Battery Optimal Charging Strategy Based on A Coupled Thermoelectric Model

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Abstract— **Battery charging strategy is a key issue in battery management system to ensure good battery performance and safe operation during the charging process. In this paper, a novel battery optimal charging strategy is proposed by applying the TLBO algorithm to a LiFePO4 battery for an optimal charging based on a coupled thermoelectric model. A specific dual-objective function including battery charging time and temperature rise (both battery interior and surface) is formulated first. Then a battery optimal charging strategy is presented in detail by using the TLBO algorithm, aiming at finding a suitable constant-current-constant-voltage (CCCV) current profile to minimize the dual-objective function. Besides, the effects of different weights in dual-objective function on the optimal charging profile are analyzed. Simulation results demonstrate that the presented optimal charging strategy can provide effective and acceptable optimal charge current profile. The strategy can be also easily implemented to other battery types to effectively balance the battery charging time and battery temperature rise during charging process.**

Keywords—battery optimal charging; teaching–learning-based-optimization; coupled thermoelectric model;

I. INTRODUCTION

Extensive consumption of fossil fuels especially non-renewable petroleum products worldwide has already led to significant environment pollutions and has huge impacts on the climate change. More strict legislations on emissions have encouraged manufacturers include automobile industry to opt for more renewable and clean energy sources. Electrification of the transport sector is one of the major initiatives launched by many governments worldwide to replace internal combustion engine (ICE) vehicles in a bid to minimize the emissions from the tale pipes of hundreds of millions of vehicles. Lithium-ion batteries have been widely used as the power supplies in electric vehicles due to their outstanding performance in terms of power densities, longevity and environmental characteristics [1]. The Li-ion battery has been applied in many areas and often needs to be charged when being idle. Therefore, a proper battery charging strategy is a key in battery applications as it has direct impact on the battery safety and behaviour.

Conventional methods for battery charging can be grouped into constant current strategy, constant voltage strategy and constant-current-constant-voltage (CCCV) strategy. The constant current strategy is easy to implement but difficult to get a proper current rate to balance the battery capacity and the charging time. The constant voltage strategy is also easy to apply but the current would be very high at the beginning of the charging process, which is harmful to the battery safety and performance [2].

The constant-current-constant-voltage (CCCV) strategy is the most popular strategy for Li-ion battery charging [3] due to its convenience and effectiveness to charge batteries. But it is still difficult to use the true operating range of batteries efficiently due to the limitation of voltage boundary. Besides, if just using CCCV strategy to charge battery without any other measures, the battery temperature would exceed the acceptable threshold especially in some high power application cases. Excessive temperature has a huge negative impact on battery performance and safety. Therefore, it is necessary to develop suitable solutions for CCCV strategy implementation.

Over the years, a number of approaches have been developed to improve the battery charging performance. Some of the approaches involve computational intelligence techniques including neural networks [4], grey prediction [5], fuzzy control [6], and ant-colony algorithm [7]. Some other strategies take the battery charging behaviors as an explicit optimization problem which is then solved using an optimization technique. The dynamic programing (DP) method [8], and pseudo-spectral technique [9] have been applied to solve the battery optimization charging problem. But these researches do not consider the battery temperature during the charging process. It should be noted that the battery temperatures (both the surface and interior) are key factors to consider for battery charging because too high or low temperature would be harmful to battery charging safety and behaviour.

In this paper, we simultaneously consider the battery charging time and battery temperature (both interior and surface) rise as two conflicting objectives and formulate a novel dual-objective function based on a newly developed battery coupled thermoelectric model. Our target is to design a battery optimal charging strategy to determine a suitable CCCV current profile which offers a desirable trade-off between the two conflicting objectives while minimizes the dual-objective function. Our prior researches [10,11] proposed the battery coupled thermoelectric models where the battery temperature (both interior and surface) and electric behavior (state of charge and voltage) can be simultaneously considered. Some recent meta-heuristic methods, in particular here the

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teaching-learning-based-optimization (TLBO) algorithm [12] will be applied to solve the nonlinear varying battery charging optimal target. The effects of different weight settings especially for charging time and temperature rise on the charging results are also analyzed and evaluated.

The paper is organized as follows. In section II, we briefly describe the coupled thermoelectric model and the corresponding parameters for a $LiFePO_4$ battery. In section III, the dual-objective function which considers the battery charging time and temperature rise is presented. In section IV, the principle of TLBO and detail procedures for battery optimal charging strategy are described. Section V illustrates the simulation result and the paper is concluded finally in section VI.

II. BATTERY COUPLED THERMOELECTRIC MODEL

A. LiFePO4 Battery Thermoelectric Model

We consider a first-order RC model as shown in Fig. 1 to describe the electric behavior of the LiFePO4 battery. The first-order RC model is composed of a battery open circuit voltage U_{OCV}, a battery internal resistance R, and a battery resistance-capacitor R_1C_1 network.

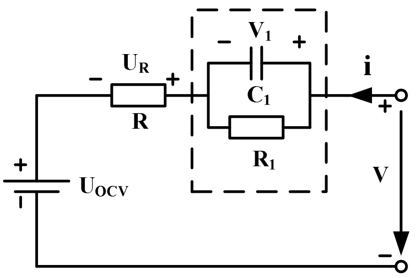

Fig. 1. Battery first-order RC model

The electrical potential balance for this first-order RC model is described by

$$V = V_1 + i \times R + U_{OCV} \tag{1}$$

where V and i represent the battery terminal voltage and current respectively. V_1 is the battery polarization voltage. R is the battery internal resistance and varies with the battery internal temperature. Neglecting the effect of temperature, the value of U_{OCV} is the function of battery SOC level independently.

Battery SOC is calculated based on battery nominal capacity shown as follows,

$$\mathrm{soc}(k) = \mathrm{soc}(k-1) - T_s \times i(k-1) / C_n \tag{2}$$

where C_n is the battery nominal capacity and T_s represents the sampling time period.

Suppose the terminal current keeps constant during the sampling period, the battery polarization voltage V_1 can be calculated by,

$$V_1(k) = a_1 \times V_1(k-1) + b_1 \times i(k-1) \tag{3}$$

where $a_1 = \exp(-\Delta T / R_1 C_1)$, $b_1 = (1 - \exp(-\Delta T / R_1 C_1))$. (4)

For the battery thermal aspect, we consider a two-stage approximation of the radially distributed thermal model described as

$$C_1 \times \dot{T}_{in} = i^2 \times R + k_1 \times (T_{sh} - T_{in}) \tag{5}$$

$$C_2 \times \dot{T}_{sh} = k_1 \times (T_{sh} - T_{in}) + k_2 \times (T_{amb} - T_{sh}) \tag{6}$$

where T_{sh} and T_{in} stand for battery surface temperature and internal temperature respectively. k_1, k_2 are two coefficients which stand for the heat dissipation rates.

Assuming $\dot{T}(k+1) = (T(k+1) - T(k)) / T_s$, this two-stage thermal model can be finally simplified as

$$T_{in}(k+1) = (1 - \frac{T_s k_1}{C_1}) \times T_{in}(k) + \frac{T_s k_1}{C_1} \times T_{sh}(k) + \frac{T_s R}{C_1} \times i^2(k) \tag{7}$$

$$T_{sh}(k+1) = \frac{T_s k_1}{C_2} \times T_{in}(k) + \left(1 - \frac{T_s(k_1 + k_2)}{C_1}\right) \times T_{sh}(k) + k_2 \times T_{amb} \tag{8}$$

In our previous work, the battery RC model and two-stage thermal model have been successfully combined together [10][11] and finally the coupled thermoelectric model is given as follows,

$$\begin{cases} x(k+1) = A \times x(k) + B(k) \\ \mathrm{V(k)} = V_1(k) + R \times i(k) + U_{OCV} \end{cases} \tag{9}$$

where $x(k) = [SOC(k), V_1(k), T_{in}(k), T_{sh}(k)]^T$ (10)

$$\mathrm{A} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & a_1 & 0 & 0 \\ 0 & 0 & 1 - T_s k_1 / C_1 & T_s k_1 / C_1 \\ 0 & 0 & T_s k_1 / C_2 & 1 - T_s (k_1 + k_2) / C_2 \end{bmatrix} \tag{11}$$

$$B(k) = [-T_s \times i(k) / C_n, b_1 \times i(k), \quad R \times i^2(k), \quad k_2 T_{amb}]^T \tag{12}$$

B. LiFePO4 Battery Thermoelectric Model Parameters

In order to design battery optimal charging strategy, it is vital to identify the parameters of the thermoelectric model. Under the laboratory conditions, a LiFePO4 battery cell with 10 Ah nominal capacity and 3.2V nominal operation voltage was tested for this study. The detailed identification process could be referred in our previous work [11] and will be not described in this paper due to space limitations.

Note that some variable parameters in this coupled model have the following distinctive features: 1) Internal resistance R may change depending on different battery internal temperature; 2) The value of battery open circuit voltage U_{OCV} is a function of battery SOC level. The relationship of battery R and U_{OCV} under different situations is shown in Fig. 2 and Fig. 3 respectively.

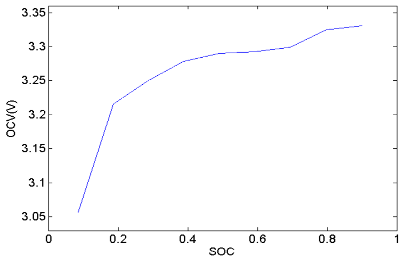

Fig. 2. Relation of battery OCV [V] and SOC

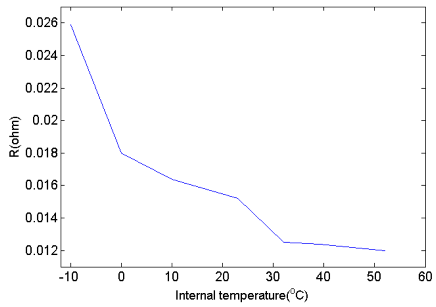

Fig. 3. Relation of battery resistance R [ohm] and internal temperature

After identifying these variable parameters, the other constant parameters for this coupled thermoelectric model can be identified by the least-square (LS) method. The results for these constant parameters are shown in Table I. According the validation tests for battery voltage and heat generation in our previous work [10], the maximum voltage error is 63mV (2.1% of battery nominal voltage), the maximum errors for internal and shell temperature are 1.41°C and 1.52°C respectively. These modelling errors are acceptable and have no major effect on designing our battery optimal charging strategy.

TABLE I. CONSTANT PARAMETERS FOR BATTERY COUPLED THERMOELECTRIC MODEL

Constant Parameters	Value
a_1	0.979
b_1	$1.8e^{-4}$
C_1	264.2
C_2	31.1
k_1	1.259
k_2	0.2994

III. DUAL-OBJECTIVE OPTIMAL CHARGING FORMULATION

In this section, we present a dual-objective function based on our battery coupled model. This dual-objective function is composed of two terms including battery charging time, and battery temperature rises (both the surface and interior). Besides, some battery physical constraints are also considered during charging process.

A. Dual-objective Function

Considering the battery charging as an optimization problem, some indicators need to be considered to guarantee the battery charging performance. Battery charging time is a key in charging process because minimizing charging time can expand the applications of battery. Besides, the temperature rises caused by injecting current into battery also play important roles in battery charging behaviour. It should be noted that there is a large gap between battery internal and surface temperature during battery charging process. In some cases especially high power applications, the different for battery internal and surface would go up to nearly 10°C [11]. Extra-high temperature especially the internal temperature will lead to huge damage to the battery behaviour and even cause serious safety problem. Therefore, the dual-objective function takes the battery charging time and temperature rise (both the interior and surface) into account.

According to the battery coupled thermoelectric model given in Section II, the sub-cost function battery charging time (CT) can be calculated as follows:

$$J_{CT} = T_s \times k_{tf} \tag{13}$$

where J_{CT} is the sub-cost function battery charging time (CT). T_S is the sampling time period (in seconds) and k_{tf} stands for the time when battery being charged to its final targeted capacity. Then $T_S \times k_{tf}$ stands for the total battery charging time.

For battery two-stage thermal model Eq. (7) and (8), we easily define two indexes for battery temperature rise respectively:

$\tilde{T}_{in}(k) = T_{in}(k) - T_{amb}$ for internal temperature rise, and

$\tilde{T}_{sh}(k) = T_{sh}(k) - T_{amb}$ for surface temperature rise.

Substituting these two battery temperature rise indexes into Eq. (7) and (8), we can finally give the temperature rise indexes described as

$$\begin{cases} \tilde{T}_{in}(k+1) = A_1\tilde{T}_{in}(k) + B_1\tilde{T}_{sh}(k) + CR(k)i^2(k) \\ \tilde{T}_{sh}(k+1) = A_2 \times \tilde{T}_{in}(k) + B_2 \times \tilde{T}_{sh}(k) \end{cases} \tag{14}$$

where $A_1 = 1 - T_s k_1 / C_1$, $B_1 = T_s k_1 / C_1$, $C = T_s / C_1$, $A_2 = T_s k_1 / C_2$, $B_2 = 1 - T_s(k_1 + k_2)/C_2$ respectively.

Assuming $T_{in}(0) = T_{amb}$ and $T_{sh}(0) = T_{amb}$, we have $\tilde{T}_{in}(0) = 0$, $\tilde{T}_{sh}(0) = 0$.

Then the sub-cost function J_{TR} for battery internal temperature rise (J_{inR}) and surface temperature rise (J_{shR}) can be described as

$$J_{TR} = J_{TinR} + J_{TshR} \tag{15}$$

where $J_{TinR} = T_s \sum_{k=0}^{k_{tf}} \tilde{T}_{in}(k)$ and $J_{TshR} = T_s \sum_{k=0}^{k_{tf}} \tilde{T}_{sh}(k)$.

The final dual-objective function *Jcharge* is a combination of these two sub-cost functions J_{CT} and J_{TR}. In other words,

$$J_{charge} = J_{CT} + J_{TR} \quad (16)$$

where the sampling time period T_s for this battery charging process is defined as 1 second. Terms in this dual-objective function can be calculated based on our battery coupled thermoelectric model.

B. Constraints and CCCV optimization formulation

The optimization target in this study is to determine a proper charging current profile to charge battery while minimize the dual-objective function *Jcharge*. The physical constraints including battery SOC level, current and voltage will be also considered during optimal charging process. The goal for this battery optimal charging strategy can be described as follows.

Minimize dual-objective function *Jcharge* subject to:

$$\begin{cases} \mathrm{soc}(k) = \mathrm{sco}(k-1) - T_s \times i(k-1)/C_n \\ V_1(k) = a_1 \times V_1(k-1) + b_1 \times i(k-1) \\ \tilde{T}_{in}(k) = A_1\tilde{T}_{in}(k-1) + B_1\tilde{T}_{sh}(k-1) + CR(k-1)i^2(k-1) \\ \tilde{T}_{sh}(k) = A_2 \times \tilde{T}_{in}(k-1) + B_2 \times \tilde{T}_{sh}(k-1) \end{cases} \quad (17)$$

$$V(k) = V_1(k) + V_2(k) + i(k) \times R(k) + U_{OCV} \quad (18)$$

$$\begin{cases} \mathrm{soc}(0) = s_0 & \mathrm{soc}(t_f) = s_{t_f} \\ \tilde{T}_{in}(0) = 0 & \tilde{T}_{sh}(0) = 0 \end{cases} \quad (19)$$

$$\begin{cases} i_{min} \le i(k) \le i_{max} \\ V_{min} \le \mathrm{V}(k) \le V_{max} \end{cases} \quad (20)$$

where s_0, s_{tf} stand for the initial and final SOC states during battery charging process respectively. i_{min}, i_{max} are the minimum and maximum bounds for current, and V_{min}, V_{max} stand for the minimum and maximum bounds for voltage respectively.

In order to solve this optimal charging problem, we divide the battery charging process into two stages: a constant current (CC) stage and a constant voltage (CV) stage. During CC stage, the terminal battery voltage begins to increase until it reaches the upper terminal voltage bound. Then, the constant voltage (CV) stage is launched until the battery capacity meets the power requirement. We assume a point k_{cc} which stands for the battery terminal voltage reaches its maximum bound V_{max} and the charging process will change to the CV stage after time k_{cc}. Keeping in mind that the battery terminal voltage needs to be kept constant during CV stage, so the dynamics of the CV stage charge current $i_{CV}(k)$ is not an optimal problem and should be defined by constant voltage V_{max} described as follows,

$$i_{CV}(k) = \left(V_{max} - V_1(k) - V_2(k) - U_{OCV}\right)/R(k) \quad (21)$$

For $k=k_{CC}, k_{CC}+1,...,k_{tf}$ stands for the CV stage until the battery reaches its final capacity, the battery terminal voltage should be fixed at the constant value V_{max}. The battery charge current profiles $i_{CV}(k)$ in CV stage should be calculated by Eq.(21). After that, the objective function for CV stage J_{charge_CV} is calculated based on the current profiles $i_{CV}(k)$.

As stated above, the target of the battery optimal charging strategy can be defined as a new equivalent optimization problem shown as follows,

$$\text{Minimize } J_{charge} = J_{charge\_CC} + J_{charge\_CV} \quad (22)$$

$$J_{charge\_CC} = w_t \times T_s \times k_{cc} + w_T \times T_s \times \sum_{k=0}^{k_{cc}-1} f_{TR}(k) \quad (23)$$

$$J_{charge\_CV} = w_t \times T_s \times (k_{tf} - k_{cc}) + w_T \times T_s \times \sum_{k=k_{cc}}^{k_{tf}} f_{TR}(k) \quad (24)$$

Subject to:

$$\begin{cases} \mathrm{soc}(0) = s_0 & \mathrm{soc}(t_f) = s_{t_f} \\ \tilde{T}_{in}(0) = 0 & \tilde{T}_{sh}(0) = 0 \end{cases} \quad (25)$$

$$\begin{cases} i_{min} \le i(k) \le i_{max} \\ V_{min} \le \mathrm{V}(k) \le V_{max} \end{cases} \quad (26)$$

where $f_{TR}(k) = \tilde{T}_{in}(k) + \tilde{T}_{sh}(k)$. k_{CC} stands for the time when the battery terminal voltage $V(k)$ first reaches the constant voltage V_{max}. k_{tf} is the time when battery reaches its final charge capacity. w_t and w_T stand for the battery charging time weight and temperature rise weight respectively.

This optimization problem means to get a proper charge current profile $i_{CC}(k)$ for CC stage which can minimize the dual-objective function *Jcharge* for the total battery charging process. It should be noted that once $i_{CC}(k)$ is obtained by the optimization algorithm, the value of k_{cc} and k_{tf} can be determined accordingly. Then other values including resistances $R(k)$, voltage $V_1(k)$ and temperature rise $f_{TR}(k)$ which are used in calculating the objective functions *Jcharge_CC* and *Jcharge_CV* can be also obtained based on the battery coupled thermoelectric model. In other words, charging current in CC stage determines the battery charging time and temperature rise (both battery interior and surface), further to determine the battery dual-objective function *Jcharge*. The value of charge current profile $i_{CC}(k)$ play an important role in battery total charging process and is chosen as our decision variables in minimizing the dual-objective function *Jcharge*.

All in all, the optimal operation for battery charging in this paper is formulated as a dual-objective concerning battery charging time and battery temperature rises (both interior and surface). The procedure of battery optimal charging considers both fitness functions *Jcharge_CC* for CC stage and *Jcharge_CV* for CV stage simultaneously.

IV. Battery Optimal Charging Strategy

With the purpose of solving the battery optimal charging profile is formulated in Section III, the principle of a heuristic method named teaching-learning-based optimization (TLBO) used in this paper is introduced first in this section, followed by the detail procedure of applying TLBO to solve the battery optimal charging strategy.

A. Teaching-learning based optimization

The teaching-learning based optimization (TLBO) method mimics the nature of a typical teaching and learning process [12], where a teacher is first elected in each learning generation and share the knowledge with the students, then students learn from mutual interaction with counterparts to gain potential useful information. TLBO has been applied in solving a number of single or multiple objective industrial optimization problems [13,14]. It is easy and convenient to adopt TLBO algorithm for battery optimal charging strategy since none specific parameters for TLBO need to be adjusted by user during algorithm implementation. The general schematic of TLBO for the value optimization is shown in Fig. 4 [12].

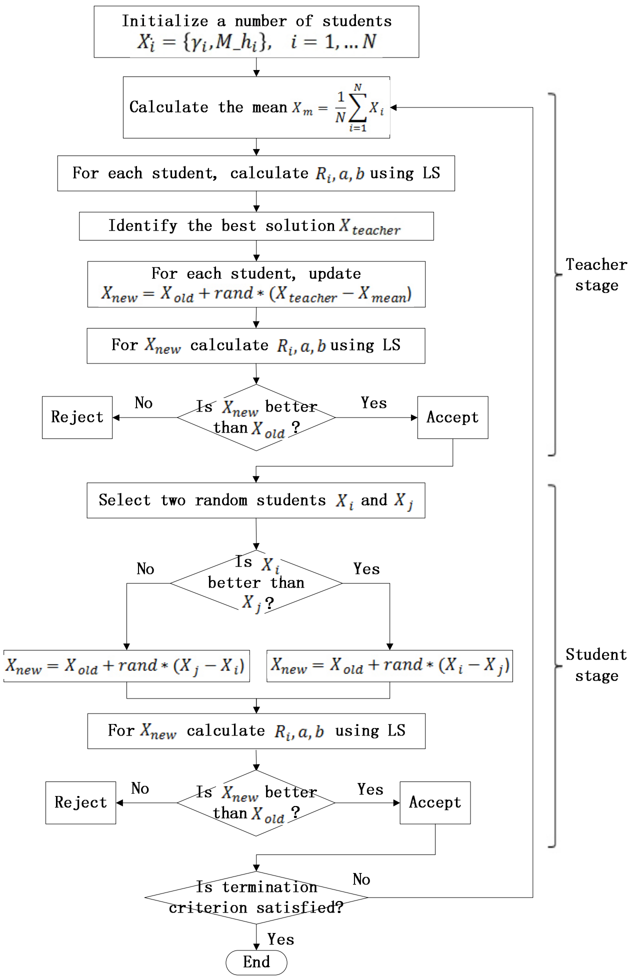

Fig. 4. General schematic of TLBO [12]

In this paper, instead of using analytic optimal control methods, TLBO is adopted to search the suitable value set of charge current profile *i(k)* in CC stage through its two phases, aiming at obtaining the proper charge current profile for battery optimal charge which can minimize the dual-objective function *Jcharge*.

B. Implementing TLBO for battery optimal charging strategy

In order to get the proper charge current profile *i(k)*for battery optimal charging strategy, the main procedure based on the TLBO algorithm are presented in detail as follows:

Step 1: Set the values of weights w_t and w_T in the battery dual-objective function *Jcharge*.

Step 2: Set the battery charging initial and target SOC levels S_0 and S_{tf} respectively. Set *Tamb* for battery ambient temperature. Set all physical constraints including i_{min} , i_{max} , V_{min} and V_{max} for the battery charging process;

Step 3: Set the population size *Np*, generation numbers *Gm*. Initialize the particle for TLBO algorithm.

Step 4: For $k=1$ to k_{max}(the maximum number of iterations) do

a) For CC stage, calculate the charging objective fitness *Jcharge_CC* in each generation until the battery terminal voltage goes up to V_{max}, after that the battery charging process will enter into CV stage.

b) For CV stage, calculate the charge current profile $i_{CV}(k)$ in each generation and then obtain the charging objective fitness *Jcharge_CV* until the battery SOC level goes up to S_{tf}.

c) Evaluate the final dual-objective function *Jcharge* based on the sub-objective fitness *Jcharge_CC* and *Jcharge_CV*, and then check the termination criteria.

d) Update the charge current for CC stage $i_{CC}(k)$ using TLBO algorithm. When criteria for optimization termination have been satisfied, terminate the whole optimization process.

Using this procedure, the CCCV charge current profile can be optimized. This optimal current profile can be applied to charge battery from S_0 to S_{tf} with the minimal cost of dual-objective function *Jcharge*. The proper current profile can be also applied to balance the conflicts among the battery charging time and temperature rises (both the interior and surface) during battery charging process. The results achieved by this optimal charging strategy are analysed in Section V.

V. RESULTS AND DISCUSSION

In this section, the following tests are conducted to investigate the performance of optimal charge current profiles for battery cell charging process based on the battery coupled thermoelectric model Eq.(9) and the battery optimal charging strategy described in Section IV. Two cases of tests including (i) verification of battery optimal charging strategy; (ii) effects of dual-objective function weights are analysed and discussed in this section. All tests adopt the same parameters settings: The sampling time period T_s is 1s. The maximum iteration number is 3000. The battery initial SOC level S_0 and final SOC level S_{tf} are set to 0.1 and 0.9 respectively. Battery physical constraints for charge current and terminal voltage are fixed as follows: $i_{min}=-30A$, $i_{max}=0A$, $V_{min}=2.6V$, $V_{max}=3.65V$. The ambient temperature during charging process is $Tamb=29^oC$.

A. Verification of Battery Optimal Charging Strategy

In order to validate the effectiveness of the TLBO algorithm for searching the battery optimal charging strategy, the population size N_p and generations number G_m are set to 20 and 50 respectively in this paper for the following experiments. The convergence characteristic of TLBO algorithm for battery dual-objective function optimization is illustrated in Fig. 5. Graph is plotted based on the evolution of battery dual-objective function *Jcharge* against the generations number G_m. The weights for battery charging time and temperature rise in *Jcharge* are all set to 1 in this experiment. It can be observed that the value of *Jcharge* decreased rapidly within less than 10 generations and finally reached nearly 27261.435 after 50 generations.

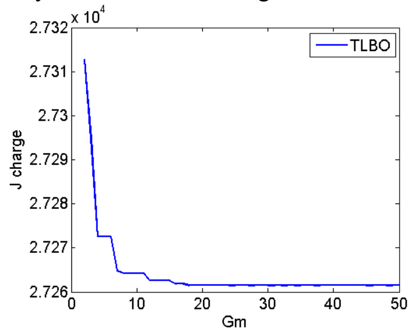

Fig. 5. Convergency of TLBO in battery dual-objective function optimization

Table II shows the battery charging time (J_{CT}) and battery temperature rise (J_{TR}=J_{TinR}+J_{TshR}) after 50 generations. The values are calculated when the weights w_t, w_E in *Jcharge* are equally set to 1. It can be seen from Table II that for this weights setting, the J_{TR} is much larger than the value of J_{CT}, nearly up to twenty-three fold. In order to make sure the sub-cost functions are fairly optimized, the following weights setting: w_t =1, w_T=0.05 are initialized respectively for the following tests presented in this section.

TABLE II. VALUES OF SUB-COST FUNCTION TERMS

Np	*Gm*	*Jcharge*	J_{CT}	J_{TR}
20	10	27265.252	1115	26150.252
20	20	27263.470	1114	26149.470
20	50	27261.435	1113	26148.435

After setting the appropriate weights for battery dual-objective function *Jcharge*, five different current profiles including the optimal current profile are chosen to compare and verify the performance of charge current optimized by our strategy during battery charging process. These charging current profiles are obtained by injecting charge current into battery during the CC stage until the battery terminal voltage goes up to its maximum value V_{max} and after that the battery is charged at the CV stage until the battery SOC level goes up to S_{tf}. The value of the optimal current profile was calculated based on our TLBO optimal strategy and other current profiles were obtained randomly based on our coupled thermoelectric model. Fig. 6 shows these five different current profiles during charging process to bring battery SOC from 0.1 to 0.9. It can be observed that larger current in the CC stage shortens the battery charging time. This behaviour is primarily due to the fact that large current causes rapid increase of battery SOC and further speeds up the increase of battery OCV.

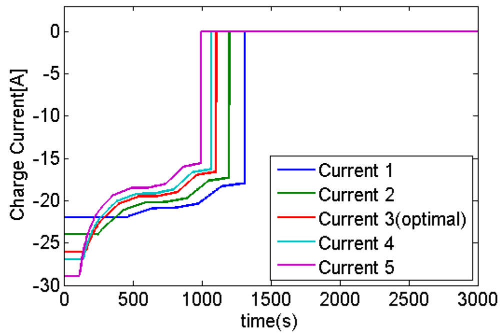

Fig. 6. Different battery charging current proflies (including the optimal profile)

Table III shows the two parts of sub-cost functions with corresponding weight in the dual-objective function *Jcharge* for these five current profiles. It can be observed that, except for the optimal current profile 3, either decreasing or increasing the charging current for CC stage results in the increase of dual-objective function *Jcharge*. For current profiles 1-2, reducing charging currents in CC stage lead to the decrease of J_{TR} but larger increase of J_{CT} during charging process, further increase *Jcharge* accordingly. For current profiles 4-5 with larger currents in CC stage, the J_{CT} is reduced during charging process but J_{TR} increases to larger values, further causing the increase of *Jcharge* accordingly.

TABLE III. VALUES OF J_{CT}, J_{TR} WITH WEIGHTS AND J_{CHARGE} UNDER DIFFERENT CHARGE CURRENT PROFILES

Current No.	w_t×J_{CT}	w_T×J_{TR}	*Jcharge*	*I*
1	1313	1434.726	2747.726	-22
2	1208	1440.727	2648.727	-24
3	1107	1516.395	2623.395	-25.791
4	1074	1551.490	2625.490	-27
5	998	1631.945	2629.945	-29

B. Effects of Dual-objective Function Weights

It is obvious that the weights in battery dual-objective cost function *Jcharge* play important roles in battery optimal charge strategy design. In this subsection, two simulation tests including various charging time weights test and various battery temperature rise weights test are conducted to investigate the effects of weights on the results of battery optimal charging strategy.

Fig. 7 illustrates the effect results of varying battery charging time weights value w_t from 0.2 to 6.4. These effects focus on the optimal charge currents and the corresponding variations of battery internal temperature and surface temperature. The temperature rise weight w_T is set to constant value 0.05, only the w_t is varied. It has clearly demonstrated that increasing w_t from 0.2 to 6.4, the total charging time will become shorter due to the larger charge current. The optimal charge current for CC stage is 29.436A when w_t=6.4 compared with the value of 23.745A when w_t =0.2. In other words, larger w_t stands for putting more emphasis on the battery charging time and less emphasis on the temperature rise during charging process, and vice versa. Besides, both the battery internal temperature and surface temperature rises will be higher when w_t becomes larger.

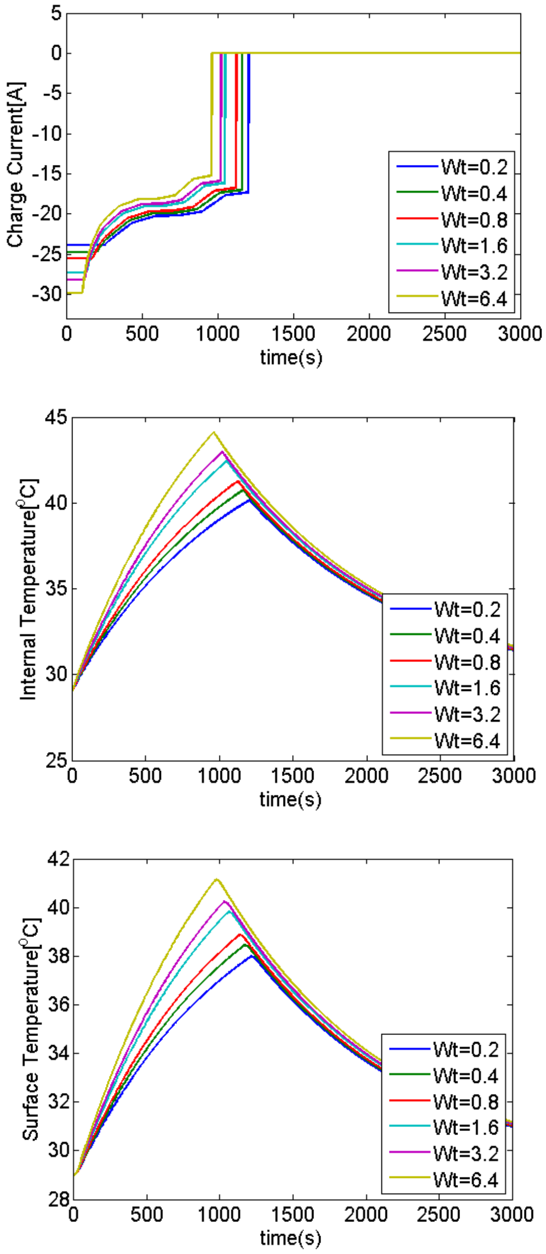

Fig. 7. Effect of different charging time weights w_t for charge current profiles, internal temperature and surface temperature.(w_T=0.05)

Another simulation is conducted to test the effect of various battery temperature rise weights w_T on battery optimal charging performance as shown in Fig. 8. Here the charging time weight is fixed as w_t =1, only the w_T is varied. When w_T increase from 0.01 to 5.00 gradually, the optimized charge currents for CC stage will increase accordingly. Even though the battery internal and surface temperatures increase more rapidly with a larger w_T, the total charging time will be shortened and hence the sub-cost function term J_{TR} will decrease. A high weight w_T means putting more emphasis on the battery temperature rising, leading to large currents for CC stage and provide short battery charging time and achieve low value for J_{TR} during total battery charging process, and vice versa.

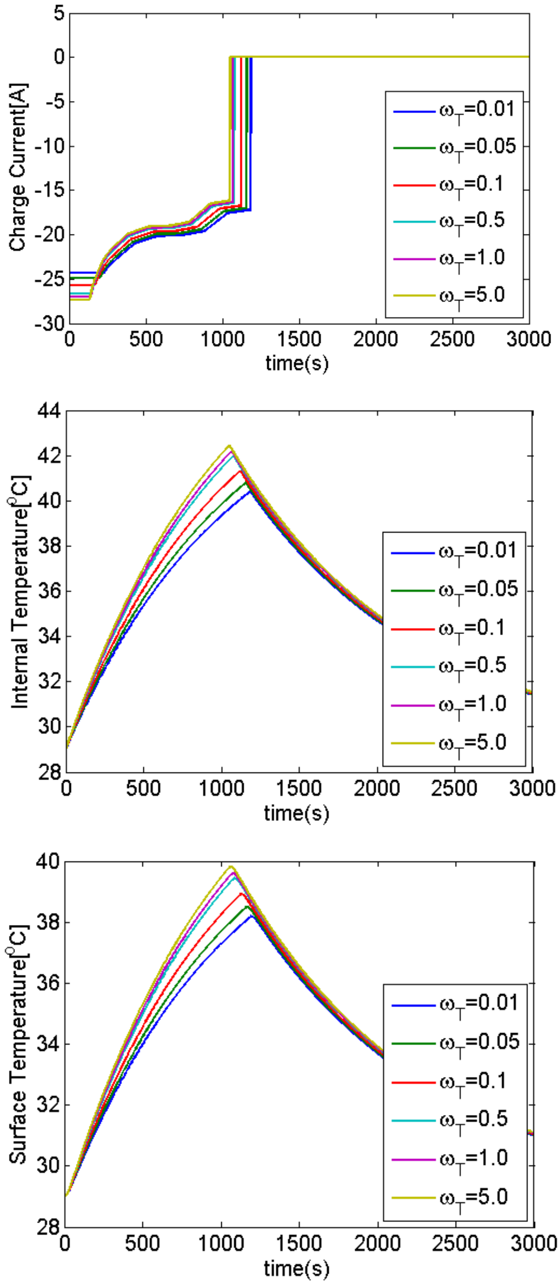

Fig. 8. Effect of different temperature rise weights w_T for charge current profiles, internal temperature and surface temperature.(w_t=1)

As a result, different weight values in *Jcharge* would lead to different optimal current profiles during battery charging process. By adjusting the weights of sub-cost function terms, the current profiles for battery charge with different focuses including charging time and temperature rise (both interior and surface) can be identified separately.

VI. CONCLUSION

Battery charging strategy is a key issue to ensure the reliability and safety of battery charging process. In this paper, a novel battery optimal charging strategy is proposed by applying TLBO algorithm to solve the optimal charging profile for a LiFePO4 battery. This is based on the development of the battery coupled thermoelectric model in our previous work, and a specific dual-objective function which is composed of two conflicting objectives: battery charging time and temperature rise (both battery interior and surface) is formulated firstly. Then a battery optimal charging strategy is presented in detail by dividing the battery charging process into a CC charging stage and a CV charging stage. The TLBO algorithm is applied for this time-varying and high nonlinear optimization, aiming at seeking a suitable constant-current-constant-voltage (CCCV) current profile to minimize the dual-objective function. Besides, the simulation tests of varying dual-objective function weights including battery charging time weight and temperature rise weight are also conducted to illustrate the influence of various sub-cost function weights on battery charging optimization result.

Simulation results show that the presented optimal charging strategy can provide effective and acceptable optimal charge current profile for battery charging. By adjusting weights of sub-cost function terms in the dual-objective function, the optimal charge current profile can give a suitable trade-off among charging time and temperature rise (both interior and surface) during battery charging process. Although the optimized charge current profile in this study only fits a LiFePO4 battery cell, the optimal charging strategy presented in this paper can be easily implemented to other different battery types to effectively balance the battery charging time and battery temperature rise during charging process.

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