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Classification and Review of the Charging Strategies for Commercial Lithium-Ion Batteries

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ABSTRACT The growing demand for lithium-ion (Li-ion) battery in electric vehicles has expedited the need for new optimal charging approaches to improve the speed and reliability of the charging process without deteriorating battery performances. Many efforts have been deployed to develop optimal charging strategies for commercial Li-ion batteries over the last decade. The active optimal charging strategies have great potential to meet the requirement. This paper is a review of the studies on constructing the optimal charging algorithms for Li-ion batteries. The battery models on which these protocols rest are stated, the generalized structures are examined, the advantages and the drawbacks of the mathematical controller algorithms are discussed, and their applications are presented. Suggestions for overcoming the shortcomings of the proposed strategies are proposed. Challenges and future directions in the development of optimal charging strategies for commercial Li-ion batteries are also discussed.

INDEX TERMS Fast charging, optimal charging strategies, lithium-ion battery.

I. INTRODUCTION

Lithium-ion (Li-ion) batteries have been commercialized for plug-in hybrid (PHEVs) and electrical vehicles (EVs) as a result of their higher energy density, longer lifespan compared to their lead-acid and nickle-metal hydride alternatives [1]– [3]. Different from fuel-driven internal combustion engine, battery charging process is much more complicated, due to its slow charging speed and unclear effects of charging strategies on battery performances [4]–[6]. Lithium-ion battery charging speed becomes a bottleneck of EVs popularization [7], [8]. The US Department of Energy (DOE) has set a charge goal of 10 miles of range per minute for fast charge [9]. For an EV with 100 mile range (24 kWh battery pack), the DOE goal is to charge full in 10 min (6C rate). However, simply increasing the charging rates may cause striking temperature rise and accelerate side reactions [10]– [12]. The trade-off between fast charge and battery health should be taken into account at the same time [13], [14]. Therefore, the battery optimal charging scheme has gained much attention in the research field of EVs/PHEVs [15]– [17]. An appropriate optimal charging protocol is desirable to improve the charging efficiency, minimize any performances attenuation, and sustain a safe operation of a LIB system. Over these years, many studies have been done in order to figure out the most suitable charging strategy.

In general, the available Li-ion battery charging strategy can be divided into three classes based on the internal mathematical models. The first category is a model-free methodology, including constant-current (CC), CC constant-voltage (CCCV), multi-stage CCCV and pulse charging techniques [5], [18], [19]. These approaches can be characterized by their predefined charging profiles with fixed current, voltage, and/or power constraints but ignoring the responses of battery dynamics. Considering the operability of model-free methods, the corresponding programs are viewed as heuristic. Hence, this motivates the necessity to explore advanced charging strategies in order to meet fast charging requirements and alleviate the impact on battery state-of-health (SOH) meanwhile.

The second category of charging strategies utilizes empirical models such as equivalent circuit-based models and neural network models [20]. These models predict battery states and calculate electrical elements using past experimental data. By means of different circuit models,

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Kalman-type filters [21], recursive least squares [3], sliding mode observers [22] and moving horizon estimations [23] were adopted to estimate battery states. Meanwhile, frequency optimization [24], multi-objective optimization [25], fuzzy control [26], linear quadratic control [27] and model predictive control [28] were formulated to improve charging performances. The empirical models are computationally fast and simple, but unable to reflect physics-based parameters and battery aging [28]. Therefore, an empirical model oriented charging control protocol may fail to work properly after certain cycles [29], [30].

The charging algorithms based on electrochemical models governed by kinetics and transport equations are more sophisticated [31]. The closed-loop optimization problems can be formulated to minimize charging time and compensate for model uncertainties and disturbances [32]. In addition, temperature variation can also be predicted with thermal-related relations. Thus, the electrochemistry-based control algorithm is close to actual battery mechanism when used as a state observer. However, the intractable computation complexity associated with full-order nonlinear partial-differential equations (PDEs) limits the further application to a real-time charging controller [33].

As a result, proposing an appropriate optimal charging scheme of commercial Li-ion battery is a challenging task. This target means that the battery should be charged as soon as possible while the temperature rise and aging effects are kept within the acceptable range. Recently, the diversity and multitude of existing studies dealing with optimal charging strategies provide a large amount of information.

In this review, we intend to summarize the recent results on various battery optimal charging algorithms. The first aspect presented here is the passive charging strategies including constant-current (CC), CC constant-voltage (CCCV), multi-stage CCCV and pulse charging technique. Their characteristics are summarized and compared. Then we move on to the generalized structure of active optimal charging protocol. Moreover, the reviewed optimal charging protocols in the text including their data, results, the investigated battery type and charging methods are summarized. Based on the information, their pros and cons were compared and discussed. Furthermore, two tables for passive charging protocols and active charging protocols, respectively were presented. The suggestions and challenges for battery optimal charging strategies are proposed in the end.

II. PASSIVE CHARGING PROFILES

The passive charging strategies are characterized by charging the battery under pre-set instructions as shown in Fig.1. The charging protocol is stopped when the battery reaches the terminal condition. Although the passive charging algorithm is easy to operate, feedbacks of battery states and health-related optimization constraints are not considered during the charging process, which may shorten the lifespan of battery [34]– [36].

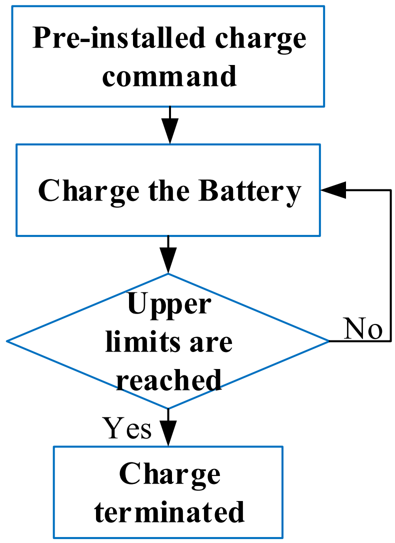

FIGURE 1. Passive charging structure.

A. CONSTANT-CURRENT CONSTANT VOLTAGE RELATED CHARGING METHODS

The constant current constant voltage (CC/CV) charging algorithm is widely adopted in charging Li-ion batteries because of its simplicity and easy implementation [37]– [39]. Under the CC/CV algorithm, the battery is initially charged with constant current until the battery voltage reaches a preset maximum charging voltage, then the charging voltage is held constant until the current is reduced to a preset minimum value [40]. The charging curve of the CC/CV is shown in Fig.2.

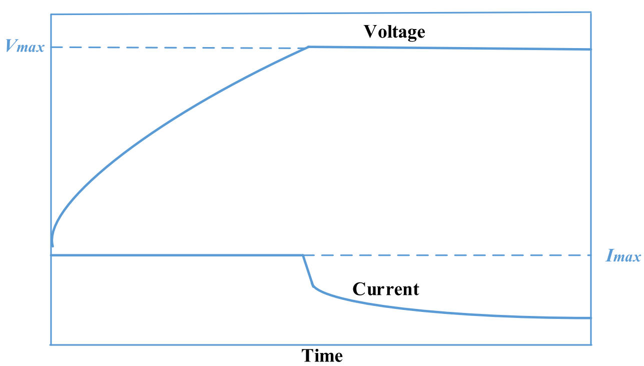

FIGURE 2. Constant current-Constant voltage curve.

Many variants of the CC/CV charging strategy were developed. A proposed multistage fast charging profile is split into three different stages, referred as CC-I, CC-II and CV-I depicted in Fig.3. The algorithm is based on the evolution of internal resistance during charging [18], [41]. Due to the cell's smaller resistance in lower SOC range, the highest current is applied. The last two stages are used as the cell's internal resistance increases rapidly. Experimental results verify that the procedure is useful for avoiding a considerable temperature rise and extending the cycle life.

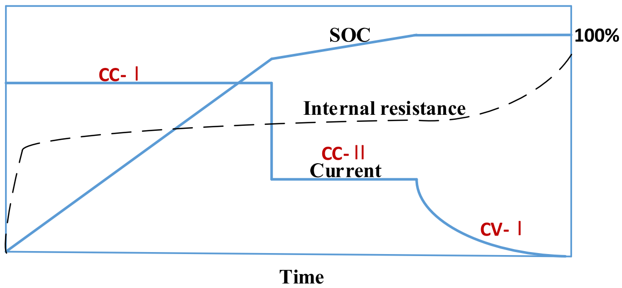

FIGURE 3. Current, state of charge, resistance profiles of the fast charging technique.

Another form of the multistage CC/CV method is introduced in Fig.4, where a $V_{\max}$ voltage is utilized to charge the battery in the initial CV-mode during a very short period t_0, subsequently followed by a standard CCCV process [36]. This boost-charging technique ensures that the fully discharged battery can be recharged to one-third of its rated capacity without inducing any extra degradation effects.

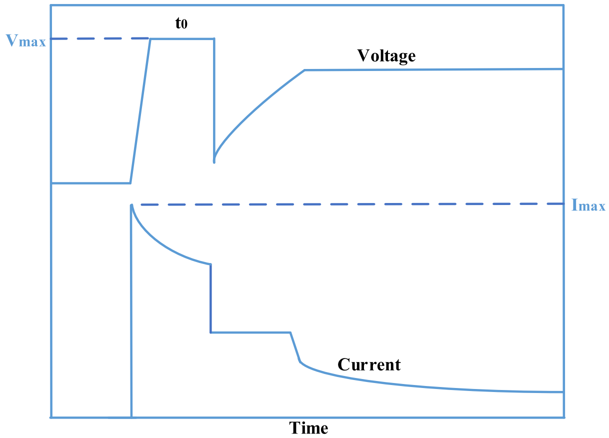

FIGURE 4. Voltage and current characteristics of boost-charging technique.

Taguchi-based approaches are also applied to determine the optimal charging pattern [6], [42], [43]. A five-step constant current charging method was proposed in Fig.5 [42]. Compared to the conventional CC-CV method, this pattern can provide 57% more cycles and reduce 11% charging time.

B. PULSE CHARGE BASED CHARGING CURVE

The pulse charge have been claimed to be a fast and efficient charging algorithm for lithium-ion batteries [44]– [46].

Purushothaman *et al.* concluded that by proper selection of the current waveform parameters, the side reactions caused by lithium saturation at the particle interface can be prevented [47]. A nonlinearly decreasing current density which conforms to the mass transfer coefficient variation could provide complete charging in less than $\frac{3}{4}$ hour [48]. However, this technique was based on simulation analysis, no corresponding experiments were carried out. In addition,

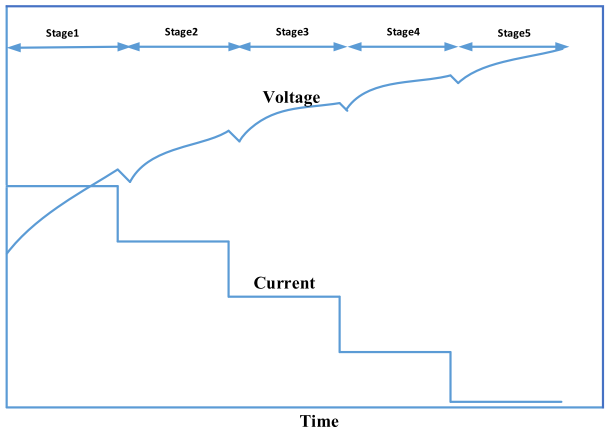

FIGURE 5. Five-step constant current charging algorithm.

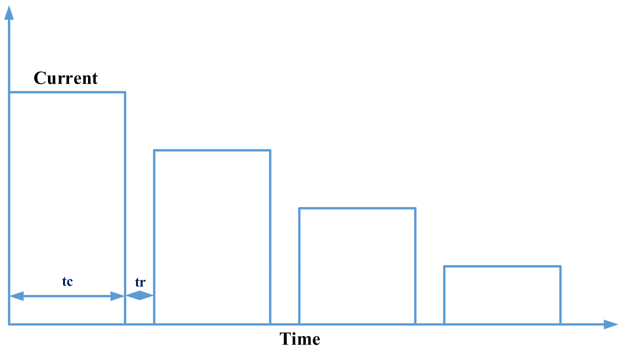

FIGURE 6. Nonlinearly decreasing pulse charge technique.

tracking the diffusion coefficient variation in real-time was computationally complex.

Similarity, a state of charge(SOC) governed fast charging method was used to charge the battery, which attempted to minimize the parasitic reactions as well [49]. The first charging stage consists of gradually increasing current pulses concerning its higher impedance at lower SOC levels. At the final stage of charging, the charging amplitude gradually decreases to make up for the lower charge acceptance by the battery at higher SOC levels. The drawback of this strategy is insufficient theory support and the value of pulse amplitude and width is arbitrary chosen.

In 2016, Lu *et al.* demonstrated the design of charging strategies for lithium ion batteries considering the balance between diffusion induced stress and total charge time based on the pulsed currents charging method [50]. For the two-stage charge methods, the galvanostatic operation is first used and then followed by a potentiostatic operation. Moreover, two connective galvanostatic stages with different currents followed by a potentiostatic stage were introduced in the three-stage charge methods.

C. SUMMARY OF THE REVIEWED PASSIVE OPTIMAL CHARGING

The data and results of the passive optimal charging protocols reviewed in this paper are summarized in Table 1, including the investigated battery type, charging methods,

TABLE 1. Comparison of the reviewed passive charging strategies.

	Resistance evolution based three-stage CC/CV charging	**Diffusion stress based charging**	**Taguchi-based five step charging**	**SOC governed multi-stage fast charging**	**Boost charging**	**Pulse charging based**
Reference	[18]	[50],[45]	[42],[34]	[49]	[36]	[47],[6],[46],[102]
Investigated battery type	Nanophosphate high power LFP cell	Not specified	Commercial ($LiMn_2O_4$) battery	Commercial ($LiMn_2O_4$) battery	Cylindrical (US18500,); prismatic (LP423048)	Not specified
Charging method	Step1: CC-I Step2: CC-II Step3: CV-I	Two-stage method: Switching the CC mode to CV when $C_{surf}=0$; Three-stage method: CC-I, CC-II, CV-I.	Step1: CC-I Step2: CC-II Step3:CC-III Step4:CC-IV Step5:CC-V	Step1: Multistage CC Step2: Multistage CC-CV Step3: Multistage CC Step4:CV	High pulse currents followed by CC-CV mode.	Nonlinearly decreasing charging current tracking the mass transfer coefficient evolution.
Charging result	100% SOC within 20 min (V_{max}=3.6 V, I_{max}=4 C)	100% SOC within 18 min (I_{max}=8 C) for two-stage method or 15.6 min (I_{max}=5 C) for three-stage method.	95% SOC in 130.7 min (I_{max}=1.4 C)	80% SOC in 41.6 min (I_{max}=2 C)	30% SOC within 5 min (V_{max}=4.3 V, I_{max}=4.5 C)	100% SOC in 43.2 min (I_{max}=8 C)
Parameter need to be optimized	1.Number of stage. 2.Current magnitude. 3.Voltage threshold.	1.Minimum value of Li^+ concentration at particle surface. 2. Number of stage.	1.Number of stage. 2.Current magnitude. 3.Charging duration at each stage.	1.Swithing point of each charging stage.	1.Volatge threshold at the initial pulse charging stage.	1.Initial charging current. 2.Current decreasing rate. 3.Pulse frequency,magnitude and duty ratio.
Advantages	1.Easy implementation 2. Extended cycle life (over 5000 cycles) 3.Invariable power capability.	1.Accelerate the charging process and lower the peak stress.	1.57% more cycles, 11.2% less charging time and improved charging efficiency by 1.02% compared to CCCV mode	1.Reducing the charging time and providing optimum battery performance and thermal management.	1. Easy implementation 2. No significant impact on cycle life.	1.The reactant concentration buildup at the electrode and the concentration overpotential are minimized
Disadvantages	1. Charge rate is not optimized. 2. Charge termination is based only on the cell voltage measurement. 3. Temperature is not controlled.	1.Battery degradation is not considered. 2. Temperature is not controlled.	1. Requires very stable current and temperature, currents must be low.	1.SOC during charging process needs to be estimated precisely.	1. Charge rate is not optimized. 2. Charge termination is based only on the cell voltage measurement. 3. Temperature is not controlled.	1. Hard to choose the proper parameters for pulse sequence. 2. No corresponding experiment was carried out.

and parameters needed to be optimized. Their strengths and limits were also presented.

As can be seen from Table 1, most studies chose the commercial cylindrical batteries as the investigated battery type for passive optimal charging strategies ranging from LMO to LFP. This cell type has a low energy but high power density. In Ref [35], the prismatic LP battery was also used for validation.

The resistance evolution based, diffusion stress based, Taguchi based, SOC governed and boost charging strategies are the variances of standard CC-CV method. The difference between them is the charging switching terms.

For the resistance based protocol, the charging process changes with cell internal resistance. For the diffusion stress based protocol, the ion concentration at surface is viewed as a trigger to activate the next charging stage. The Taguchi Orthogonal Arrays based charging method divides the charging process into five CC stages. At each stage, the current was optimized. The SOC governed multi-stage charging method tried to decide the charging current based on the SOC change while charging. In boost charging, a short period of high current was applied to the battery to reach the identified voltage threshold. The number of stages, current magnitude in each stage, and stage duration were three critical parameters needed to be optimized for the multi-stage charging algorithm. Due to the model-free characteristic, these methods could be implemented easily and were proved to have a better performance in charging speed, cycle life or power capability compared to CC-CV charging. However, battery health related indexes such as battery degradation and temperature were not considered and well controlled.

In nonlinear decreasing pulse charging profile, the charging current waveform is varying regarding pulse frequency, duty ratio and current magnitude. From Table 1, the pulse-based charging method requires 5 parameters to be optimized online to achieve the ideal performance. As a result, the computation stress on the controller is the highest among the reviewed passive optimal charging strategies. Therefore, the implementation of pulse-based charging algorithm could be complicated in the real applications.

To the best of our knowledge, the existing passive charging techniques are unable to fulfill the overall optimal charging objective in terms of implementation, charging duration and health-conscious requirements, which urge the development of the active charging algorithm.

III. GENERALIZED ACTIVE OPTIMAL CHARGING STRUCTURE

The commonly-used active battery charging management structure is often composed of three important elements. They are the battery model, state estimator, and model based controller. Taken the process noise into consideration, a closed-loop control structure for the battery optimal charging strategy is formed as depicted in Fig.7.

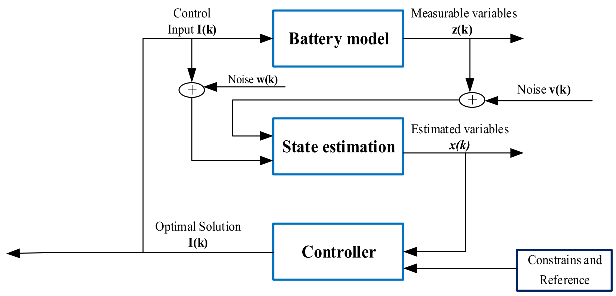

FIGURE 7. Active optimal charging structure.

Generally speaking, the battery model is carefully designed to be lower-order and easy implementable for an outstanding controllability [14], [50], [51]. The aim of constituting such a battery model is to simulate the real battery system dynamics under the specified loading current profile. The output variables of the model integrated with the noise vector are used as input for observer. Given that the battery contains a lot of state variables, many of which are unmeasurable, such as concentration and overpotential. Thus, a robust and effective model-based estimator is required to observe internal states of the battery system [51]. Based on the reduced-order battery model and state estimator, an active charging strategy is formulated with optimal control algorithm. Meanwhile, for better charging performances, constraints of battery health-related variables (temperature rise, side reaction rate and so on) need to be considered as outputs references.

A. COMMONLY-USED BATTERY MODEL

For controlling and estimating battery states online, it is imperative to rely on a fast and accurate real-time simulation on BMS [52]– [54]. Fig.8 shows the general classification of control-oriented Li-ion battery models.

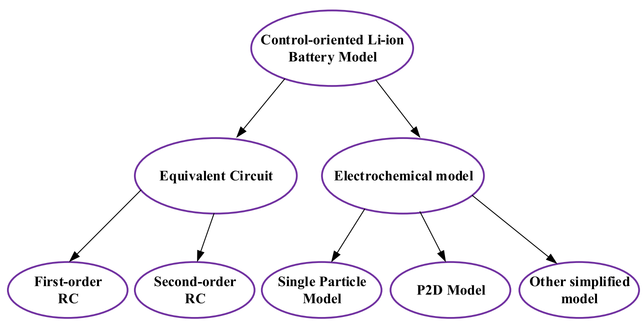

FIGURE 8. Classification of commonly-used battery models.

Recently, the equivalent circuit models have been widely used in BMSs due to its advantage of fast computation [55]– [57].

Hu *et al.* presented a dual-objective optimal charging strategy for LiNMC and $LiFePO_4$ batteries based on the first-order RC model [58]. The influences of the charging voltage threshold, temperature, and health status on the charging results were analyzed for the two types of batteries.

$$\frac{dz(t)}{dt} = \frac{\eta I(t)}{3600C_n} \tag{1}$$

$$\frac{dU(t)}{dt} = -\frac{U(t)}{\tau_1} + \frac{R_1}{\tau_1} I(t) \tag{2}$$

$$\frac{dh(t)}{dt} = -\left|\kappa I(t)\right| h(t) + \left|\kappa I(t)\right| H \tag{3}$$

$$V(t) = V_{oc}(z(t)) + R_0 I(t) + U(t) + h(t) \tag{4}$$

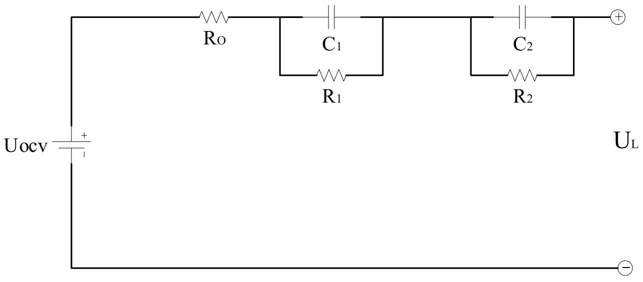

FIGURE 9. Equivalent circuit model.

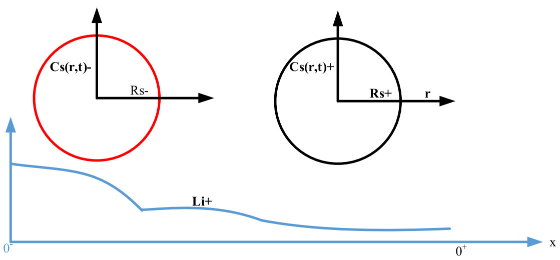

FIGURE 10. Single particle model.

where *I, U,* C_n, z and h are the current, output voltage, nominal capacity, SOC and hysteresis voltage for $LiFePO_4$ cell, respectively.

In 2017 [33], an equivalent circuit composed of an ideal voltage source,an internal resistor, and two resistor-capacitor (RC) pairs was put forward for model-based charging management as illustrated in Fig.9. For battery thermal modeling, the average cell temperature is approximately equal to the radial average temperature:

$$T_a = \frac{1}{2}(T_s + T_c) \tag{5}$$

where T_s is the surface temperature, T_c is the core temperature and T_a is the average temperature. The governing equations for T_s and T_a are expressed as:

$$\frac{dT_s(t)}{dt} = \frac{T_f - T_s(t)}{R_u C_s} - \frac{2(T_s(t) - T_a(t))}{R_s C_s} \tag{6}$$

$$\frac{dT_a(t)}{dt} = \frac{T_f - T_s(t)}{2R_u C_s} + \frac{T_s(C_s - C_c) - T_a(C_s - C_c)}{R_s C_c C_s} + \frac{Q(t)}{2C_c} \tag{7}$$

where T_f is the ambient temperature, R_C and R_u are separately the heat conduction resistance and convection resistance. C_s and C_C are the surface heat capacity and core heat capacity, respectively. However, its model parameters need to be firstly determined according to experimental results and battery aging factors are not considered.

These electrochemical-based models have significant advantages over those equivalent circuit models because of their physical based equations [51], [59], [60]. The Partial-Two-Dimensional (P2D) model is unquestionably rigorous and accurate [37], [61]. The Single-Particle-Model (SPM) is useful in realizing quick responses but it is unsuitable for simulating high (dis)charge rates [20], [62], [63]. The drawbacks of the SPM and P2D have motivated the development of simplified versions of the P2D model to be used in battery charging control.

Perez *et al.* developed an optimal fast charging protocol via a coupled single particle model with electrolyte and thermal dynamics [64]. In the coupled model, the anode and cathode solid concentration dynamics were described with two PDE single particle subsystems. The electrolyte concentration in three different domains (anode, separator cathode) was captured with a three-PDE electrolyte subsystem. The temperature was fed back into the voltage output and solid/electrolyte dynamics. Due to the coupled electrochemical-thermal dynamics, the optimization problem is highly nonlinear.

Zou *et al.* have done considerable work on proposing physics-based low-order battery models to simulate charging strategies [33]. In 2018, a PDE-based SPM with electrolyte states was formulated to simulate the battery dynamics as expressed in Eq.8-11. The model order was reduced based on three assumptions [52].

$$\dot{\bar{C}}_s^-(t) = -\frac{3}{FR_p^- a_s^- L^-} I(t) \tag{8}$$

$$\bar{C}_s^+(t) = [n_s - L^- \varepsilon_s^- \bar{C}_s^-(t)]/(L^+ \varepsilon_s^+) \tag{9}$$

$$C_{ss}^\pm(t) = \bar{C}_s^\pm(t) + \lambda_1 \omega_1^\pm(t) + \lambda_2 \omega_2^\pm(t) \tag{10}$$

$$\frac{dC_e^\pm(0,t)}{dt} = \frac{D_e^\pm \mu^\pm}{L^{\pm,2} \varepsilon_e^\pm}\left[C_e^\pm(0,t) - C_{e0}^\pm\right] \mp \frac{1 - t_c^0}{FL^\pm \varepsilon_e^\pm} I(t) \tag{11}$$

In particular, the electrolyte concentration C_e and the anode over-potential of side reactions η_s^- were included in the output vector considering aging effects. The state-space function of battery model is listed as:

$$u(t) := I(t) \tag{12}$$

$$x(t) := [\bar{C}_s^-(t), \omega_1^-(t), \omega_2^-(t), \omega_1^+(t), \omega_2^+(t), \times C_e^-(0,t) - C_{e0}^-, C_e^+(0,t) - C_{e0}^+, T]^T \tag{13}$$

$$y(t) := [SOC(t), T(t), C_e^-(0,t), \eta_s^-(t)]^T \tag{14}$$

$$z(t) := [V(t), T(t)]^T \tag{15}$$

system input vector is *u(t), x(t)* is state vector, $z(t)$ is measurable system output vector and controllable output vector is *y(t).*

B. CLASSIFICATION OF OPTIMAL CHARGING STRATEGIES

The optimal charging targets are often related to the battery health-aware performances in two aspects, which are the temperature rise and aging rate. Therefore, the optimal charging strategy is formulated considering battery performances and charging speed at the same time.

The battery aging associated properties are selected from part of battery internal states. The overpotential of side reactions occurring at cathode electrode or anode electrode and the solid electrolyte interface (SEI) growth δ_{SEI} are considered as side effects results [4], [65], [66]. The electrolyte concentration C_e is also viewed as an incentive to side effects [31], [67], [68]. Considering the particle mechanical stress induced by diffusion, the lithium concentration at the surface of particles C_s is limited no less than zero [50], [64]. Based on empirical equations between capacity loss and total discharge Ah throughout, the state of health (SOH) is selected as degradation representatives [64]. The sharp temperature rise may lead to battery thermal runaway. Hence, battery temperature control is taken into account along with aging prevention in most cases [33], [51].

In order to solve the optimal charging problem, it is necessary to formulate an effective charging strategy based on the battery model.

Zou *et al.* employed a linear time-varying (LTV) model predictive controller (MPC) to optimize charging profiles [51]. By using a fast moving horizon estimation (MHE) to observe battery internal states in the presence of model mismatch, noise, and disturbances, the fast charging process was formulated as a constrained LTV-MPC problem. Meanwhile, health-related constrains were also included in solving the problem. The cost function for tracking a reference trajectory SOC^r with input current $u(k)$ and corresponding overall optimization current were organized as below:

$$u^*(k) = \arg\min_{u(k),s} \sum_{i=0}^{N} \left\| y_1(k+i) - y_1^r(k+i) \right\|_Q^2 + \|\Delta u(k+i)\|_R^2 + \|s\|_P^2 \tag{16}$$

$$J(\mathbf{x}(k), \mathbf{u}(k)) = \sum_{i=0}^{N} \left\| y_1(k+i) - y_1^r(k+i) \right\|_Q^2 + \|\Delta u(k+i)\|_R^2 \tag{17}$$

$$\begin{aligned} s.t.\ & \forall i \in \{0, \ldots, N\}, \\ & \hat{x}(k+i+1) = A_k \hat{x}(k+i) + B_k u(k+i) + \hat{\varphi}(k) \\ & \hat{y}_1(k+i) = C\hat{\mathbf{x}}(k+i) + d \\ & \hat{\mathbf{x}}(k) = \hat{\mathbf{x}}_{k|k} \\ & Hu(k+i) \le L \\ & \varepsilon_k \hat{\mathbf{x}}(k+i) + F_k u(k+i) \le S_k + s \\ & s \ge 0 \end{aligned} \tag{18}$$

Both the computational efficiency and charging rate of the MPC-based charging strategies are higher than traditional CCCV counterparts. However, the proposed charging strategy applied a maximum current of 15 C to charge the battery in the beginning, and the cell voltage exceeded the upper bound of 4.2V during charging. In Ref [33], the possibly fastest charging mode of the MPC-based algorithm is investigated by setting the weight factor to zero. It is found that the time required to charge the investigated battery from 10% SOC to the specified capacity level is no less than 788 s.

Liu *et al.* implemented the generalized predictive control (GPC) assisted with a proper battery model to control the battery internal within certain range during the charging process [69]. A controlled auto-regressive integrated moving average (CARIMA) model was used as an online self-tuning predictive model for a GPC controller. The predictive control sequence was obtained by minimizing a multistage cost function which combined both battery charging time and energy loss:

$$J = (1-a_1) * t_f + a_1 * \int_{t=0}^{t=t_f} i(t) * (V(t) - U_{OCV}(t)) + i(t) * T_{in}(t) * dU_{OCV}(t)/dT_{in}(t)dt \tag{19}$$

t_f denotes the time when the battery reaches its final SOC level. $0 \le a_1 \le 1$ is the weighting factor to balance the two objectives (charging time and energy loss). The main drawback of the GPC-based control strategy is that many tuning parameters should be chosen carefully in advance and the polynomial matrices are high-dimension, which adds up difficulties to real-time application.

Lin *et al.* developed the optimal charging strategies using the dynamic programming (DP) technique [70]. Both charging time and battery degradation were traded off and optimized. The charging time t_f, SEI growth δ_{SEI} and lithium plating $\delta_{plating}$ were considered in the cost function in SOC domain:

$$\min_{I(SOC)} \int_{SOClo}^{SOChi} (\alpha \cdot t_{char} + \beta \cdot \delta_{SEI} + \gamma \cdot \delta_{plating}) \tag{20}$$

By fixing different weight factors (α, β, γ) at specified values, the minimum time strategy and health-conscious fast charging strategy were investigated. For the minimum time strategy, it took 19 min 18 s to achieve a target SOC of 61% from 1.7% SOC and the charging duration increased to 29 min 7 s for the health-conscious strategy. Unfortunately, the weight factors for the recyclable lithium consumed in SEI growth and lithium plating were treated as equal at random.

In [64], the Legendre-Gauss-Radau (LGR) pseudo-spectral method with adaptive multi-mesh-interval collocation was employed to solve the resulting nonlinear multi-state optimal charging problem. The objective function J is given by:

$$\min_{I(t),x(t),t_f} \int_{t_0}^{t_f} 1 \cdot dt \tag{21}$$

where $(t_f - t_0)$ is the charge time to reach a desired target SOC. The optimization variables are the input current $I(t)$ and final time t_f, with state variables:

$$x(t) = [c_s^+(r,t), c_s^-(r,t), c_e^+(x,t), \times c_e^{sep}(x,t), c_e^-(x,t), T_c(t), T_s(t)]^T \tag{22}$$

Two charging strategies were proposed using the linear quadratic control theory by Fang *et al.* in 2017 [27]. One of them is based on linear quadratic control with fixed terminal charging rate. The other one is formed with tracking a reference charging path. A linear quadratic state-feedback formulation for tracking a reference trajectory r_N can be expressed as:

$$\begin{aligned}\min_{u_0,u_1,\ldots,u_{N-1}} & \frac{1}{2}(x_N - r_N)^{\mathrm{T}} S_N (x_N - r_N) \\ & + \frac{1}{2}\sum_{k=0}^{N-1}\left[(x_k - r_k)^{\mathrm{T}} Q (x_k - r_k) + u_k^{\mathrm{T}} R u_k\right] \\ s.t.\ & x_{k+1} = Ax_k + Bu_k, x_0 \end{aligned} \tag{23}$$

Another form of the quadratic constraint program was presented by Trippe *et al.* [71] in 2014, which minimized total charging cost, charging electricity cost and battery aging cost. Eq.18 describes the linear objective function of the optimization problem, where charging power P and battery aging cost c_{aging} are the variables to be optimized. The electricity price is reflected by pr and Δ_t is the time step. n_{park} and t are indices for the number of the parking events of a car and the charging time respectively. The main drawback of Annette's strategy is that the tremendous information on vehicle usage history is needed [71].

$$\arg\min_{P,c_{aging}} \sum_{n_{park}} \sum_{t} \left(P\left(n_{park}, t\right) \cdot pr\ (t) \cdot \Delta t + c_{aging}\left(n_{park}, t\right)\right) \tag{24}$$

In 2016, Pramanik and Anwar introduced an optimal strategy for charging under Pontryagins principle with both state and input constrains [72]. The proposed charging algorithm is capable of shortening the charging time while satisfying the temperature constraint compared with standard CCCV charging. The performance index was defined as:

$$P.I. = \int_0^{T_f} \left[\alpha(I_{\max} - I(t))^2 + \beta(T_{\max} - T(t))^2 + \delta I^2(t)\right] dt \tag{25}$$

The performance index was chosen as such to minimize the effort and to keep the current and bulk cell temperature close to the maximum thresholds. Combined with battery model, the Hamiltonian function was constructed:

$$\begin{aligned} & H(C_s, T, \lambda_1, \lambda_2, t) \\ &\quad = \alpha(I_{\max} - I(t))^2 + \beta(T_{\max} - T(t))^2 + \delta I^2 \\ &\qquad + \lambda_1\left(-\frac{6i_0}{RF}\sinh\left(\frac{\alpha F}{RT}\eta(t)\right)\right) \\ &\qquad + \lambda_2\left(\frac{1}{\rho^{avg}c_p}\left[h_{cell}\left(T_{\max} - T\ (t)\right) + I\ (t)\ V\ (t)\right.\right. \\ &\qquad \left.\left. - \sum_{i=1}^{n}\left[\int_{0^-}^{0^+} \frac{3\varepsilon}{R} FJ(t)(U_i(t) - T(t)\frac{\partial U}{\partial T})dx\right]\right]\right) \end{aligned} \tag{26}$$

$$\lambda_1^{*\bullet} = \frac{\partial H(\bullet)}{\partial C_s} = 0 \tag{27}$$

$$\begin{aligned} \lambda_2^{*\bullet} &= \frac{\partial H(\bullet)}{\partial T} = 2\beta(T_{\max} - T) + \lambda_2^* \frac{h}{\rho^{avg}c_p} - \lambda_2^* \frac{h}{\rho^{avg}c_p} \\ &\times \left[\sum_{i=0}^{n}\left[\int_{0^-}^{0^+} \frac{3\varepsilon}{R} FJ(t)\left(U_i(t) - T(t)\frac{\partial U}{\partial T}\right) dx\right]\right] \\ &+ \lambda_1^* \frac{\alpha F}{RT^2}\eta\left[\frac{6i_0}{RF}\cosh\left(\frac{\alpha F}{RT}\eta\right)\right] \end{aligned} \tag{28}$$

where α, β are tunable parameters which gives the flexibility to tune the charging performance based on charging current and maximum rated limit. By solving the equation, the optimal current trajectory at each time step was obtained:

$$I(t) = I_{\max} - \lambda_2 \frac{V(t)}{\rho^{avg}c_p} \times \frac{1}{2\alpha} \tag{29}$$

C. SUMMARY AND COMPASIRON

The characteristics of the reviewed active charging strategies are summarized in Table 2. Their pros and cons are highlighted. In order to demonstrate the connections and differences among the reviewed optimal charging strategies more clearly, we intend to analyze them from two crucial aspects, which are internal battery model and optimal control algorithms.

1) ASSESSMENT OF THE REVIEWED BATTERY MODELS

As can be seen in Table 2, the commonly-used battery type are $LiFePO_4$, $LiCoO_2$, and NMC. Many different kinds of battery models are utilized to estimate the battery internal states. The first-order RC [69] model and second-order RC model [27] have been used in control and optimal applications due to its simple circuitry representation and easy to configure and identify the parameters compared to other mechanism models. The SPM is the most frequently used electrochemical model in battery optimal charging. Both of them are often coupled with thermal and aging dynamics, which are of great importance to control and optimize charging curve.

Generally, thermal effect is incorporated into the controller via a two-stage approximation of the radially distributed thermal model for equivalent circuit models [57]. However, the energy dissipated by electrode is assumed to represent the Li ion contribution and have an impact on the total heat generation [73]– [75].

An empirical equation between input current and capacity fade is adopted to indicate the aging effects for equivalent second-order RC model [57]. In SPM, the Li ion concentration in both solid and electrolyte phase and the overpotential of side reactions are constrained within a narrow range to prevent the battery from degradation. As for the SOC estimation method, the equivalent circuit model calculates the SOC by coulomb counting, while the SPM predicts it based on the Li ion concentration distribution and integration [64].

Methods like electrochemical models and equivalent models perform well but cannot be directly extended to other batteries (technology, design, materials) [76]– [78]. Moreover, these two approaches are not performant to model

TABLE 2. Comparison of the reviewed active optimal charging strategies.

	Model Predictive Control (MPC) based	Generalized Predictive Control (GPC) based	Dynamic Programming (DP) based	Legendre-Gauss-Radau pseudo-spectral based	Pontryagins minimum principle based	Linear Quadratic based	Linear optimization
Reference	[51],[32],[33], [76]	[69]	[70]	[64],[57]	[72]	[27]	[71]
Investigated battery type	Not specified	$LiFePO_4$	$LiFePO_4$	$LiFePO_4$	$LiCoO_2$	Not specified	18650 NMC
Battery model	SPM with electrolyte	First-order RC model	SPM with electrolyte	SPM with electrolyte	SPM	Second order RC model	Not specified
Characteristic	1.Model-based, closed loop and health-aware. 2. Battery internal states were observed by MHE algorithm.	1.Cell internal temperature was within a desirable range. 2. The CARIMA model was developed as online self-tuning tool.	1.DP was first employed to the optimal charging problem.	1.Solid and electrolyte phase concentration constraints and temperature constraints were satisfied. 2.Different input current bounds for fast charging is provided.	1.A performance index that aims at balancing the cell temperature and charging current was defined.	1.Health-aware and user involved.	1.Several Electric vehicles in Singapore and four different scenarios were evaluated.
Charging result	100% SOC in 781s (I_{max}=15C)	80% SOC in 1498.21s (I_{max}=3C)	100% SOC in 1158s (I_{max}=6C) for fast charging or 1747s (I_{max}=5C) for health-conscious charging	50% SOC in 4.4822 min (I_{max}=8.5C)	100% SOC in 2758s (I_{max}=2C)	95% SOC in 2h (I_{max}=3C)	Constant power constant voltage mode (CPCV) with $I_{cut\text{-}off}$=110mA
Parameter need to be controlled online	SOC T C_e η_{side}	I V SOC	SOC C_e θ V	I θ C_e C_s T	I T	V I	SOC
Parameter need to be optimized	Not specified	Not specified	t_{char} δ_{SEI} $\delta_{plating}$	t_{char}	SOC	SOC	$P_{charging}$ c_{aging}
Advantage	1.Promoting the charging rate by 22%. 2.Safety related constraints could be satisfied. 3.Computation time < 10 ms.	1.Battery fast charging and internal temperature control were tackled simultaneously 2.Easy Implementation	1.Charging time and battery degradation were traded off and optimized. 2. Both SEI growth and Li plating were considered for aging mechanism.	1.Constraint satisfaction to ensure battery safety and longevity. 2.Obtaining new optimal charging protocols as the cell is cycled.	1.Battery temperature was controlled and abusive conditions were prevented. 2.Higher efficiency without compromising electrochemical kinetics.	1.Meeting user-defined charging objectives with awareness of the hazards.	1.Optimizing the charging process cost and battery aging cost.
Disadvantage	1.Hardware-in-the-loop validation experiment was not carried out.	1.Battery degradation effects were not considered.	1.Battery temperature was not controlled and optimized.	1.Aging dynamics was not incorporated.	1. Battery aging factor was not considered. 2.No corresponding experiment was conducted.	1.Only simulation validation, lacking corresponding experiment.	1.Battery aging model is simple without calendar aging and CV charging aging.

I=Current, V=Voltage, SOC=State of charge, θ = Electrode stoichiometric, C_e =Electrolyte concentration, C_s =Solid concentration, T =Temperature, η_{side} = Overpotential of side reactions, t_{char} =Charging time, δ_{SEI} = Solid e electrolyte interphase growth, $\delta_{plating}$ =Li^+ plating, $P_{charging}$ =Charging power, c_{aging} =Aging cost.

all degradation mechanisms occurring during the battery life [79]– [81].

2) OPTIMAL CONTROL ALGORITHMS SUMMARY

Every presented method tries to solve the optimal charging problem by different manners but each one has its own disadvantages. Most studies choose the maximum current (up to 6C) [70] to charge the battery in the beginning, this might bring high stress on power electronics [82]– [84]. In addition, many studies validate the effectiveness of optimal charging with accelerated life tests [71], but this methodology has one main drawback. An accelerated life test is usually done with a test bench. Hence, the impact of all environmental variables occurring in real life conditions is not taken into account, which produces some errors.

Each of the presented algorithm can perform well in finding out a balanced solution for the two competing objectives: charging time and battery state-of-health. As is illustrated in Table 2. It is seen that the MPC-based control strategy is the most popular method to be employed [33], [51], [85], [86]. There are two reasons for the popularity of MPC techniques. First, its performance in constraint and nonlinearity handling and model-based optimal or suboptimal control makes it applicable to a wide range of industrial problems [87]. Second, it has a good robustness and stability over many kinds of noises [88], [89]. However, it has two limits:1) Hardware-in-the-loop experiment was not conducted to validate the strategy.2) The sensitivity of the proposed MPC framework to parameter uncertainties including the weighting matrices and initial values were not studied. Due to the high non-linearity of this problem, the electrolyte dynamics approximation, SEI and plating static map were developed to make the Dynamic Programming (DP) based charging optimization possible [70]. The inconvenience here is the complexity to handle massive data in controller induced by DP process. The Legendre-Gauss-Radau (LGR) pseudo-spectral based method transcribed this infinite-dimensional optimal control problem into a finite-dimensional optimization problem with algebraic constraints at the discretized nodes [57], but the convexity and convergence was not guaranteed. For Pontryagins minimum principle based strategy [72], the algorithm calculates the states and co-state values to produce the corrected input current at each iteration. Therefore, the initial value for state variables were required to be precise. Regarding the linear optimization based methods [27], they have more computational appeal in terms of time and space complexity because of their exceptional simplicity. Whereas the choice of the gain matrix is a multifaced issue, because it needs to account for both battery health protection and charging speed and more broadly, the economic cost and user satisfaction.

IV. SUGGESTIONS AND CHALLENGES

Based on the above review of the open literatures concerning the optimal strategies of battery charging, it seems that the most promising candidate for the health-aware optimal charging would be closed-loop and model-based. Two elements are essential for this: 1. A simplified and controllable battery model. 2. An optimization approach which is computationally efficient and well-fitted with the battery model. In light of this, here is a list of issues regarding the two aspects that should be addressed in the future investigations:

A. SUGGESTIONS FOR THE CONTROL-ORIENTED BATTERY MODLES

1. The electrochemistry-based battery model can have a high fidelity in reproducing battery dynamics which plays an important role in health-conscious charging protocol. For battery aging prevention, most studies chose side reaction related parameters as a part of cost function [51], [90]. For instance, the overpotential of side reactions is constrained below zero to alleviate degradation [51]. However, to the authors knowledge, the aging mechanism of battery charging has not been investigated thoroughly. What are the consequences on selecting higher or lower bonds? Apart from SEI growth, which parameter should be calculated and taken into consideration for a better optimal curve?

2. The battery properties change as battery ages [91]– [94]. Therefore, the real-time controller should update battery parameters based on the input history data such as current, voltage and temperature. Finally, the on-line observation and the battery control and optimization performances will be improved.

B. SUGGESTIONS FOR THE CHARGING OPTIMIZATION ALGORITHMS

1.Most of the optimal control strategies reviewed in this paper are implemented by solving the optimal problem with series of new performance indexes and constrained linear matrix inequalities. However, the implementation cost in hardware is not paid much attention to. In fact, to achieve better charging performances, the computation burden also increases significantly [95]– [97]. Hence, it is imperative to develop a simple and fast optimal algorithm that can be simulated in BMSs effectively.

2. As a result of the wide diversification in battery types and sizes due to the wide range of applications, the reviewed optimal charging method might not be directly extended to other batteries (technology, design, materials) [98]– [100]. Thus, it is meaningful to develop universal optimal charging strategies. This feature may be realized by the controller to auto-detect the battery chemistry responses when they are biased to some external signal or by big data-driven approach [101].

C. CHARGING STRATEGIES AT LOW TEMPERATURES

1. Fast charging at subzero temperatures is an challenging task due to the poor low-temperature performance of Li-ion batteries [104]. The Li plating is assumed to be the major unwanted side reactions at low temperatures [105]. Though some efforts have been deployed to overcome these problems. A two-phase charging protocol composed of constant current (CC) and constant voltage (CV) phase is presented

to prevent battery degradation from Li plating [106]. By adding a rapid internal heating step before charging, the cell is charged above a temperature that can prevent Li plating [107]. The related studies are still insufficient. It is important to systematically investigate the battery electrochemical model characteristics and aging mechanisms under low temperatures, which finally lead to optimized charging strategies.

V. CONCLUSION

Battery optimal charging strategies have been intensively researched and developed in recent years. This paper has presented a thorough review of recent optimal charging methodologies for commercial lithium-ion batteries. They are commonly grouped based on their mathematical model and embedded structure: passive and active controllers. Every of them is described in detail along with their advantages, disadvantages and examples. While passive charging strategies are simple to implement, it is clear that they do not provide an optimal solution to maximize charging speed and minimize deterioration. They lack the ability to maintain a good robustness when noises occur. Active charging algorithm will improve the performance of the battery and efficiency of the charger. Multiple battery state variables are integrated to the cost function which is important to formulate a battery model based charging protocol. Active charging controllers are implemented using different optimal methodologies which have been summarized. The study has shown that MPC-based techniques are the most popular and potential methods to figure out the optimal charging problem. The main drawback is that the present MPC algorithm can only applied into linear system which means that the full-order battery model should be properly simplified before being simulated. As a result, the accuracy of the control might be affected. The following aspects of the optimal charging strategies should be addressed in the future investigations: 1) To include an overall aging effects caused by charging process; 2) To evaluate the precision of embedded battery model under proposed charging current; 3) To update battery parameters in real-time; 4) To investigate the implementation cost of proposed charging algorithm in BMSs hardware; 5) To propose universal optimal charging strategies; 6) To shed lights on battery optimal charging at low temperatures.

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