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ORIGINAL RESEARCH PAPER

Charging control strategies for lithium-ion battery packs: Review and recent developments

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Abstract

The expanding use of lithium-ion batteries in electric vehicles and other industries has accelerated the need for new efficient charging strategies to enhance the speed and reliability of the charging process without decaying battery performance indices. Numerous attempts have been conducted to establish optimal charging techniques for commercial lithium-ion batteries during the last decade. However, a few of them are devoted to the comprehensive analysis and comparison of the charging techniques from the control-oriented perspective for a battery pack. To fill this gap, a review of the most up-to-date charging control methods applied to the lithium-ion battery packs is conducted in this paper. They are broadly classified as non-feedback-based, feedback-based, and intelligent charging methods. Finally, the paper concludes with a comprehensive discussion of the strengths and weaknesses of the reviewed techniques.

1 | INTRODUCTION

Renewable and clean energy sources are necessary to assist in developing sustainable power that supplies plenty of possible innovative technologies, such as electric vehicles (EVs), solar and wind power systems [1, 2]. They must reduce our current reliance on some limited sources of energy such as fossil fuel and uranium to alleviate worries about energy, environment, and economy [3]. Consequently, the need for storage has raised up dramatically while rechargeable electrochemical batteries are employed in practically every energy storing device [4].

Recent advancements in lithium-ion batteries demonstrate that they exhibit some advantages over other types of rechargeable batteries, including greater power density and higher cell voltages, lower maintenance requirements, longer lifetime, and faster-charging speeds with lower self-discharge rates [5, 6]. However, some drawbacks limit the broad adaption of the lithium-ion batteries, associated explicitly with their high cost, short life-cycle, constrained performance temperature, and possible safety infractions caused by overcharge, over-discharge, short circuit, and production defects [5, 7]. In addition, a single lithium-ion cell's voltage is limited in the range of 2.4–4.2 V [8], which is not enough for high voltage demand in practical applications; hence, they are usually connected in series as a battery pack to supply the necessary high voltage [9]. However, a battery pack with such a design typically encounter charge imbalance among its cells, which restricts the charging and discharging process [10]. Positively, a lithium-ion pack can be outfitted with a battery management system (BMS) that supervises the batteries' smooth work and optimizes their operation [11]. Consequently, plenty of studies have been dedicated to advancing the BMS functions, such as state-of-charge (SOC) and state-of-health (SOH) monitoring, thermal control as well as intelligent cell balancing [12]. Battery charging control is another crucial and challenging part of the BMS since it can control the overcharging, overvoltage, charging rate, and charging pattern. These functions lead to a better battery performance with improved lifetime and reduced safety hazard and capacity fade risks [13].

There has been a substantial amount of literature published to analyze and compare the performance of different types of battery charging methods focusing on the lithium-ion battery systems [14–17]. For instance, paper [14] classifies different charging techniques of lithium-ion batteries based on their charging time and lifespan. In light of this, a detailed review of the literature regarding current charging techniques for the lithium-ion battery has been provided. Authors in [16] presented the recent developments in various battery optimal charging algorithms. The first aspect presented in their work is passive charging, where their characteristics are summarized and compared. Then, they introduced the generalized structure of active optimal charging protocol. Finally, the reviewed optimal charging protocols, including their data, results, and examined battery types and charging methods, are briefly compared. Paper [17] reviews numerous studies and organizes the relevant research under three topics: impedance modeling, data acquisition, and application under the premise of electric vehicle implementation. Consequently, the advantages and drawbacks of the research in each subject are discussed. Based on the research, the capabilities and importance of impedance in onboard BMS are revealed.

Despite these efforts, no study comprehensively reviews the recent work about the charging methods applied to the lithium-ion battery packs. Subsequently, those techniques suitable for the battery packs involving several series or parallel-connected battery cells have never been taken into classification. This emphasizes the need for cell balancing at the same time as charging to enhance the batteries' charge efficiency and health. Besides, none of the review papers consider the control-oriented classification of lithium-ion battery charging techniques. Accordingly, for a coherent comprehension of the state-of-the-art of battery charging techniques for the lithium-ion battery systems, this paper provides a comprehensive review of the existing charging methods by proposing a new classification as non-feedback-based, feedback-based, and intelligent charging methods, applied to the lithium-ion battery packs. Subsequently, their strengths and shortcomings are discussed. The main contributions of this paper can be summarized as follows:

1. There is no comprehensive review paper to consider a control-oriented classification for the charging lithium-ion battery packs. This paper considers this for the first time, including reviewing the charging methods proper for the battery packs comprising several connected cells;
2. In this paper, the charging methods for the lithium-ion battery packs are categorized based on non-feedback-based, feedback-based, and intelligent approaches, which have never been classified like this in other studies. This classification provides researchers a benchmark for better interpreting and understanding various charging methods applied to lithium-ion battery packs.

The remainder of this paper is organized as follows. In Section 2, simplified representations of different battery charger circuits are presented. In addition, a novel classification of charging techniques for lithium-ion battery packs is proposed based on a control-oriented perspective. In Sections 3, 4, and 5, the non-feedback-based, feedback-based, and intelligent charging methods are reviewed and discussed, respectively. A discussion is presented in Section 6 to comprehensively review the introduced charging methods along with their strengths and weaknesses as well as related literature. Section 7 concludes the paper.

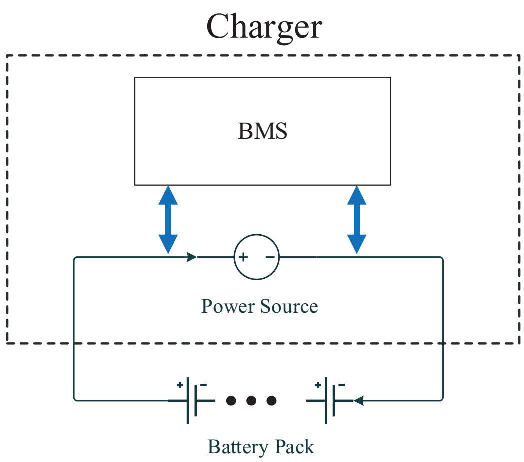

FIGURE 1 Battery charging system with BMS

2 | CHARGING SYSTEM MODEL

The optimal operation of any rechargeable battery system depends on its charger circuit topology and the associated control scheme. A battery charger has three primary functions: initiate charging, rate optimization, and charge termination. Simply speaking, the charging process measures the voltage across the battery, then initiates the charging process until a specific voltage is reached, after which the charging process is terminated [18]. This way, every charging system has a BMS that coordinates all charging operations. In other words, the battery, charger, and load communicate through the BMS as shown in Figure 1.

2.1 | Battery charger circuit topologies

Circuit topologies for lithium-ion battery charging systems monitored by the BMS fall broadly into three main categories: linear, switch mode, and pulse chargers, as shown in Figure 2.

A linear charger performs in the same simple way as a linear regulator, as shown in Figure 2a. In linear regulators, the linear regulating element reduces the input voltage to a specific output voltage through a resistor or a transistor. There is a difference between the linear regulator and linear charger as the charger has added circuitry meant to control and protect battery charge. Its simplicity and low price make linear chargers appealing, but constant current continuously flows through the regulating element, resulting in heat dissipation and an inefficient charger.

With pulse chargers, as illustrated in Figure 2b, the current is pulsed into the battery by switching a transistor. An extra circuit in pulse chargers can control pulse width and period to improve efficiency and make charging faster. A pulse charger is more straightforward than a switch-mode charger and more efficient than a linear charger. An input voltage for pulse chargers needs to be tightly controlled. Because of this, an increase in cost is incurred.

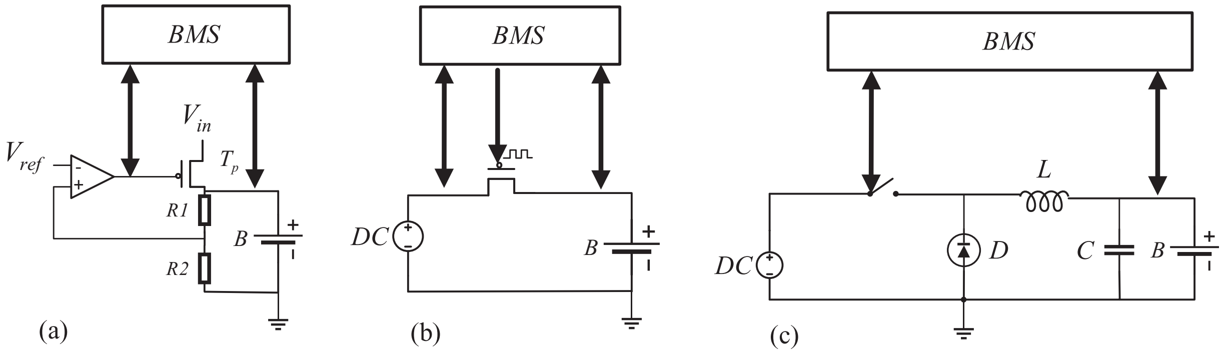

FIGURE 2 Simplified representation of different battery charger circuits: (a) linear charger; (b) pulse charger; (c) switch mode charger

The switch-mode chargers and switch-mode power supplies are the same, except that switch-mode chargers utilize a complex circuit design to regulate charging and protect the battery. Since the switches for switch-mode chargers are not always on, they consume less power to operate and dissipate less heat. However, switch-mode chargers are much more complicated and costly than linear chargers. Figure 2c shows the simple representation of the switch-mode charger.

2.2 | Battery charging control schemes

In this paper, different battery charging algorithms that have been published recently are evaluated and classified from the perspective of the control algorithm, basically divided into non-feedback-based, feedback-based, and intelligent techniques as shown in Figure 3 and briefly described below:

- Non-feedback-based charging methods are open-loop control techniques commonly found with linear and pulse charging systems where either the current waveform or the voltage waveform or both are transformed to improve charging profiles. These kinds of charging control techniques are widely used in battery charging applications [13, 16, 19, 20], and regarding the control-oriented structure could be further categorized as traditional, fast, optimized, and electrochemical-parameter-based (EP-based) charging methods.
- Feedback-based charging methods utilize a closed-loop control structure to monitor the switch-mode chargers by taking into account a valid battery model such as equivalent circuit model (ECM) or electrochemical model (EM) [21–29].
- Intelligent charging methods are estimation-based-tracker algorithms usually used in charging a battery pack containing several series or parallel connected cells. Accordingly, a nominal model of battery cells is utilized to generate an optimal average trajectory regarding the batteries' efficiency and healthcare parameters such as SOC balancing and SOH. For this purpose, a multi-objective optimization problem is typically formulated and solved. Also, a distributed charging strategy may be needed to ensure that the cells' measured parameters follow the pre-scheduled trajectory, where observers can correct the cells' model bias online [23, 30–32].

3 | NON-FEEDBACK-BASED CHARGING METHODS

Batteries with non-feedback-based charging strategies are charged under pre-set instructions, and chargers cease the charging process when the battery reaches the terminal condition. Despite the fact that these algorithms are easy and straightforward to implement, the feedback of battery state and health-related optimization parameters are neglected during the charging process, which causes charging process degradation [33–35]. In general, the available lithium-ion battery non-feedback-based charging strategies can be divided into four model-free methodology classes, including traditional, fast, optimized, and electrochemical-parameter-based (EP-based) charging approaches as shown in Figure 3 [36–40].

3.1 | Traditional approaches

Many charging approaches have been developed conventionally to solve battery charging problems with various objectives and termination conditions. These typical approaches fall into three main groups: constant current (CC), constant voltage (CV), and constant current-constant voltage (CC-CV).

The CC charging scheme is a straightforward method of charging batteries with a low, constant current to achieve a full charge at the end of the charging cycle. Once the CC charging time reaches a predefined threshold, the charge is terminated. A battery's behavior in CC charging is highly dependent on the charging current. Hence it is crucial to find a charging current that optimizes charging speed and capacity utilization [41].

CV charging is also a conventional charging method that applies a constant voltage to charge the batteries. Besides avoiding over-voltage and irreversible side reactions, another advantage of using CV charging is that the battery life will be extended. This approach, however, needs a high current to maintain constant terminal voltage during the early stages of the

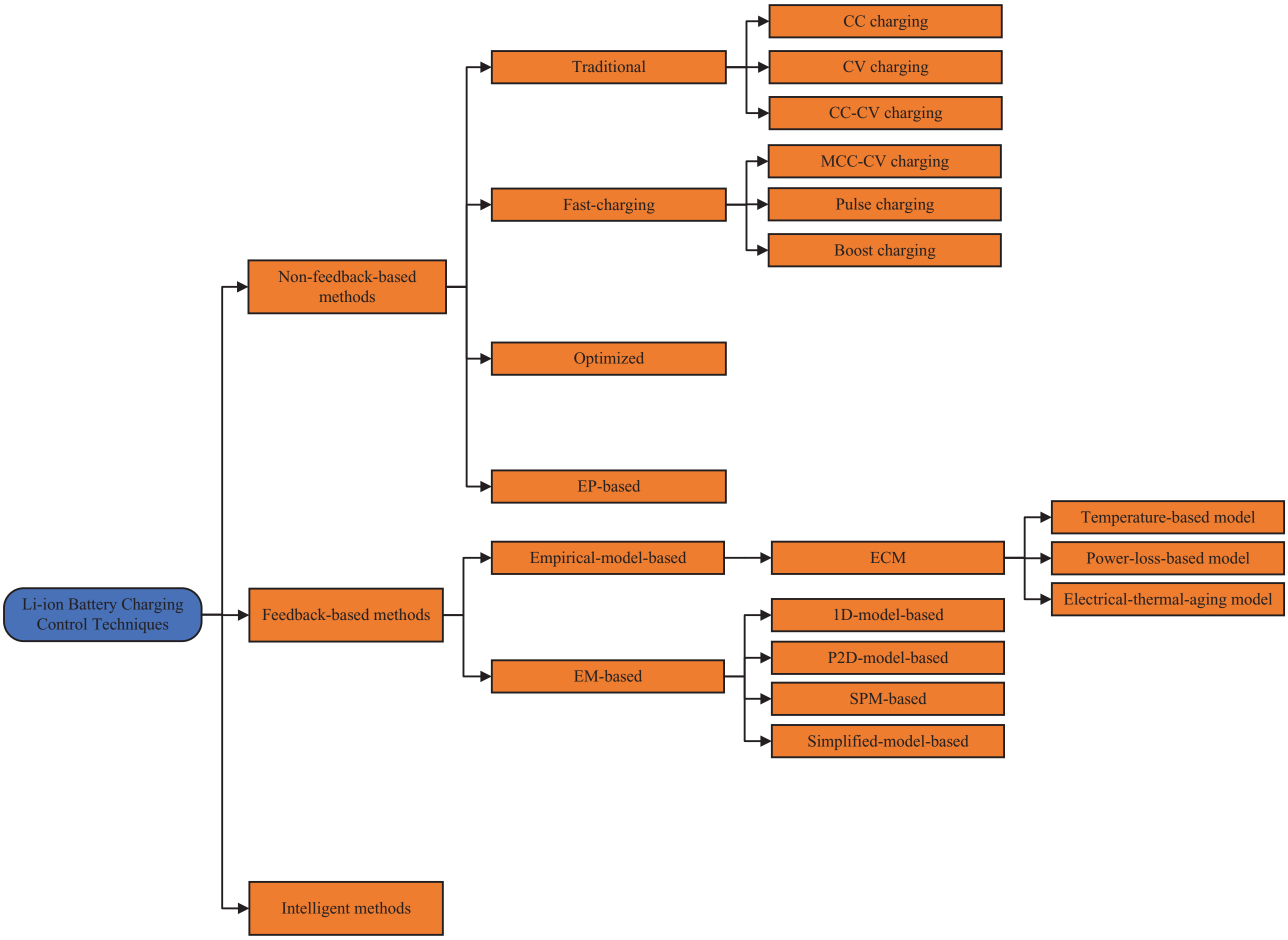

FIGURE 3 Control-oriented classification of lithium-ion battery charging techniques

charging process, which is quite detrimental to the battery lattice and could cause its poles to break. Setting a proper constant voltage to obtain the right balance among charging speed, electrolyte degradation, and capacity utilization is a real challenge [36].

Integrating CC and CV charging has created a hybrid charging approach named CC-CV. The simple CC-CV charging algorithm is widely implemented for many types of electrochemical batteries, including the lithium-ion batteries [34, 42, 43]. In the CC-CV algorithm, the battery is initially charged to a preset maximum voltage with a constant current. Then the charge voltage is held constant until a preset minimum current is reached [12, 16, 44]. The charging profile of the standard CC-CV charging is shown in Figure 4.

In CC-CV charging algorithms, the CC and CV stages complement each other somehow, with the capacity loss due to high electrochemical polarization potential in the CC stage effectively compensated by the corresponding large electrochemical polarization potential at CV stage. Thus, the CC-CV charging approach is superior to the sole CC charge alone as well as the sole CV charge and has been chosen to provide a benchmark for the evaluation of the performance of various battery charging approaches. While the standard CC-CV charging method is relatively simple, the real challenge is choosing the correct constant current value at the CC stage and constant voltage at the CV stage. The total charging time in the CC-CV charging method varies depending on the battery capacity and the value of the charging current in the CC mode. Generally, the battery life and

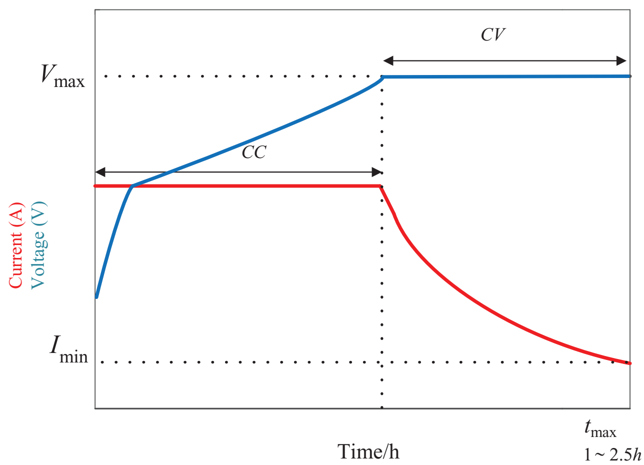

FIGURE 4 CC-CV charging profile

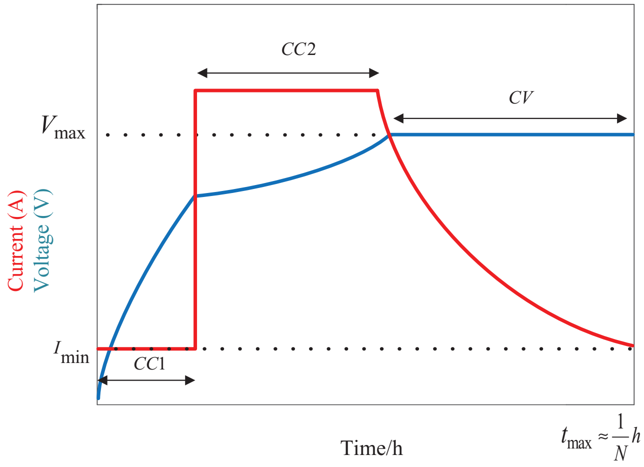

FIGURE 5 Two-stage MCC-CV charging profile

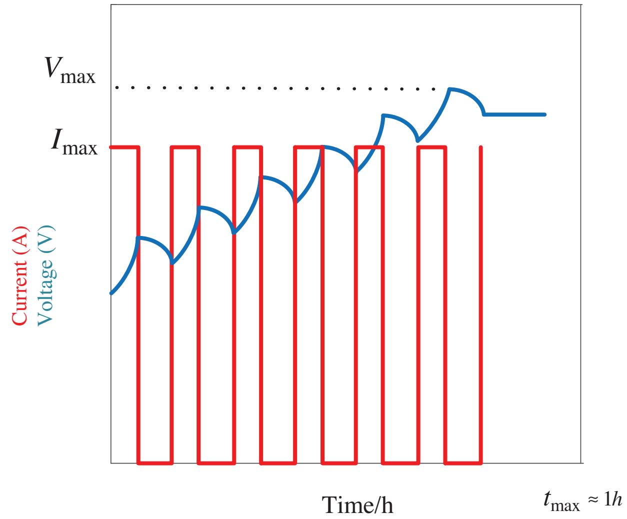

FIGURE 6 PC charging profile [15]

charging efficiency increase as the charging current decreases under the CC mode. In addition, batteries charged with the CC-CV algorithm requires no microcontrollers; instead, only a voltage sensor, current sensor, and temperature sensor are required. Consequently, the CC-CV charging algorithm is simple to implement [37].

3.2 | Fast charging approaches

Many researchers have shown that the fast-charging idea that adjusts the current levels during charging may lead to reduction in cell degradation and shorter charging time. These approaches are commonly designed to reduce heat generation, lithium plating, and mechanical stresses [45]. Subsequently, the lithium-ion battery fast charging techniques can be categorized mainly into multistage constant current-constant voltage (MCC-CV), pulse charging (PC), boost charging (BC), and sinusoidal ripple current (SRC) charging [15].

One of the first fast-charging strategies is the MCC-CV. It uses multi-CC stages, followed by a final CV stage. Higher current levels will often be used in the initial stages of CC since it is hardly probable that the anode potential becomes negative. However, some authors have taken a reverse approach, in which the current level increases in later CC stages due to the lower resistance of cells [36, 46–48]. Paper [46] studies the charging strategy's effect on the lithium-ion battery life using the MCC-CV charging method. Accordingly, the utilized MCC-CV charging technique consists of two CC steps, starting from low current charging to initiating 10% of capacity. It then succeeded by a high current charging as long as the cell voltage reaches 4.2 V. The resulted outcomes revealed that the battery's life cycle is explicitly dependent on the charging procedure even if the same charging rate is applied. Also, it is shown that for a standard two CC stages MCC-CV, if the current rate is NC, a charging time of $1/N$ can be calculated for various averaged C-rates, as shown in Figure 5

PC is a charging method that has been explored as one of the fast-charging techniques for lithium-ion batteries. This technology employs continuous current pulses with certain pulse width until the battery is fully charged. Accordingly, the charging current is periodically interrupted with short rest intervals or discharge pulses, as shown in Figure 6. Actually, this strategy is meant to lower concentration polarization by reducing the risk of anode potential becoming negative at the local scale or by reducing mechanical stresses due to uneven extraction and lithium insertion [15, 49–52].

In [49], authors examine the PC technique's effects on lithium-ion batteries' charge-discharge characteristics. The findings reveal that pulse charging is useful in removing concentration polarization, improving the power transfer rate, and decreasing charge time by eliminating the actual constant voltage charging in the traditional method. With their proposed method, charging time is reduced, and active materials are utilized better, resulting in higher discharge capacity and longer battery life. In this case, the battery needs about one hour to be fully charged by the PC method at the $1C$ charging rate. Another research that employed a PC approach for charging lithium-ion batteries is described in [50], in which the lithium saturation is avoided by correctly selecting the parameters, allowing significantly higher rates of charging. Subsequently, full charging is demonstrated in less than $3/4$ of an hour with nonlinearly decreasing current density profiles.

A BC algorithm is similar to the CC-CV technique but has additional charging intervals at the beginning of the charging process. By enabling the charger to spend more time delivering its maximum current, this method lowers recharge time owing to a high voltage mode. The charging process is characterized by the highest average current in the early stages of charge, followed by the CC-CV stage with more moderate currents. In this case, to avoid long-lasting charging, one should temporarily raise the charging voltage during batteries recharge above the normal float setting. Accordingly, the first stage of the boost-charge could assume a simple CC profile, a CV profile where the cell instantly reaches maximum voltage through a high current (CV-CC-CV) or an entire double CC-CV (CC-CV-CC-CV) profile. The boost-charge stage should provide higher currents or higher maximum voltages than the following CC-CV step to reduce the overall charging time. As illustrated in Figure 7, before the charge is fully transferred into the cell, a high current I_{boost} is applied, and a maximum voltage V_{boost} or a time value t_{boost} can be used to limit the boost interval. The charger then switches to CC-CV mode after the boost interval, where I_{boost} and t_{boost} can adapt the charge rate [53–55].

For an example of battery charging with the BC method, the authors in [54] examine the feasibility of this technological approach while comparing its long-term characteristics to those obtained using CC-CV charging strategies. This study reveals that close-to-full discharged batteries could be charged for a short time with very high currents without introducing detrimental effects. By doing so, a battery with a completely discharged state was easily recharged to one-third of its rated capacity in just five minutes without inducing any other degradation consequences. It is also shown that both cylindrical and prismatic lithium-ion batteries can be charged with BC.

3.3 | Optimized

This subsection discusses the optimized methods that have been found in the literature for the corresponding non-feedback-based charging protocols. In various applications, factors such as current rate and voltage threshold have a significant impact on charging performance; therefore, it is vital to optimize these critical factors and create optimal charging profiles. There have been many attempts to address this problem by improving battery charging performance with various charging objectives. In the non-feedback-based methods, the battery states are predicted, and the electrical elements are calculated using historical experimental data. Accordingly, different types of estimation algorithms and optimization techniques are adopted to estimate and improve the charging performance [56–65]. The following part gives some examples from these approaches found in the literature.

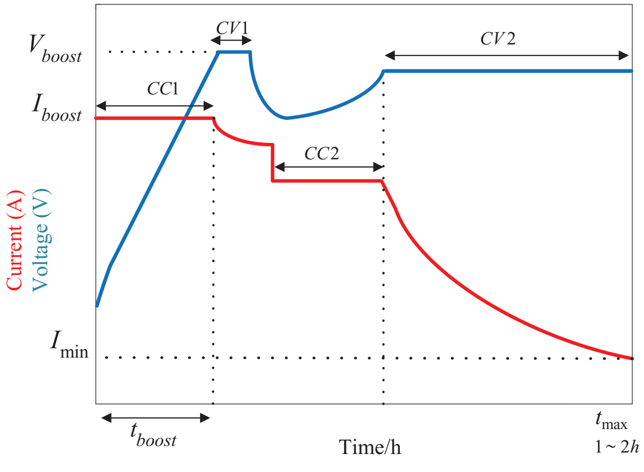

FIGURE 7 BC charging profile [15]

3.3.1 | CC-CV charging optimization

The CC-CV charging process is a basic method for charging lithium-ion batteries. Many methods have taken the CC-CV charging process, and accordingly, some suggestions have been given to improve it [43, 66, 67].

In order to illustrate CC-CV charging optimization, paper [66] proposes a charging technique for the lithium-ion battery charging by utilizing a flyback DC-DC converter. Accordingly, the proportional-integral (PI) controller tuned by the particle swarm optimization (PSO) algorithm is used. The PSO algorithm optimizes the parameter values of PI controller, which maintain constant current and constant voltage during charging leading to highly efficient charging results. In another work, in paper [43] a battery charger is proposed, including a charging circuit and a dc-dc buck converter applied with a variable supply voltage (ASV). Accordingly, an accurate and ripple-free charging current is achieved utilizing the charging circuit switched between different charging modes. Accordingly, the redundant power loss is reduced on the charging circuit by applying an adaptive supply voltage on the buck converter. Additionally, in this paper, the non-switching and zero current detection control strategies are being used to reduce the power consumption of DC-DC converter in CV mode. The experimental results prove the theoretical analysis of the proposed charger. This battery charger is as efficient as 88.3%, and the maximum efficiency improvement achieved with this charger is 11.6% compared to the charger with a fixed supply voltage. Paper [67] proposes a method to automatically switch from the CC to the CV threshold during the charging process using a novel clamp coil and inductive power transfer (IPT) battery charger. This charger offers high robustness with no battery SOC detection and wired feedback connections. The proposed system employs a standard series-series (SS) compensation topology in the primary and secondary to deliver CC charging. Additionally, the inherent CC-to-CV conversion capability also eliminates open-circuit risk during CC charging. Experiments confirm the theoretical analysis well.

3.3.2 | MCC-CV charging optimization

The MCC-CV charging method provides a solution to the lengthy charging process that lasts in the CV phase of the CC-CV. In order to shorten the charging time, a high current must be used to charge the battery. However, this causes the voltage to reach its upper limit before the expected charging capacity is achieved. This problem can be solved by implementing an optimized MCC-CV charging technique. This way, the charging process continues until the battery voltage reaches the upper limit of the cut-off voltage, after which the charging process switches to the following preset current. This charging process is then repeated until the full range of preset charging currents is reached. At each stage, the charging current falls gradually, preventing the battery from reaching the maximum limit of cut-off voltage too quickly. Besides the upper cut-off voltage,

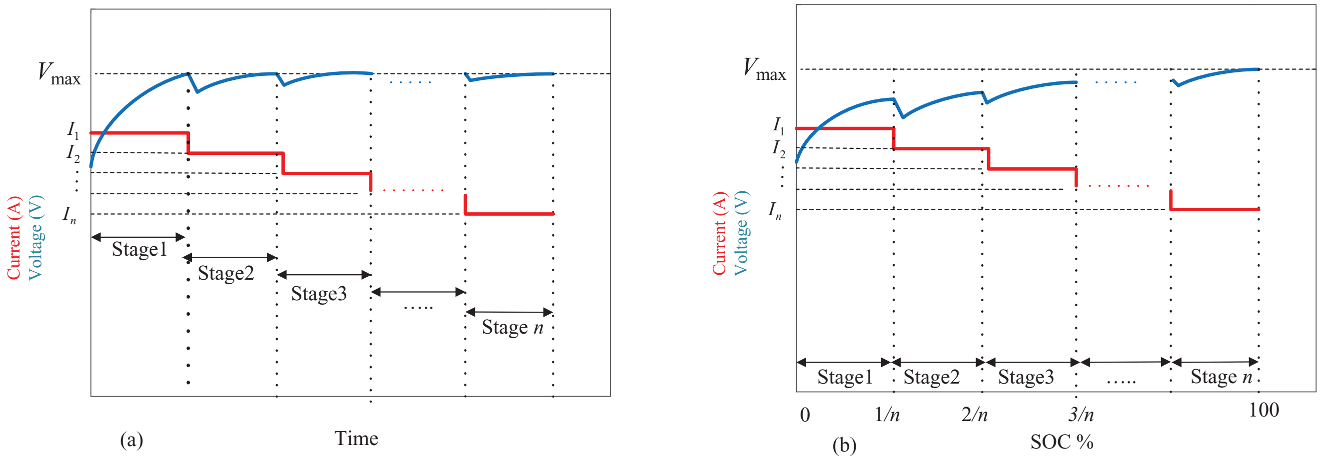

FIGURE 8 MCC charging profile with n stages: (a) upper-cut-off-voltage-based, (b) SOC-interval-based [13]

the shifting condition may also be set based on the SOC interval limit. Accordingly, this part introduces the charging methods for the voltage-based [68–70] and the SOC shifting conditions [71–73]. subsequently, the following equation calculates the current for each stage using a multi-target function:

$$J(I_c) = \varepsilon_1 J_1(I_c) + \varepsilon_2 J_2(I_c), \tag{1}$$

where I_c is the charging current, J_1 and J_2 are the functions of I_c, which stand for different optimization objectives; $\varepsilon_1 \geq 0$ and $\varepsilon_2 \geq 0$ are arbitrary weight coefficients, which can be adjusted based on the importance of each corresponding objective.

By solving the optimization problem in Equation (1) under the given constraints, it is possible to determine each stage's charging current. Accordingly, Figures 8a and 8b show the MCC-CV charging profile involving n stages in which the current shifting condition is based on a defined upper cut-off voltage and SOC intervals, respectively.

As an illustration of the upper-cut-off-voltage-based MCC-CV approach, an optimization approach based on particle swarm optimization (PSO), in conjunction with a fuzzy-deduced fitness evaluator (FDFE), has been developed in [70] to determine the optimal charging pattern that secures the most significant discharge within the shortest charging time. The optimization problem's objective function is maximizing the cost efficiency of the performed charging scheme considering the charging time and the normalized discharge capacity to combine them into a unified cost function to adequately examine the multiple performance characteristics index in the charging process. Based on the experimental results, it is evident that the obtained pattern can charge the batteries to above 80% capacity in 51 min. Compared with the conventional constant current-constant voltage method, the devised approach improves batteries' charging times, lifetimes, and charging efficiency by approximately 56.8%, 21%, and 0.4%, respectively.

For illustrative purposes of the SOC-interval-based MCC-CV method, in [73], a new charging approach of lithium-ion batteries has been proposed by utilizing both the Taguchi method (TM) and SOC estimation, in which the TM is applied to seek an optimal charging current pattern. An adaptive switching gain sliding mode observer (ASGSMO) is considered for SOC estimation while controlling and terminating the charging process. The experimental results indicate that the proposed charging method can significantly reduce charging time, limits the temperature variation, and maximizes the energy efficiency over CC-CV charging.

3.3.3 | Pulse charging optimization

The PC optimization is meant by adding a short-time rest interval (i.e. duty) or discharging period through the charging process to diminish or eliminate polarization voltage in batteries. Charge efficiency can be improved by increasing the ion concentration equilibrium during the charging process, which affects the degree of ion diffusion in a lithium-ion battery. Consequently, the battery life can be increased and charge time optimized with this strategy; so it is widely used in advanced battery-charge systems [51, 52, 74]. Accordingly, different types of pulse charging can be classified into two groups: voltage pulse charging and current pulse charging.

Several techniques can be used to charge batteries utilizing voltage pulses, including duty-varying voltage pulses and variable-frequency voltage pulses. To determine the duty in a commercial battery pulse charge system, a duty-varied voltage pulse-charge strategy is proposed in [74] and [75]. This method improves the battery charge speed and charges efficiency by detecting the suitable pulse charge duty and supplying the appropriate charge pulse to the battery. Experiments indicate that the charging speed and the efficiency are improved by 14% and 3.4% with the proposed strategy compared to the standard CC-CV charge strategy. Also, compared with conventional duty-fixed voltage pulse-charge, the proposed approach improves the charging speed and efficiency by about 5% and 1.5%, respectively. These lead to a longer life for lithium-ion batteries. Subsequently, To determine the optimal pulse charge frequency in a lithium-ion battery, a variable frequency pulse charge system (VFPCS) strategy is proposed in [76]. This method can identify the optimal pulse charge frequency and provide an optimal PC charging to the battery, decreasing the charging time. Compared to the standard CC-CV charge system, the proposed method increases the charging speed by about 21%.

The current PC approach applies the CC pulse with defined pulse width as long as the battery is fully charged. The authors in [77] studied how pulse width current affects the charging efficiency and capacity loss of a lithium-ion battery. Accordingly, four lithium-ion batteries of the same type with the same capacity were used and affected by several controllable current pulses. Each ten charge-discharge cycle was analyzed to determine the effect of the charging method on the capacity loss. The batteries were charged using constant current (1C) for 30 min to fill half of each battery's total capacity and then continued by pulse current at different pulse widths till each battery had full capacity. Furthermore, one hour of continuous charging was done for each battery for the sake of comparison to that of pulse current charging data. Consequently, battery capacity degradation has been observed on a similar scale. However, the percentage of loss of capacity is different. Based on the results, it was established that charging using pulse width current in 8 minutes can reduce the charging time and limits the capacity loss. As a result, due to the reduced capacity loss and the shortened charging time, this method is considered as one of the effective charging methods.

3.3.4 | Boost charging optimization

The previous discussion on boost charging involves applying a very high current for short periods at the beginning of the charging cycle to charge a completely depleted battery, followed by charging at CC-CV with moderate currents. Boost charging will, therefore, not negatively impact lithium-ion batteries. In reality, this additional charge interval will decrease the charging time without any loss in life, as batteries are more resistant to lithium plate failure at lower SOC. However, defining the boost time t_{boost} and boost current I_{boost} is a challenge that can be covered by proposing a reasonable control charging optimization method [37, 55].

3.4 | Electrochemical-parameter-based charging method

Electrochemical-parameter-based (EP-based) charging optimization techniques involve more complex charging protocols, including adaptive procedures that regulate charging current based on the properties of lithium-ion cell 'during the charging time. Accordingly, various methods have been introduced, which calculate the optimal charging profile to ensure fulfillment of electrochemical constraints. The optimality conditions usually entail the charging time and capacity fade reduction or the increasing of the charge stored at a given time instant [78–80]. Accordingly, the following constraints must be satisfied simultaneously: solid-phase and electrolyte-phase concentrations [81], intercalation-induced stresses [80], temperature [82], and lithium plating [78].

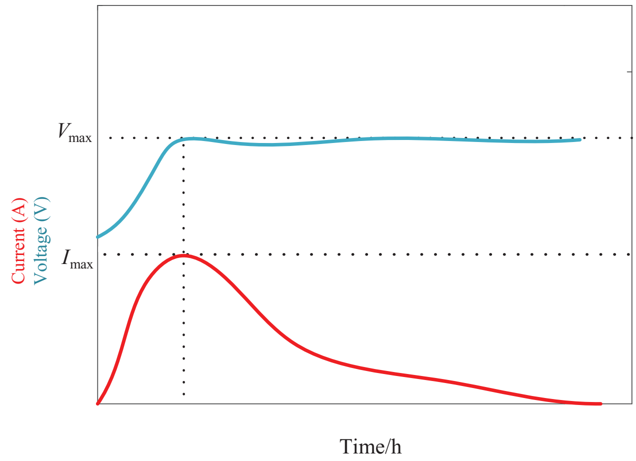

FIGURE 9 Charging with a preset voltage trajectory [55]

In several charging procedures, varying-current profiles are used, to begin with, high charging currents and decrease those currents with increasing SOC. Various optimization methods are used to achieve fast charging without exceeding specific voltages, temperatures, stress, or concentration thresholds [80, 83]. Accordingly, the charging profiles may be derived experimentally or mathematically from simulation models to establish the maximum charging currently practicable without causing lithium plating. Paper [84] proposes a fast lithium-ion battery charge using a varying current decay (VCD) charging protocol. Following the VCD protocol, the battery's performance was compared with the performance of batteries charged using conventional protocols. The results showed reduced capacity fade with the number of cycles charged. However, [84] and [85] reveal that maximum charging currents have hardly ever been determined in practical applications because those currents appear to vary considerably with temperature and degradation of the cell. The need for accurate information about the actual polarization or concentration within the cell necessitates the need for additional estimation procedures within the cell that include determining internal variables of the cell that are affected by the short and long-term load history. Also, there are some protocols for charging batteries that feature a lower charging current at the beginning with the internal resistance being at its highest levels at low SOC, and a low charging current or steadily rising current to minimize losses as shown in Figure 9 [55].

As other examples of utilizing EP-based charging approaches, papers [86] and [87] get benefits of implanting reference electrodes to achieve a faster charging. It has been reported that [87] implanted reliable reference electrodes within the cells in order to provide anode potential signals throughout the charging process, whose performances were thoroughly investigated. Accordingly, both anode potential and temperature were strictly maintained within the safety regions with the charger current modulated. Consequently, using the proposed

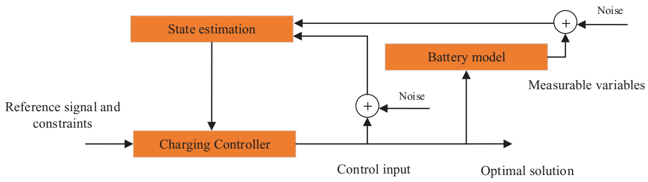

FIGURE 10 Feedback-based charging structure

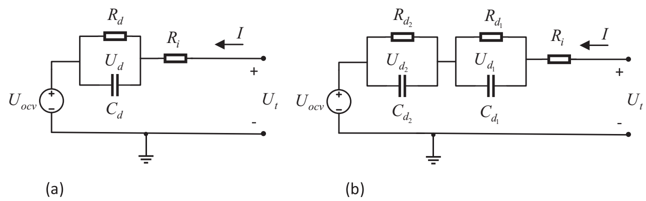

FIGURE 11 RC network ECM: (a) first-order, (b) second-order

approach, the full charging capability of the cell was exploited and charging speed was achieved twice as fast as the strategy of the manufacturer.

Though the non-feedback-based charging algorithms are simple to realize, health-related considerations and feedbacks of battery states are not included during the charging process, which could potentially shorten the lifespan of the battery [35, 54, 73]. To the best knowledge of the authors, the current non-feedback charging techniques cannot achieve the overall optimal charging objective in terms of charging duration, implementation, and requirements for health-conscious applications. This problem calls for other more advanced charging algorithms, which will be introduced in the following sections.

4 | FEEDBACK-BASED CHARGING METHODS

A typical feedback-based battery charging management design includes battery model, state estimator, and model-based controller. A model-based charging method calculates the optimal charging rate of a battery based on its empirical or EM model aiming to optimize the charging process by controlling the polarization voltage [65, 88–93]. Accordingly, taking into account the process noise, the optimal charging strategy for the battery is described with a closed-loop control structure represented in Figure 10. A battery model is generally intended to be low-order and easily implementable for a remarkable level of controllability [81, 94–96]. A battery model of this kind is constructed to simulate the fundamental battery cycle dynamics under the specified charging current profile. Subsequently, an observer is used to analyze the output variables of the model integrated with the noise vector caused by the unmeasurable state variables of the battery, such as concentration and overpotential. Therefore, accurate and precise model-based estimators are necessary to observe the internal states of a battery system. Accordingly, the optimized charging strategy is developed based on a reduced-order battery model and state estimator. Moreover, to achieve better charging performances, factors affecting battery health such as temperature rise, side reactions rate, and so on are needed to be considered.

4.1 | Empirical-model-based

The empirical-model-based charging method which is based on the battery's ECM, is widely employed in the BMS of the electronics and automobile industries due to its advantages such as fast computation [97–101]. These models are based on the historical experimental data collected for the battery in order to predict its future states. Accordingly, based on the distribution of electric charge and discharge signals such as cell potential and current, the main elements of the models are determined. In particular, empirical models have the advantage of simplicity and ease of implementation. On the other hand, they also suffer from some drawbacks such that the parameters of the physical model cannot be determined. In addition, battery characteristics do not change as the battery ages, and empirical models are not applicable to other types of batteries. Therefore, after a certain charging cycle, models based on empirical data fail to function properly. In general, this method can be divided into temperature-based, power-loss-based, and electrical-thermal-aging models which are described as follows [102–107].

4.1.1 | Temperature-based model

In [108] a first-order RC battery model is constructed to analyze the battery's dynamic characteristics during charging. Based on the equivalent circuit model shown in Figure 11a, the dynamic model is described using an open circuit voltage U_{ocv}, an ohmic resistance R_i, and a resistive-capacitive network RC, with components that can be described as diffusion resistance R_d and diffusion capacitor C_d, respectively. The offered method balances the increased charging temperature and time necessary to reach charging capacity. Accordingly, the genetic algorithm is applied to the ECM, and thermal models, and the charge capacity is measured experimentally. Experiments show that the proposed charging method can decrease both the charging time duration and charging temperature rise.

In Figure 11, U_d is the polarization voltage (also known as the diffusion voltage from the RC network), and I is the load current; U_t is the terminal voltage.

In another study, the authors in [64] propose a model-based control approach in order to manage battery charging operations. Based on Figure 11b, a fully coupled electrothermal model is utilized to formulate the charging strategy as a linear-time-varying model predictive control problem. In addition, various constraints are specifically established to prevent the battery from overcharging and overheating. To provide the state-feedback control, the battery internal states involving SOC and core temperature are estimated through a nonlinear observer. Accordingly, this paper reveals that their proposed method is

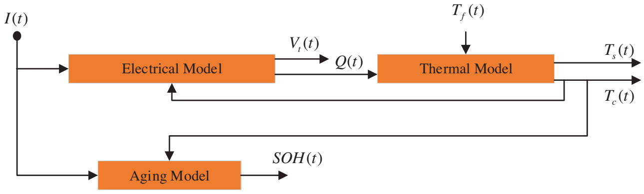

FIGURE 12 Electro-thermal-aging model diagram

capable of optimally balancing time and temperature rise. Additionally, simulations show that this model predictive control algorithm is well suited for real-time deployment.

4.1.2 | Power-loss-based model

Paper [109] studies the charging strategies for the lithium-ion battery using a power loss model with optimization algorithms to find an optimal current profile that reduces battery energy losses and, consequently, maximizes the charging efficiency. Subsequently, a cost function for power loss minimization is formulated as:

$$J = (x_1(t_f) - SOC^*)^2 + \int_0^{t_f} P_{loss}\, d\tau, \quad (2)$$

where SOC^* stands for the battery desired state of charge, P_{loss} represents the power loss in the resistive components of the battery model shown in Figure 11b, and $\vec{x} = [SOC\ v_{c_1}\ v_{c_2}]$ denotes the state variables of the circuit with v_{c_1} and v_{c_2} as the capacitor voltages. In the case that the temperature is constant, CC-CV is nearly optimal for energy loss minimization. If the temperature is viewed as a state variable, an optimal profile different from CC-CV should be found. By using the new profile, batteries will warm up on cold days, reducing the need to rely on existing battery heating systems. Consequently, a vehicle can achieve significant energy savings by engaging in driving soon after its charging process ends because of its heat. Accordingly, the authors in [109] present not just a classic optimization problem of classical form, but also one with a high degree of nonlinearity and time variation. Accordingly, the charging techniques obtained in their work have a considerable impact on how plug-in hybrid electric vehicles are charged and deployed.

4.1.3 | Electrical-thermal-aging model

A combined electrical-thermal-aging battery model is proposed in [100]. A two-state thermal submodel that entails a multi-objective optimal control problem determines the core temperature of an electro-thermal sub model. Figure 12 illustrates combining three sub-models to get a coupled electro-thermal-aging model, which is used to optimize the charging protocol.

Subsequently, to solve the resulting highly nonlinear six-state optimal control problem, they utilize the Legendre–Gauss–Radau (LGR) pseudo-spectral algorithm with adaptive multi-mesh-interval collocation. The optimal tradeoff between charge time and degradation depends on both electrical and thermal constraints, where the minimum-time, minimum-aging, and balanced charge conditions are analyzed in detail. Additionally, the effects of the upper voltage bound, ambient temperature, and cooling convection resistance on the circuit are examined. Accordingly, the objective cost function J for the whole charging process is expressed as:

$$J = \beta \frac{t_f - t_0}{t_max - t_0} + (1-\beta)[SOH(t_0) - SOH(t_f)],\ 0 < \beta < 1, \quad (3)$$

where t_0 and t_f indicate the initial and final charging times, respectively; β represents the weights of the relative significance among the charging time and capacity loss. Accordingly, experimental results for comparing their proposed method with a traditional charging protocol are presented, and their tradeoffs are discussed. Additionally, optimization results have been presented for three illustrative charging paradigms: the minimum time charge, the minimum aging charge, and a balanced charge, where it is assumed that there is no modeling, measurement, or control uncertainty. Moreover, aging results depict the effects of the charging protocols during the individual charge durations.

The ECM- and waveform-based charging approaches cannot take into consideration the battery's internal chemical reactions, internal potential change, and Lithium-ions concentrations. This problem can be addressed by improving the optimal charging based on the EM-based methods, which are described in what follows[81, 110].

4.2 | Electrochemical-model-based methods

The EM-based charging techniques are based on chemical and electrochemical kinetics and transport equations that can be deployed to simulate the characteristics and reactions of the lithium-ion battery [111–114]. A lithium-ion battery may experience some side reactions when the charging current is very high, which can cause the battery temperature to rise rapidly [115]. In this case, the EM-based method relies on applying as high a charging current as possible to restrict side reactions that may cause the precipitation of lithium inside the battery. Following this, one-dimensional-based (1D) model, Pseudo-two-dimensional (P2D) model, single particle model (SPM), and simplified-model-based methods are among the best-recognised EM-based charging methods [80, 116–119].

4.2.1 | One-dimensional-model-based method

Paper [120] presents a lithium-ion battery one-dimensional model with a reduced set of partial differential algebraic equations that can serve as an observer. Using a coarse spatial grid, these equations can be solved, resulting in a simplified model with a simpler charging structure that still reflects the main dynamics. In another work, the authors of [121] solve the optimization problem under temperature constraints and potential imbalance ranges utilizing a nonlinear model predictive control (NMPC). In [83], based on the one-dimensional EM charging method, dynamic optimization is carried out to estimate the optimal charging current profile via control vector parametrization (CVP). Subsequently, the system behavior is analyzed by simulating an efficient and straightforward reformulated model of the lithium-ion battery system. Consequently, the dynamic optimization becomes feasible due to the computationally efficient feature of the reformulated model. It is determined that if the battery is charged utilizing the optimal profile assessed by dynamic optimization, more power can be preserved as compared with typical charging of the battery. Accordingly, the authors tried to realize the dynamics of lithium-ion battery with competing transport and reaction phenomena at different scales and locations inside the battery.

4.2.2 | Pseudo-two-dimensional-model-based method

In the pseudo-two-dimensional (P2D) model, the Porous electrode theory, the concentrated solution theory, and the kinetics equations have been utilized to form an efficient charging technique [122–124]. This model has been widely applied in lithium-ion battery research, and its predictions are pretty accurate and have shown consistency with experimental data [80, 103, 125]. The authors in [80] show the use of a dynamic optimization framework to derive optimal charging profiles using a reformulated P2D model considering intercalation-induced stresses. Accordingly, the analysis indicates that the average pore wall flux varies considerably from the local pore wall flux; thus, a P2D model is required to capture the peak radial and tangential stresses correctly. Consequently, as the interface between the anode and the separator faces more stress than the rest of the anode, more innovative charging profiles can be derived to reduce mechanical and electrical damage caused by stress.

The P2D model-based charging method has mostly been used for the lithium-ion battery design, but they cannot be implemented in real-time control systems because of their prohibitively high computational cost [126]. With the incorporation of nonuniformity of electrodes, a variety of electrochemical state estimators have been developed mostly based on the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and the particle filter (PF) [127–129]. However, these state estimators are computationally complex. Recently, new techniques have been developed that can be applied to P2D models to achieve online state estimation. One example is how the authors in [130] developed a method for estimating the state of lithium-ion batteries in advanced battery management systems by using a degradation-conscious, high-fidelity electrochemical thermal model. Thus, the computational burden caused by the nonlinear nature of the battery model is effectively reduced by utilizing an ensemble-based state estimator based on the singular evolutionary interpolated Kalman filter (SEIKF).

4.2.3 | Single-particle-model-based method

In order to minimize the computational effort, a simplistic version of the P2D model, namely the single-particle-model (SPM) charging method, has been introduced [80, 100, 131]. In the SPM, the electrolyte characteristics are ignored, and the transport phenomena are simplified. Besides, the impacts of the thermal conditions on the performance of lithium-ion battery are reflected [132–134]. The SPM has the following advantages: (1) it is straightforward; (2) it does not require much computation; (3) it can be applied for various functions, such as online estimation and lithium-ion batteries' life modeling [132]. Despite its advantages, it comes with a drawback because of thick electrodes and high discharge rates, which require precise tuning related to electrolyte properties [111]. However, there exist improved versions of the SPM that are meant to solve these problems [135, 136].

4.2.4 | Simplified-model-based method

While the P2D-model-based charging method is remarkably rigorous and accurate, it is too complex and slow to apply to the BMS. Moreover, the SPM-based method is improper for batteries with high discharge rates and thick electrodes. The shortcomings with the SPM-based approach and the complexity of the P2D-model based method prompted the development of simplified versions of the P2D model that could be implemented in various BMS applications. These simplified models have been developed especially for optimization control techniques. The BMS based on simplified models has some advantages over the empirical models due to using physical-based equations that lead to more accuracy. Besides, these methods can be utilized for the lithium-ion cells' parameter estimation and age prediction and can be modified as the batteries age to prevent some significant inaccuracies of the empirical based models [80, 85, 117, 136–139].

The authors in [137] developed a reduced-order model (ROM) utilizing proper orthogonal decomposition (POD) for a physical lithium-ion battery model. The process of obtaining the appropriate orthogonal modes and analyzing their optimality are also included. Accordingly, the POD-based ROM for a lithium-ion battery is employed to simulate a charge or discharge process as well as the behavior of a battery pack. As a result, the computational time to complete the ROM is significantly less than the physical model, and there is excellent agreement between the two models. In paper [136], a seventh-order electrolyte enhanced (simplified) single particle model (ESPM) under electrolyte diffusion and temperature-dependent parameters (ESPM-T) is proposed. Accordingly, temperature dependence can be easily realised by explicitly addressing the impedance transfer function coefficients in terms of model parameters. A commercial finite volume model is also compared to the ESPM-T model, and the results demonstrate that the ESPM-T has accurate matching pulse responses across a wide range of temperature (T) and cutting-edge rates (I).

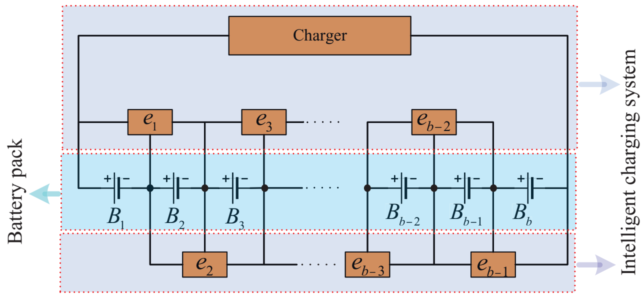

FIGURE 13 Schematic of a typical intelligent charging system for a serially connected battery pack [142, 147]

Existing battery model-based charging approaches suffer from significant limitations. For example, the ECM-based methods do not usually capture information about the internal state of the battery pack and are only reliable under a limited range of conditions, hence cannot generally be extended to all charging scenarios. Furthermore, full-order electrochemical models tend to be infeasible for real-time implementation due to their intended high fidelity. Accordingly, further optimising the charging process for individual cells in a pack is required to avoid local degradation or overcharging. In this respect, the BMS must provide cell balancing capabilities, which is the idea behind intelligent charging.

5 | INTELLIGENT CHARGING METHODS

Since the internal impedance of each battery is not exactly identical, series-connected batteries must be balanced while charging in order to preserve their capacity [140–142]. Moreover, a lithium-ion battery pack must not be overcharged, therefore requires monitoring during charging and necessitates a controller to perform efficient charging protocols [13, 23, 32, 143–147]. Accordingly, Figure 13 illustrates the schematic diagram of an intelligent charging system with cell to cell balancing topology for a battery pack containing b number of serially connected cells and $b-1$ number of equalizers e_i, $1 \leq i \leq b-1$ [142, 147].

The study in [146] offers a model predictive controller (MPC) that can be used to design optimal charging protocols utilizing statistical data regarding the state of health of the battery. The designed controller balances the competing factors, such as battery lifetime, and charging time. Accordingly, only the optimal charging is considered since discharging is user-dependent. The authors claim that their proposed framework may also be applied to optimize the discharge profile. However, a sophisticated power electronic circuit is required to incorporate this. Further, because both the objective function and constraints are based on the total charging time, the prediction time horizon must be adjusted to match the total charging time. Subsequently, multiple constant currents (like multi-stage CC charging) are considered for the remaining charging time applying a control horizon. To implement the proposed method online, they have presented a state estimator that can approximate the initial concentrations of the system based on the data from voltage and current measurements. As a result, using the MPC and state estimator together, lithium-ion batteries can be improved in terms of life and charge carrying capacity.

The voltage and current profiles derived using this study for a single cycle are presented in Figure 14. Based on their proposed intelligent charging mode, it is observed that charging takes approximately 2400 s. However, a standard CC-CV charging process takes approximately 6600 s.

The authors in [32] established an optimal charging control method for the lithium-ion battery pack using a cell to pack balancing topology as shown in Figure 15. In their study, following a multi-module charger, a user-involved methodology with the leader-followers structure is developed to control the charging of a series-connected lithium-ion battery pack. In other words, they are exploiting a nominal model of battery cells. An efficient average SOC trajectory is first produced by defining and solving a multi-objective optimization problem concerning user demand and battery pack power loss. The next step involves proposing a distributed charging strategy. It tracks the cells' SOCs on the pre-planned trajectory, where observers are designed for online compensation of the cells' model bias. This work highlights the superiorities of the suggested leader-followers-based charging structure. Accordingly, this method integrates offline scheduling and online closed-loop control for battery pack charging. It brings advantages to significantly minimize the computational burden for the charging control and enhance the robustness to prevent the harmful effects caused by the model bias of the cell.

Over the past few years, artificial intelligence (AI) methods have become increasingly popular thanks to their ability to provide the most accurate results in less time than other methods, especially when it comes to battery SOC and SOH estimations [148–158]. In [149], the authors employed machine learning approach to optimize parameter spaces for a six-step, ten-minute fast-charging protocol, that minimized the anxiety that some drivers have when charging their electric vehicles. In this regard, an early-prediction model that predicts cycle life from first-cycle data is combined with a Bayesian optimization algorithm that efficiently probes the parameter space of charging protocols. This leads to a time reduction per experiment. As a result, they optimized a fast-charging protocol for a lithium-ion battery pack within only one month; similar results would have taken two years without the aid of AI. In another work, the authors in [150] proposed a battery health and uncertainty management pipeline (BHUMP) as a machine-learning-based solution to trade-off between accuracy and computational efficiency of the battery SOH estimation. As opposed to the conventional methods, this pipeline is able to adapt to different charging protocols and discharge current rates and predicts without knowledge of multiple battery characteristics, including design, chemistry, and temperature. In [151], a feed-forward artificial neural network (ANN) was used for the first time to estimate the SOC of lithium-ion pouch cells. In order to develop calendar life data, galvanostatic charge/discharge cycles were applied under

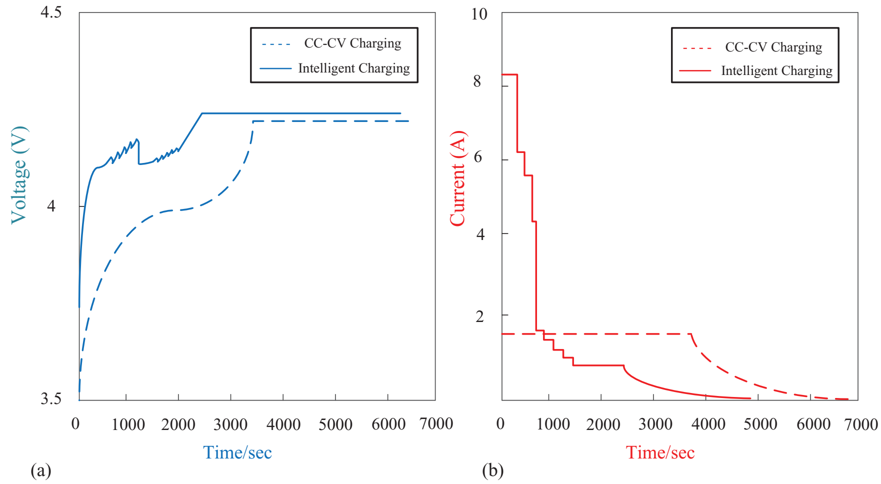

FIGURE 14 Voltage and current profiles by using the proposed intelligent charging as compared with the standard CC-CV. (a) Voltage profile. (b) Current profile [146]

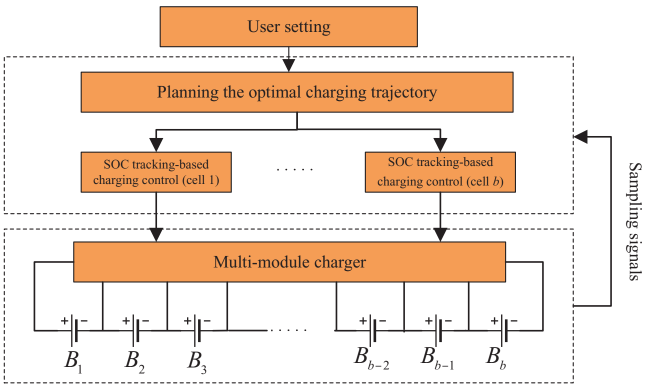

FIGURE 15 An intelligent user-involved optimal charging control technique [32]

different storage conditions (fully discharging or fully charging) and temperatures (35°C and 60°C). For a duration of 10 months, data was collected at varying C-rates at one-month intervals. A separate ANN was trained for the discharge and charge data in order to include the hysteresis effect. Based on the performance of the ANN, the Root Mean Square Error (RMSE) for discharge data was 1.17% and 1.81% for charging data, confirming the network's ability to identify input-output dependency. In [155], the authors presented a new method for accurately estimating SOC by applying machine-learning-based optimization. In this respect, recurrent nonlinear autoregressive (RNARX) neural network as a well-known subclass of machine learning algorithms was magnified in terms of computational capability by using lightning search algorithm (LSA), thus increasing SOC estimation accuracy. In addition to its accuracy and robustness, the proposed method can also be used to estimate cells' SOC under a broad range of charging and discharging conditions. In [157], a novel battery charging control method was proposed based on reinforcement-learning (RL) to minimize battery charging costs. This method has the important feature of not requiring a high-accuracy battery model, as it is model-free. Therefore, it overcomes the limitations of battery models and the risks associated with parametric uncertainties inherent in real-world implementations. Further, given the necessity for accurate predictions of electricity prices, a long short-term memory (LSTM) network was utilized to improve the prediction accuracy. Consequently, to minimize the cost of charging, an optimal charging profile was designed as the final control objective. As a result, the presented control algorithm provides a basic framework for a more complex electricity market in which there exist different energy storage systems, generators, and loads. In another work, authors in [158] showed that the complicated multivariable channel geometry optimization problem can be efficiently solved by using machine learning and the Markov chain Monte Carlo gradient descent optimization. Their results indicate that, under certain geometrical conditions, thermal capacity, specific energy, and specific power can all be improved considerably. Moreover, this can also result in a significant reduction in the maximum first principal stress in the region of the separator next to the cathode, improving mechanical integrity. The optimization of channel design leads to 79% larger specific energy than conventional cell designs without electrolyte channels. Consequently, the method and design strategy proposed result in significant performance improvements for charging and discharging batteries.

6 | COMPARISON AND DISCUSSION

6.1 | Comparison

Different charging techniques are proposed to achieve tradeoffs among optimization objectives such as charging time, temperature rising rates, charging efficiency (or minimal energy loss), and battery life cycles. It is essential to compare some of the most fundamental aspects of these charging techniques to determine which one is the most suitable for a particular application. Accordingly, Table 1 provides such a comparison from different aspects.

In general, among the non-feedback-based charging approaches, the traditional charging control techniques benefit from ease of implementation, high capacity utilization, and low complexity. However, it is hard to optimize some more advanced objectives such as charging speed, power loss, and

TABLE 1 Comparison of different battery charging methods applied to lithium-ion battery systems

Charging methods		Advantages	Disadvantages	Literature
Non-feedback-based	Traditional	Easily implemented; high capacity utilization; low complexity.	Hard to balance objectives such as charging speed, power loss, and temperature variation; long charging time; low efficiency; short cycle life; lack of robustness against noises.	[34, 36, 37, 41–43]
	Fast-charging	Easily implemented; fast charging time.	Hard to balance objectives such as battery cycle life , charging speed, and capacity utilization; short cycle life; lack of robustness against noises.	[15, 36, 46–55]
	Optimized	Current rate and voltage threshold are optimized; a very accurate and ripple-free charging current is achieved; power loss is reduced; high efficiency, short charging time, high cycle life.	Lack of robustness against noises; difficult to implement.	[37, 43, 51, 52, 55, 66, 68–74, 77, 145].
	EP-based	Reduced capacity fade; high efficiency, short charging time, high cycle life.	Lack of robustness against noises; difficult to implement.	[55, 78–85]
Feedback-based	Empirical-model-based	Widely employed in the BMS; fast charging; fast computation; high efficiency; high cycle life.	Complexity and indeterminacy of the model's physical parameters; battery characteristics do not adjust as the batteries age.	[64, 81, 97–100, 102, 103, 108, 109]
	EM-based	Restrains side reactions that may cause the precipitation of lithium inside the battery; fast charging time; high efficiency; high cycle life.	High complexity; high computational cost.	[80, 83, 85, 103, 111, 115–117, 120–123, 125, 131–138]
Intelligent		Suitable for battery packs with multiple cells; it balances the cells' SOC during charging, enhances the batteries' health, and trades off between competing factors as it maximizes battery life and battery charging time.	High control complexity; it usually needs a multi layer control structure.	[23, 32 140, 141, 143, 144 146]

temperature variation with these methods. Therefore, they usually suffer from a long charging time, low efficiency, and short cycle life. Fast charging techniques offer a short charging time; however, their control is considerably more complex than the traditional methods. A variety of improved charging techniques such as improved CC-CV charging, MCC-CV charging, pulse charging, and boost charging are already developed based on CC, CV, and CC-CV. With these techniques, the current rate and voltage threshold are decided more accurately. An accurate and ripple-free charging current is achieved with these methods. In addition, they reduce the power loss, enhance the charging efficiency, give rise to charging speed, and increase the batteries' cycle life. Although, it is challenging to implement these kinds of charging approaches because of their high complexity. Table 1 also illustrates that the EP-based charging techniques reduce the capacity fade and increase the charging efficiency, speed, and cycle life but at the cost of losing simplicity.

Among the feedback-based charging methods, the empirical-model-based charging techniques are widely employed. These techniques provide low computation, high efficiency, and improved cycle life as compared to non-feedback-based methods. However, these techniques are still relatively complex. Besides, the parameters of the physical model cannot be determined, and battery characteristics do not change as the battery ages. As another technique of feedback-based charging, EM-based requires comparably higher computational effort, costly charging tools, and massive data recording in comparison to empirical-model-based techniques. Hence, the waveform-based charging strategies based on simplified models with predetermined energy input should be adopted with EM-based charging methods. This way, however, is highly dependent on the battery parameters' accuracy. Several optimization algorithms have been devised to attain the best charging current for the multi-stage charging schemes used in EM-based methods. In this regard, the charging period has been significantly minimised, and the battery life cycle extended; however, further effort must be dedicated to minimizing the computational and operating costs of the EM-based charging techniques.

Intelligent charging technique is ideal for battery packs containing multiple cells because it balances the cells' SOC during charging. Consequently, compared to non-feedback-based and feedback-based methods, the batteries gain greater health, more cycle life, and higher charging capacity. Furthermore, they make a trade-off between competing factors, like battery life and charging time. These charging techniques, however, have high control complexity since they usually require a multilayer control structure.

6.2 | Discussion and suggestion

Table 1 systematically reviews and compares the present charging methods for lithium-ion battery packs. Different charging methods are compared with their performances in minimizing the charging time, enhancing the charging efficiency, and extending the battery life. The reviewed literature shows that charging with the non-feedback-based methods is one of the most widely used charging strategies because of its relatively simple and straightforward structure. However, these techniques are not highly efficient. They need to get optimized to enhance the charging performance. In light of this, it is important to complement further study with more valuable experiences. In fact, the internal charging mechanism of a lithium-ion battery is closely tied to the chemical reactions of the battery. Consequently, the chemical reaction mechanisms, such as internal potential, the polarization of the battery, and the alteration of lithium-ion concentration, have a significant role in the charging process. These necessitate a precise electrochemical model to be analyzed.

The feedback-based charging techniques appear to be the most promising option for the optimal charging of a single lithium-ion battery cell concerning health considerations; however, it is crucial to make the battery charging system controllable and straightforward. It is also essential to choose an optimization method that is computationally efficient and well-suited to the battery model. This review study also reveals that, based on specific optimization objectives, feedback-based charging methods can be flexibly combined with other models. For example, a combination of ECM and a temperature model can solve the optimal current distribution when the temperature rise rate must be strictly controlled. In a similar way, when the power loss requires to be decreased, a power loss model can be integrated with ECM to reach the optimization target. The charging method using the aging model has impressed much attention by obtaining better-charging performance. Accordingly, future studies can consider battery degradation on electrical parameters and charging current patterns through investigating the aging mechanism of battery charging.

For a battery pack with multiple connected cells , the intelligent charging method offers a multi-layer control structure with great flexibility that balances complexity and efficiency. This approach allows for multi-objective battery charging to be achieved simultaneously. The batteries' charging performance is enhanced, and the battery cells' SOC gets balanced.

From the last discussion, it can be concluded that for battery packs with many series-connected cells, the intelligent charging technique, as a smart charging approach, outperforms all other charging techniques in terms of shorter charging time, higher efficiency, and extended cycle life. However, this method is not highly efficient for charging a single lithium-ion battery due to its control complexity, leading to an expensive charging system for such a single battery application. Moreover, the charging efficiency is highly dependent on the cells' SOC balancing topology. Therefore, the intelligent method must be complemented by more research to determine which charging method and balancing topology are most suitable for each other. In turn, this would also reduce the charging control complexity. Much research remains to be done on the connection between cell level and pack level battery charging. While multiple charging strategies for single battery cells have been demonstrated recently, the effects, feasibility, and cost of implementing them in battery packs have not been get examined well.

7 | CONCLUSION

This review paper takes a novel control-oriented perspective of categorizing the recent charging methods for the lithium-ion battery packs, in which the charging techniques are treated as the non-feedback-based, feedback-based, and intelligent charging approaches. Accordingly, the proposed charging methods' classification provides comprehensive data about the most up-to-date charging methods. In addition, a comprehensive comparison between different charging techniques is given that provides a general guideline for the proper charging method selection of the lithium-ion battery balancing system in practical applications. The results coming from the reviewed literature and comparison reveal that the non-feedback-based charging methods gain a simple structure, but noises can compromise their robustness. The feedback-based charging methods gain some advantages over the non-feedback-based charging techniques due to the structure of their closed loop control. However, they cannot adapt their characteristics as the battery ages; moreover, they are not applicable for the battery packs containing several connected battery cells. Subsequently, the intelligent charging method benefits both non-feedback-based and feedback-based charging schemes. It is suitable to charge the battery pack considering the battery cells' balancing and health. However, its control complexity is higher than other lithium-ion battery packs' charging methods due to its multi-layer control structure. Recently, the AI-based fast charging, as a kind of intelligent method, is shown to be promising for charge optimization in time-consuming experiments by providing more accurate battery SOC and SOH estimation results in less time.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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