with different discharge rates and temperatures. As can be seen, the influence of the discharge rate on battery capacity is observable when the operating temperature is below 30°C. In contrast, when the operating temperature is above 30°C, the discharge rate shows negligible influence on the capacity. The battery capacity ratio is shown in Figure 6 at different temperatures with a discharge current of 1C, and the battery capacity clearly decreases with a drop in temperature. Only 95.3% of the available capacity is released when the temperature drops to 10°C; however, when the temperature is higher than 30°C, the capacity increase is not obvious. In order to model this relationship, a piecewise linearization is employed,

\[
\gamma = \frac{C_T}{C_b},
\]

where \(C_T\) denotes the battery capacity at different temperatures.

After data processing and identification, the OCV with respect to different SOCs is shown in Figure 7. When the SOC is located within 30% to 90%, the OCV is relatively stable, i.e., between 3.28 and 3.34 V. Note that for normal operation of EVs, the battery SOC is only operated in a restricted range, i.e., 20% or 30% to 100%; as such, we set the battery SOC range from 20% to 90% for general consideration in this study. It can be found from Figure 7 that when the SOC changes from 20% to 90%, the OCV exhibits little difference at different temperatures.

The other parameters, i.e., internal resistance, polarization resistance, and the time constant, are identified based on the GA. More details about the identification algorithm can be referred to in our earlier works.9,45,46

Here, the root mean square error (RMSE) is employed to evaluate the identification efficacy between the output of the established ECM and the HPPC experiment data,

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (V_{\text{model}} - V_{\text{test}})^2},
\]

where \(N\) denotes the number of test sampling points, \(V_{\text{model}}\) denotes the terminal voltage of the established model, and \(V_{\text{test}}\) is the data from the HPPC test.

Based on the identification results, we find that \(R_0\) remains almost unchanged with different battery SOC levels but decreases as the temperature rises. The detailed variation with respect to temperature is listed in Table 1. Other parameters, including polarization resistance \(R_p\) and time constant \(\tau\), are determined with different operating temperatures and battery SOC levels. The correlations among SOC, \(R_p\), \(\tau\), and temperature are given in Table 2 and Table 3, respectively.

As discussed above, when the operating temperature is 30°C, the battery can release more energy, the plateau area occupies a larger range, and simultaneously, internal resistance and polarization resistance are lower. Thus, in this study, we assume that 30°C is regarded as the optimal operating temperature.

After identifying the parameters, \(R_0 = f_{R_0}(T)\), \(R_p = f_{R_p}(T, s)\), \(\tau = f_\tau(T, s)\), and \(V_{\text{OCV}} = f_{V_{\text{OCV}}}(s)\) can be built based on linear interpolation, as shown in Tables 1–3 and Figure 7, respectively.
2.4 | Model validation

A comparison of the real experimental voltage and the ECM output is demonstrated in Figure 8. The largest error spikes appear when the load current jumps abruptly. It can be seen that the maximum absolute error (ME) is less than 0.08 V. In addition, the mean absolute error (MAE), mean square error (MSE), and $R^2$ are introduced to evaluate the overall performance of the model and parameters, as formulated in (12). The model validation performance can be found in Table 4. From this point, we can conclude that the model can capture battery dynamics properly.

$$ME = \max(|V_{\text{model}} - V_{\text{test}}|)$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (V_{\text{test},i} - V_{\text{model},i})^2$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |V_{\text{test},i} - V_{\text{model},i}|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (V_{\text{test},i} - \frac{1}{N} \sum_{i=1}^{N} V_{\text{test},i})^2}{\sum_{i=1}^{N} (V_{\text{test},i} - \frac{1}{N} \sum_{i=1}^{N} V_{\text{test},i})^2}$$

(12)

Table 5 summarizes the thermal model validation results at different initial SOC values. According to the discussion mentioned above, the battery power loss model can be included in the thermal model. As can be seen in Table 5, the maximum error is 0.67°C, which occurs at a low initial charging SOC with a high current, confirming that the built thermal model and charging power loss model can simulate the battery temperature and power loss characterizations with high accuracy.

![Figure 8](https://wileyonlinelibrary.com)
Now, the cost function for the temperature rise, i.e., $J_{\text{temp}}$, can be formulated as

$$J_{\text{temp}} = \hat{T}(n) = d \sum_{l=1}^{n} (1-c)^{n-l-1} P_{\text{loss}}(l).$$

Consequently, the final objective function $J_{\text{charge}}$ can be formulated as

$$J_{\text{charge}} = \hat{J}_{\text{charge}} = \hat{J}_{\text{loss}} + \hat{J}_{\text{temp}}$$

where $\sigma(k) = \theta_1 T_s \alpha(k) + \theta_2 d (1-c)^{n-k-1} \alpha(k)$. Here, two penalty factors, $\theta_1$ and $\theta_2$, are added to the objective function. When the operating temperature is lower than the optimal operating temperature, i.e., 30°C, the objective function changes to minimize the charging energy loss while the battery is heated by its internal resistance. Under this condition, $\theta_1$ and $\theta_2$ are set as 1 and 0, respectively. When the operating temperature is higher than the optimal operating temperature, normally, the temperature increment is limited within $1^\circ\text{C}$ to $5^\circ\text{C}$, and the energy loss is more than 0.65 Wh. In this case, however, both factors can be regarded as having the same influence, and thus $\theta_1$ and $\theta_2$ are both set to 1. As such, we can determine that

$$\begin{cases} 
\theta_1 = 1, \\
\theta_2 = 0, & T_{\text{op}} < 30 \\
\theta_2 = 1, & T_{\text{op}} \geq 30.
\end{cases}$$

In addition, it is worth pointing out that the objective function can include other functions related to battery charging current or efficiency optimization; therefore, the optimization framework that we have proposed is still feasible.

To guarantee charging safety and rationality, some constraints are imposed in the optimal process. It is

### TABLE 5  Thermal model validation results

| s(0) | Charging Rate | Simulation Result (°C) | Experimental Result (°C) | Absolute Error (°C) |
|------|---------------|-------------------------|--------------------------|---------------------|
| 20%  | 1.5C          | 3.78                    | 4.31                     | -0.67               |
|      | 1C            | 1.89                    | 1.86                     | 0.03                |
|      | 0.8C          | 1.38                    | 1.35                     | 0.03                |
|      | 0.5C          | 0.71                    | 0.80                     | -0.09               |
|      | 0.3C          | 0.35                    | 0.39                     | -0.04               |
| 40%  | 1.5C          | 2.64                    | 3.05                     | -0.41               |
|      | 1C            | 1.64                    | 1.99                     | -0.35               |
|      | 0.8C          | 1.08                    | 1.28                     | -0.20               |
|      | 0.5C          | 0.56                    | 0.74                     | -0.18               |
|      | 0.3C          | 0.29                    | 0.33                     | -0.04               |
assumed that the optimal charging process takes \( n \) seconds to attain a specified target SOC, ie, \( s_n \), and the initial SOC \( s(0) \) is set to \( s_0 \). In addition, \( s_0 \) and \( s_n \) should be limited to between 0 and 1. Thus,

\[
0 \leq s(0) = s_0 \leq s(n) = s_n \leq 1. \tag{22}
\]

According to (2), this relationship can be rewritten as

\[
s_n - s_0 = T_s/C_b \cdot \sum_{k=0}^{n-1} I(k) = 0. \tag{23}
\]

Note that when a battery is charged based on the optimal current, the terminal voltage should be lower than or at most equal to the maximum safe charging voltage threshold. Moreover, the charging current should not exceed the maximum allowed charging current specified by the battery manufacturer.

\[
I_k \leq I_{\text{max}}. \tag{24}
\]

### 3.2 Objective function optimization

In order to determine the optimal charging strategy, the Lagrange multiplier method is introduced in this study for achieving the extreme value of the objective function. We assume that both (20) and (23) have continuous first partial derivatives, such that the Lagrange function can be defined with a new variable \( \lambda \), the Lagrange multiplier

\[
L = J_{\text{charge}} + \lambda \left( s_n - s_0 - T_s/C_b \cdot \sum_{k=0}^{n-1} I(k) \right). \tag{25}
\]

The derivatives of Lagrange function \( L \) with respect to \( I(k) \) and \( \lambda \) are

\[
\begin{align*}
\frac{\partial L}{\partial I} &= 2\sigma(k)I(k) - \frac{T_s}{C_b} \\
\frac{\partial L}{\partial \lambda} &= s_n - s_0 - T_s\sum_{k=0}^{n-1} I(k).
\end{align*} \tag{26}
\]

Two necessary conditions should be satisfied,

\[
\begin{align*}
\frac{\partial L}{\partial I} &= 0 \\
\frac{\partial L}{\partial \lambda} &= 0.
\end{align*} \tag{27}
\]

Given this, \( I(k) \) and \( \lambda \) can be determined as

\[
\begin{align*}
I(k) &= \frac{\lambda T_s}{2\sigma(k)C_b} \\
\lambda &= \frac{2(s_n - s_0)C_b^2 \sum_{k=1}^{n-1} \sigma(k)}{T_s^2}. \tag{28}
\end{align*}
\]

On the basis of (29), the optimal charging current profile is related to \( n \) and \( \sigma(k) \), where \( \sigma(k) \) is a function of \( R_0 \) and \( R_p \). \( n \) and the optimal charging current are computed via the following steps, as shown in Figure 9.

1. Initialize \( n \);
2. Solve (29) with the constraint conditions listed in (22) to (24);
3. Calculate \( s_n \);
4. If \( |s_n - 0.9| \leq \xi \), where \( \xi \) is set as 0.0001, then the optimal \( n \) is the previous value, and the optimal charging current is the current solution; otherwise, update \( n \) and go to step 2 until the convergence condition is met.

In this manner, the optimal current profile can be resolved, by which the charger can charge the battery SOC from 20% to 90% while minimizing \( J_{\text{charge}} \). In the next step, experimental verification is presented, and the results are analyzed and discussed.

FIGURE 9 The procedure for obtaining the optimal charging current
4 | VERIFICATION AND DISCUSSION

In this paper, experiments are designed and performed to validate the feasibility and generality of the proposed optimal charging strategy. First, three different charging current profiles are applied as the benchmark to manifest the feasibility of the proposed charging method. Second, different operating temperatures are applied to test the robustness of the strategy. Third, the proposed optimal charging strategy is implemented using another type of battery with lithium nickel-manganese-cobalt oxide (LiNMC) as its anode materials to demonstrate the algorithm’s generality. Fourth, three different aged cells are experimented on based on the optimal charging current to extend the strategy’s flexibility.

4.1 | Charging strategy verification

Practically, the CC charging method is the simplest charging strategy, which is regarded as the standard charging strategy to compare with the proposed optimal charging strategy. Here, to prove the feasibility of the

| Charging Strategy | Temperature Increment, °C | Energy Loss, Wh | Time, s |
|-------------------|---------------------------|-----------------|-------|
| 0.8C CC           | 1.72                      | 0.65            | 3152  |
| 0.8C optimal charging | 1.54                     | 0.63            | 3130  |
| 1C CC             | 2.95                      | 0.68            | 2521  |
| 1C optimal charging | 2.09                     | 0.66            | 2503  |
| 1.5C CC           | 5.87                      | 0.76            | 1681  |
| 1.5C optimal charging | 4.02                     | 0.74            | 1664  |
proposed charging strategy, six different CC profiles, including the optimal charging profiles, are compared at an operating temperature of 30°C. These charging current profiles are applied to charge the battery until the SOC reaches \(s_n\). The proposed charging method is applied to optimize the CC strategy, including a 0.8C, 1C, and 1.5C CC charging current.

The resolved charging current profiles and experimental results of the terminal voltage variation are illustrated in Figure 10. It can be found from this profile that the charging current in the early stage changes slightly and begins to decrease after a period of charging. Long time reduction of the charging current at the end of the whole process results in a small drop in the terminal voltage, which is displayed in the 1C and 1.5C current curves. However, for the 0.8C optimal charging current and terminal voltage curves, the charging current only reduces within a small range, and as such, the terminal voltage stops dropping. After charging the battery SOC from 20% to 90%, the battery keeps still for 1 hour, and the ending voltage for 0.8C, 1C, and 1.5C optimal charging is 3.3421, 3.3414, and 3.3410 V, respectively, which indicates that the maximum difference is less than 0.002 V. Therefore, the reduction in terminal voltage does not lead to a drop in the SOC, and we can conclude that the algorithm can reach the setting target precisely even with different planning trajectories. This can also prove the efficacy of the built battery ECM and thermal model from different perspectives.

Figure 11 presents the charging temperature rise under different charging strategies. The temperature increment based on the optimal charging strategy is lower than that of the normal CC charging strategy during the whole charging process. A comparison of these experimental results is illustrated in Table 6. Among these results, energy loss and charging time can be improved based on the proposed charging strategy. Figure 12 shows the improvement of the proposed charging strategy over the traditional CC charging method. It can be found that the proposed strategy exhibits the capability of simultaneously optimizing the temperature increment, energy loss, and charging time, going from 10.47% to 29.15%, 1.08% to 2.94%, and 0.7% to 1.01%, respectively, compared with the results of the CC charging strategy.

To demonstrate the performance improvement when applying our proposed optimization strategy, the

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**TABLE 7** Experimental results comparison under various operating temperatures

| Operating Temperature, °C | Charging Strategy | Temperature Increment, °C | Energy Loss, Wh | Charging Time, s |
|---------------------------|-------------------|---------------------------|-----------------|-----------------|
| 20                        | CC                | 5.57                      | 1.00            | 1681            |
|                           | Optimal           | 7.06                      | 0.77            | 1601            |
| 30                        | CC                | 5.87                      | 0.76            | 1681            |
|                           | Optimal           | 4.02                      | 0.74            | 1664            |
| 40                        | CC                | 4.93                      | 0.67            | 1681            |
|                           | Optimal           | 2.93                      | 0.65            | 1574            |
| 50                        | CC                | 5.02                      | 0.62            | 1701            |
|                           | Optimal           | 3.85                      | 0.61            | 1607            |

---
polarization voltage profiles based on the CC strategy with 1C current and the corresponding optimal charging strategy are shown in Figure 13. Between 0 and 1630 seconds, the polarization voltage based on the optimal charging strategy is inferior to that based on the CC charging strategy; on the other hand, after 1630 seconds, the polarization voltage of the optimal charging strategy is higher than that based on the CC charging method. However, at the end of the charging process, a smaller current is implemented by the optimal strategy to decrease battery polarization. Hence, we can say that the polarization voltage of the improved charging strategy is lower than that of CC charging, and as a result, the charging time, temperature increment, and energy loss of the optimal charging method are lower than that of the CC charging method.

4.2 | Verification study under different operating temperatures

In order to validate the robustness of the proposed strategy, a battery is charged with the optimal charging current profiles, plotted in Figure 14, at different operating temperatures. The experimental results are listed in Table 7. Figure 15 shows the improvements in terms of temperature increase, energy loss, and charging time, which reveal that the proposed strategy performs superiorly in reducing temperature increment, energy loss, and charging time in comparison with the CC charging strategy. This performance is primarily attributed to the lower polarization voltage brought about by the optimal charging current. It can be inferred that no matter whether the environmental temperature is within its normal range, the built charging algorithm is still capable of achieving satisfactory charging performance. In addition,
it is worth pointing out that the built charging strategy elevates the battery temperature to some extent, and the energy loss can be decreased even when the environmental temperature is less than the optimal temperature.

4.3 | Verification with different battery types

To extend the applicability of the proposed strategy, a different battery with LiNMC as its anode, of which the nominal capacity is 5 Ah and the rated voltage is 3.6 V, is experimented on. All experiments are carried out at 30°C, and the 1C CC charging method is benchmarked to compare the charging performance. Figure 16 shows the battery temperature varies with SOC during the charging process. It is evident that the temperature increases more slowly based on the built strategy than based on the CC charging strategy.

The experimental results for different charging strategies are compared in Figure 17 and Table 8. Table 8 indicates that the charging temperature increase, charging energy loss, and charging time of the LiNMC battery, based on our method, are reduced by 19.43%, 16.22%, and 1.19%, respectively. To sum up, we can conclude that the proposed methodology can be effectively extended to other types of lithium-ion batteries only if the internal resistance varies with the battery SOC.

4.4 | Verification study with aging cells

In addition, the flexibility of the strategy is validated with batteries of different aging states in this study. To accelerate battery degradation, the cell is cycled with a charging current of 0.5C and a discharging current of 2C at 25°C. After a certain cycle operation, the battery is experimented on to calibrate its SOH first. In order to make the environmental conditions consistent, all the tests are carried out at 30°C, and the 0.5C CC charging method is benchmarked to compare the charging performance. The charging performance versus the SOH values are presented in Figure 18 and Table 9. It can be noticed that the charging temperature rise, energy loss, and charging time of the built strategy are reduced by 7.81%, 10.14%, and 9.68%, respectively, compared with those of the CC charging strategy, until the SOH reaches 82.38%. This proves that even as the battery degrades, the proposed algorithm is still effective in reaching the setting target.

5 | CONCLUSIONS

To reduce both the temperature increment and energy loss of battery charging, an optimal battery charging strategy is proposed. An ECM that considers the effect of the operating temperature, a battery power loss model, and a battery thermal model are established with detailed mathematical analysis. The optimal charging current profile is derived based on the cost function, which is a weighted sum of the energy loss and temperature increment index. By comparing the proposed charging strategy with the traditional strategy through experimental validation, the proposed strategy is shown to possess strong advantages in the following four aspects:

1. The new method accurately reveals the relationship between optimal charging current, internal resistance, and polarization resistance.
2. The new method is capable of reducing the temperature increment, energy loss, and charging time by more than 10.47%, 1.08%, and 0.7%, respectively, when compared with the CC charging strategy.
3. The temperature effect on the battery parameters is considered in the proposed strategy and thus a wide application temperature window can be guaranteed.
4. The proposed strategy can be expanded to different battery types and different aging status.

The next step of our work will focus on the SOH and the battery lifetime influence induced by the proposed
charging method. Furthermore, a battery pack optimal charging method may also be a potential research focus.

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