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An advanced Lithium-ion battery optimal charging strategy based on a coupled thermoelectric model

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A B S T R A C T

Lithium-ion batteries are widely adopted as the power supplies for electric vehicles. A key but challenging issue is to achieve optimal battery charging, while taking into account of various constraints for safe, efficient and reliable operation. In this paper, a triple-objective function is first formulated for battery charging based on a coupled thermoelectric model. An advanced optimal charging strategy is then proposed to develop the optimal constant-current-constant-voltage (CCCV) charge current profile, which gives the best trade-off among three conflicting but important objectives for battery management. To be specific, a coupled thermoelectric battery model is first presented. Then, a specific triple-objective function consisting of three objectives, namely charging time, energy loss, and temperature rise (both the interior and surface), is proposed. Heuristic methods such as Teaching-learning-based-optimization (TLBO) and particle swarm optimization (PSO) are applied to optimize the triple-objective function, and their optimization performances are compared. The impacts of the weights for different terms in the objective function are then assessed. Experimental results show that the proposed optimal charging strategy is capable of offering desirable effective optimal charging current profiles and a proper trade-off among the conflicting objectives. Further, the proposed optimal charging strategy can be easily extended to other battery types.

1. Introduction

To meet the unprecedented challenges on environmental protection and climate change, electric vehicles (EVs) and hybrid electric vehicles (HEVs) are developing rapidly in recent years [1]. Compared with conventional internal combustion engine (ICE) based vehicles, EVs are powered by batteries that may be charged from renewable power generated from the wind, solar or other forms of renewable sources [2]. Among all batteries types, Lithium-ion (Li-ion) batteries are preferable power supplies for EVs due to a number of favourable characteristics such as power density, less pollution, and long service life [3]. For Li-ion batteries, a proper battery charging strategy is essential in ensuring efficient and safe operations.

The charging strategy is a key issue in the battery management system (BMS) of EVs [4]. An optimal charging operation will protect batteries from damage, prolong the service life as well as improve the performance [5]. On the one hand, long charging time will inevitably affect the convenience of EV usage and limit its acceptance by customers [6]. However, too fast charging will lead to significant energy loss and battery performance degradation. It is therefore rational to consider the charging time as one of the key factors in designing the EVs charging control. Secondly, large energy loss implies low efficiency of energy conversion in battery charging, which needs to be addressed. Finally, both the battery surface and internal temperatures may exceed permissible level when it is charged with high current, and the overheating temperatures may intensify battery aging process and even cause explosion or fire in severe situations [7,8]. Thus, the battery charging time, energy loss, and temperature rises are important factors to be considered in designing the battery charging process.

Conventional methods used for battery charging can be divided into constant current (CC) strategy, constant voltage (CV) strategy and Mas Law strategy [9,10]. The constant current strategy simply uses a small constant current to charge battery along the whole process to avoid the steep rise in both the battery voltage and temperature. However, it is difficult to achieve a proper current rate to balance the battery charging time and the desired capacity. Another simple charging strategy utilizes CV to avoid over-voltage.

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Nomenclature

V	battery terminal voltage
R_1, R_2	battery diffusion resistances
C_1, C_2	battery diffusion capacitances
V_1	R_1C_1 network voltage
V_2	R_2C_2 network voltage
U_{OCV}	battery open circuit voltage
i	charge current
R	battery internal resistance
soc	battery state of charge
C_n	battery nominal capacity
T_s	sampling time period
T_{in}	battery internal temperature
T_{sh}	battery surface temperature
T_{amb}	battery ambient temperature
D_1	battery internal thermal capacity
D_2	battery surface thermal capacity
k_1,k_2	battery thermal conduction coefficients
Q	battery thermal dissipation
J_{CT}	battery charging time cost function
J_{EL}	battery energy loss cost function
J_{TR}	battery temperature rise cost function
J_{TinR}	battery internal temperature rise cost function
J_{TshR}	battery surface temperature rise cost function
J_{Charge}	battery charging triple-objectives cost function
s_0	battery charging initial SOC
s_{tf}	battery charging final SOC
i_{min}	battery minimum charging current
i_{max}	battery maximum charging current
V_{min}	battery minimum terminal voltage
V_{max}	battery maximum terminal voltage
$J_{charge_{C}C}$	battery constant current process cost function
$J_{charge_{C}V}$	battery constant voltage process cost function

This strategy however requires a high current at the beginning of the charging process which can be quite harmful to the battery life. While the Mas Law strategy calculates the charge current based on the 'Mas Three Laws' principle [11,12] discovered by American scientist J. A. Mas in researching the maximum acceptable charge current. According to the Mas Three Laws, the charging receptivity is proportional to the square root of the discharging capacity and the logarithm of the discharging current. Further, the charging receptivity after several different discharging rates is equal to the total charging receptivity after each rate. It should be noted however that the Mas Law strategy is mainly used to develop pulse charging strategy for significantly improving the charging acceptance ability of lead-acid batteries rather than Li-ion batteries [13,14].

The constant-current-constant-voltage (CCCV) strategy, which integrates the CC strategy and CV strategy, has become the most popular strategy for Li-ion battery charging [15]. In this strategy, a CC is injected into battery first and the battery terminal voltage increases until the maximum safe threshold is reached. Then the battery starts to be charged at a CV until the battery capacity meets the target. Although the CCCV strategy is simple to apply, the open problem is to select an appropriate charging current at the CC stage. High current may cause large energy loss, and the temperature may exceed permissible levels especially in high power applications. On the other hand, low charging current may prolong the battery charging time, affect the convenience of EV usage and limit its acceptance by customers. Therefore, it is vital to develop a better strategy based on CCCV to improve the overall charging performance and to guarantee the battery operation safety.

Various approaches have been proposed to improve the battery charging performance in the literature. Methods involving computational intelligence techniques such as neural networks [16], gray prediction [17], fuzzy control [14,18], and ant-colony algorithm [19] have been proposed to optimize the charging current profile. Jiang et al. [14] propose a constant-polarization-based fuzzy-control charging strategy to adapt charging current acceptance with battery state of charge (SOC) stages. The charging time can be significantly shortened without obvious temperature rise compared to standard CCCV. Although these intelligent approaches are based on criteria such as fast charging and extended energy capacity, it is relatively expensive to tune the parameters in these algorithms. Further, none of the aforementioned charging approaches consider the energy loss during the battery charging process.

Some other strategies consider the battery charging as an explicit optimization problem. Hu et al. [20] present a dual-objective optimal charging strategy for both lithium nickel-manganese-cobalt oxide (LiNMC) and lithium iron phosphate ($LiFePO_4$) batteries to offer an optimal trade-off between the energy loss and the charging time. The effects of the battery maximum charging voltage, ambient charging temperature and battery health status are analyzed. Zhang et al. [21] use the dynamic programming (DP) method to solve the trade-off problem concerning the charging time and the energy loss. A database based optimization approach is also proposed to decrease the computation time during the optimization process. These two strategies have balanced the charging time and the charging efficiency, while the battery temperature during the charging process is not considered. It should be noted that the battery temperature is a key factor for battery charging as too high or low temperature would harm the battery.

Abdollahi et al. [22] propose a closed-form optimal control solution to solve the optimal charging of a Li-ion battery. An objective function which considers the time-to-charge, energy losses and a temperature rise index is used to acquire the optimal CCCV solution. But some model parameters such as internal resistance are assumed to be constant in calculating the optimal charging current, this however will inevitably affect the efficacy of the method as variations of the battery internal resistance cannot be ignored due to its significant impact on the battery performance [23]. In addition, this strategy only considers the objective function for the CC stage in order to apply the variational method, and this inevitably affects the efficiency of the CV stage due to the fact that the current profile at the CC stage is derived separately using a different objective function. As a result, the CCCV charging is unlikely optimal as a whole. It is therefore vital to optimize the whole CCCV process to achieve a desirable performance.

In this paper, we propose to simultaneously consider the battery charging time, energy loss and battery temperature rise (both interior and surface) as three conflicting objectives, and a triple-objective function based on a battery coupled thermoelectric model is formulated. Our goal is to design a battery optimal charging strategy to determine an optimal CCCV profile with a satisfactory trade-off among the three conflicting objectives. This is however a challenging and difficult issue. Our earlier study [24] proposes the coupled thermoelectric battery model where the battery thermal behavior especially the battery internal temperature and electric behavior (SOC and voltage) are simultaneously considered. Besides, variable parameters such as the internal resistances can be calculated for different operation conditions. Based on our early developed thermoelectric model, this paper