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Charging optimization in lithium-ion batteries based on temperature rise and charge time

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HIGHLIGHTS

- Temperature rise and charge time constraint charging strategy is introduced.
- Genetic algorithm is wielded to optimize the charge current trajectories.
- The proposed method can reduce charge time notably with rational temperature rise.
- Battery charge performance and aging using the proposed approach are evaluated.

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ABSTRACT

Lithium-ion battery fast charging issues have become a main bottleneck of large-scale deployment of electric vehicles. This paper develops a polarization based charging time and temperature rise optimization strategy for lithium-ion batteries. An enhanced thermal behavior model is introduced to improve the solution accuracy at high charging current, in which the relationship between polarization voltage and charge current is addressed. Genetic algorithm (GA) is employed to search for the optimal charging current trajectories. The effects of weighting coefficients of charging time and temperature rise on battery charging performance are discussed. The charging time of the optimized charging protocol is reduced by 50%, and the associated temperature rise is almost identical, compared to 1/3C constant current-constant voltage (CC-CV) charging. Aging experiments demonstrate that the proposed charging method has a similar capacity retention ratio to that of 0.5 CC-CV charging after 700 cycles, thereby accomplishing a good balance between charging speed and lifetime.

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1. Introduction

Electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) have been being rapidly developed in recent years, driven by the urgency to curb air pollutions caused by petroleum-dominant vehicles. The use of EVs and PHEVs will be increasingly widespread worldwide, and their annual sales will reach 100 million by 2050 [1]. Compared to internal combustion engine (ICE) fueled trivially; traction battery charging is much more complicated, due to its slow charging speed and unclear effects of charging strategies on battery durability. Lithium-ion battery fast charging challenges constitute a principle bottleneck of EVs applications. Therefore, battery charging control is a thriving area of research in the field of EVs/PHEVs.

Numerous charging methods have been reported in the literature, with various objectives, e.g., increasing charging speed, enhancing charging performance, and maximizing battery life. Ref. [2] proposed a charging strategy of lithium batteries, based on an integration of Taguchi method and SOC estimation to search an optimal charging current profile. Guo et al. proposed an optimum charging technique for lithium ion batteries using a universal voltage protocol, which has the potential to improve charging efficiency and cycle life [3]. Ref. [4] developed a dual-objective optimal charging strategy based on equivalent circuit models, whereby charging time and charging energy loss are optimally traded off. Ref. [5] uses dynamic programing optimization

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algorithm to find a sub-optimal charging protocol under a certain balance between charging time and charging loss. Ref. [6] proposes an online tracking algorithm to allocate and track the optimal charging frequency for common batteries in real time under any condition. Ref. [7] presents a framework for optimizing lithium-ion battery charging subject to side reaction constraints, which can help avoid damage phenomena. Methods for battery charging optimization can be mainly categorized as improved charging current waveforms based methods [2,3,5,6,8–10], battery model based methods [4,7,11–16], polarization based methods [17,18], and enhanced battery material based methods [19]. Improved charging current waveforms based methods are generally simple to control and implement. However, they are often heuristic and lack of theoretical foundations in choosing battery charging current in an optimal manner. Battery model based methods can predict charging current by employing, e.g., a lumped equivalent circuit model, an ac-impedance model, or an electrochemical model. They combine external electrical behavior with internal reaction mechanisms, searching for optimal charging current. Diverse modeling and identification methods are developed to acquire parameters with high precision [20–24]. Nevertheless, effects of battery temperature and health fade on model parameters need to be further investigated. Polarization based methods provide acceptable charging current with constraints on battery polarization voltage. The polarization modeling and its quantitative effects on battery life are worth further examination. The enhanced battery material based methods improve the capability of battery charging acceptance by adding additives to the electrode materials or using new materials. However, stability and safety of such batteries need to be further examined, which cannot be applied in real-world EVs in a short term.

Temperature has a significant impact on lithium-ion battery performance and lifetime [25–27]. Battery activity increases as temperature is elevated. Nevertheless, if temperature increases over allowable limits, the stability of battery cathode lattice structure is getting worse, which not only accelerates battery degradation, but also results in battery safety hazards. Accelerated aging in thermal cycling for LMO batteries at 40 °C was observed, which are mainly caused by active material losses in both electrodes, generalized loss of lithium inventory, and inhibited kinetics [28]. During rapid charging, temperature gradient will inevitably increase since average charging current is enlarged, leading to lifetime decrease if operated in unreasonable thermal excursions. However, maximum charging currents differ at discrepant regions of battery state of charge (SOC), which makes balancing charging speed and temperature rise possible. In our previous study [18], an acceptable charging current curve has been pursued in accordance with lithium-ion battery polarization voltage behavior. The charging curve is able to prevent polarization from being out of range and thus be conducive to increasing charging capacity and charging speed.

This paper focuses on constraint analysis of temperature rise, optimal charging strategy, and reliable algorithm towards optimized charging patterns. There are three major contributions added to the related literature. First, an enhanced thermal behavior model is introduced to improve the solution accuracy at high charging current, and the relationship between polarization voltage and charge current is addressed. Second, a polarization based charging time and temperature rise optimization strategy for lithium-ion batteries is proposed to equilibrate charging speed and lifetime. Finally, genetic algorithm (GA) is wielded to search for the optimal charging current trajectories, taking temperature rise constraint and charging time into account. The implication of weighting coefficients is also explored.

The remainder of the paper is organized as follows. Section 2 describes the thermal model. Section 3 formulates the optimal charging strategy, reconciling temperature rise with charging time. Section 4 presents experimental validations, followed by conclusions summarized in Section 5.

2. Enhanced thermal behavior model

Battery surface is assumed to has a uniform temperature when charge current is within some limits, which can be regarded as a particle cell for thermal modeling. The thermal behavior model can be expressed by the following equation [29]:

$$C_{\text{cell}}\frac{dT_{\text{cell}}}{dt} = Q_{\text{S}} + Q_{\text{O}} - Q_{\text{B}} \tag{1}$$

where C_{cell} represents heat capacity of battery, T_{cell} expresses battery temperature, Q_{S} is reversible reaction heat by entropy change ΔS, Q_{O} is the energy loss by the overpotential during charge and discharge cycles, and Q_{B} is the transferred heat. It should be noted that the average heat capacity is adopted in the study since it differs among active material components of battery. The temperature change of battery is governed by both endothermic transition and exothermic transition. The battery temperature is gradually rising while absorption of heat is greater than heat release due to heat accumulation.

The reversible reaction heat by entropy change can be described by

$$Q_{\text{S}} = T_{\text{cell}}\Delta S\frac{I}{nF} \tag{2}$$

$$\Delta S = -\frac{\partial \Delta G}{\partial T_{\text{cell}}} = nF\frac{\partial E}{\partial T_{\text{cell}}} \tag{3}$$

where F is Faraday constant, I is charge current, n is the number of moles of electrons transferred in the cell reaction ($n = 1$ for a lithium-ion battery), ΔG is Gibbs free energy change for the cell reaction, and E is cell equilibrium that can also be replaced with close-to-equilibrium open-circuit voltage in approximate treatment. The differential $\partial E/(\partial T_{\text{cell}})$ is negative, and Q_{S} is endothermic during charging.

The transferred heat is expressed by

$$Q_{\text{B}} = hA(T_{\text{cell}} - T_{\text{amb}}) \tag{4}$$

where h is heat transfer coefficient, A is the total surface of cell, and T_{amb} is ambient temperature.

Cell overpotentials comprise mass transport polarization overpotential, charge transfer overpotential at positive and negative electrodes, and ohmic overpotential. It is usually for overpotential heat Q_{O} to be described as the square of current multiplied by overpotential resistance $Q_{\text{O}} = I^2R_{\eta}$, in which the overpotential resistance R_{η} is regarded as constant [22], and the R_{η} at SOC = 0% is always applied. However, the polarization voltage has a linear relationship to charge current, rather than a proportional relation, and its slope is a function of SOC, which has been reported in our prior paper [12]. The simulation error of temperature using conventional calculation method will be consequently enlarged as the current increases. Considering the influence of SOC on polarization overpotential and ohmic overpotential, the overpotential heat can be rearranged as follows:

$$Q_{\text{O}} = Q_{\text{P}} + Q_{\text{J}} \tag{5}$$

$$Q_{\text{P}} = IU_{\text{P}} \tag{6}$$

$$Q_{\text{J}} = I^2R_{\Omega} \tag{7}$$

where Q_{P} represents the energy loss by polarizations, U_{P} is cell polarization voltage expressed as $U_{\text{P}} = kI + b$ [16], and Q_{J} represents the energy loss by ohmic resistance.

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