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A FAST AND SAFE QUASI-OPTIMAL CHARGING STRATEGY FOR LI-ION BATTERIES

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ABSTRACT

This paper presents a fast and safe quasi-optimal multistage constant current (MCC) charge pattern optimization strategy for Li-ion batteries. It is based on an integrated electro-thermal model that combines an electrical equivalent circuit (EEC) battery model with a thermal battery model. The EEC model is used to predict the battery's terminal voltage continuously as charging progresses, while its temperature rise is also estimated continuously by employing the thermal model. This integrated electro-thermal battery model is utilized to search for an optimal MCC charge pattern that charges the battery in minimum time, while simultaneously limiting its temperature rise to a user-specified level. The search for the optimal charge pattern is carried out on a stage-by-stage basis by using a single-variable optimal search strategy that can be easily implemented on a battery management system. The paper also includes some simulation results obtained from an integrated electro-thermal model of a commercially available medium-power Li-ion cell. These results indicate that the proposed quasi-optimal MCC charging strategy performs as expected and can serve as a useful, easy-to-implement alternative to existing computationally intensive optimal charge strategies proposed by other researchers.

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1. INTRODUCTION

With the proliferating usage of Li-ion batteries in numerous applications ranging from portable and hand-held devices to large electrical appliances and transportation vehicles, the need for fast and safe charging strategies for such batteries has emerged as a very important and fertile area of research. Through the concerted efforts of several researchers over last five years, a variety of such fast charging methods have already been proposed in the literature [1]-[11].

Following the lead of Zhang et al [1], we can categorize the battery charging optimization schemes into four different categories: i) methods based on improvement of battery materials [3]-[4], ii) methods based on improvement of charging current [5]-[7], iii) polarization based methods [8]-[9], and iv) methods based on electrical equivalent circuit (EEC) and battery thermal models [10]-[12]. All these methods have their relative advantages and disadvantages. For instance, methods based on improved battery materials seem to hold a great deal of promise for future but requires extensive experimental studies to prove their safety and reliability before mass applications. Similarly, methods based on improved charge current waveforms are simple to implement, but a majority of them are based on heuristic strategies, lacking mathematical objectivity and foundation. On the other hand, polarization-based methods offer a good alternative, but they are more complicated compared to methods based on EEC and thermal models. The methods based on EEC and thermal models use an EEC model to predict the battery terminal voltage, while simultaneously estimating the temperature rise by employing a battery thermal model. These two models are used together to search for an optimal charging pattern. These methods have been shown to be useful for development of fast charging strategies that take battery stress and safety into consideration.

In this paper, we present a multistage constant current (MCC) charge pattern optimization strategy that also limits battery temperature rise. MCC charging strategy is chosen here because several researchers have found it to be less stressful than conventional constant current constant voltage (CCCV) charge strategy, and recently Lu et al [2] have also furnished a theoretical proof of its safety aspects. Although similar problems have been addressed by other researchers, we present a fast-quasi-optimal charging strategy that can be useful for electric vehicles or other applications that require easily implementable and fast near-optimal solutions.

The organization of this paper is as follows. Section 2 presents a brief overview of EEC and thermal models of a Li-ion battery. The problem of battery charge pattern optimization is discussed in Section 3. Section 4 introduces a simplified charge pattern optimization problem. Section 5 presents results of simulation studies. Finally, some concluding remarks are provided in section 6.

2. ELECTRO-THERMAL MODEL OF A LI-ION BATTERY

A brief overview of the Electro-Thermal of a Li-ion battery is presented in this section. The Electro-Thermal model consists of a lumped-parameter EEC model for modeling the battery's overpotential and a thermal model to predict its temperature rise during charging. First, we discuss the EEC model and then summarize the thermal model.

2.1. Electrical Equivalent Circuit Model of a Li-ion Battery

A popular five-parameter EEC model [12], used in this study and elsewhere, is shown in Figure 1 below.

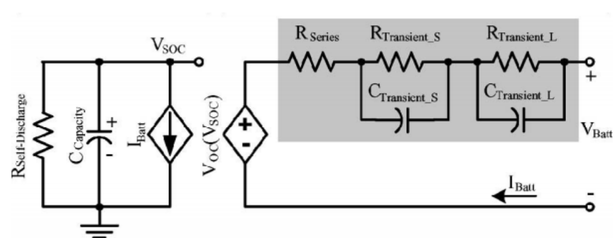

Figure 1: Chen and Mora's Second-Order Electrical equivalent circuit (EEC) model

This five-parameter EEC battery model is widely used in literature to model the current-voltage relationship of a Li-ion battery during both charging discharging. The model consists of two circuits, namely, an Energy balance circuit and a voltage response circuit. In the energy balance circuit, $C_{Capacity}$ represents the battery capacity. The self-discharge resistor $R_{self\text{-}Discharge}$ represents the gradual loss of charge in the positive and/or negative electrodes when the battery is idle. V_{SOC} represents the voltage across $C_{Capacity}$, which has a value between 0 and 1 volt. V_{SOC} equals to 1V when the battery is fully charged and equals to 0 V when it is fully discharged. Therefore, V_{SOC} is equivalent to the state-of-charge (SOC) of the battery. The value of V_{SOC} depends on the magnitude and the direction of the battery current, I_{Batt}.

The voltage response circuit on the other hand simulates the battery's transient response to a given current, I_{Batt}. $R_{Transient\_S}$ and $C_{Transient\_S}$ model the transient short-term time constant, whereas $R_{Transient\_L}$ and $C_{Transient\_L}$ model the transient long-term time constant. Also, $V_{oc}$is the open circuit voltage which is a voltage-controlled voltage source depending on SOC. Finally, R_{Series} represents the internal series resistance of the battery.

For better clarity, the voltage response circuit of the EEC model is also shown in Figure 2 below.

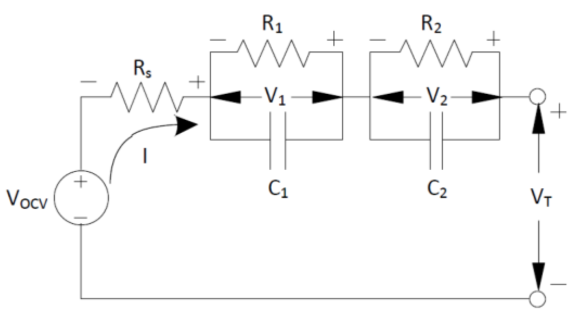

Figure 2: Simplified EEC model for Li-ion

A state space representation of the EEC model can be expressed as:

$$\dot{V}_1 = -\frac{1}{R_1 C_1} V_1 + \frac{1}{C_1} I \quad (1)$$

$$\dot{V}_2 = -\frac{1}{R_2 C_2} V_2 + \frac{1}{C_2} I \quad (2)$$

$$V_T = V_{OCV} - V_1 - V_2 - I R_S \quad (3)$$

where $V_1$and V_2 are the voltages across the capacitors and system states. Current I is the input, and battery terminal voltage V_T is the output.

An accurate and robust parameter estimation method is required for applications of EEC models. The estimation method is expected to be robust in the presence of both unmodeled system dynamics and measurement noise. Two such estimation techniques are: A direct Continuous Time (CT) system identification method, and an Indirect Discrete Time technique (IDT). A previous study for parameter estimation of EEC models [13] shows that both methods perform equally well if the model happens to be a time-invariant system. However, if the system is time-varying, then a CT system identification method would be a better choice for better accuracy and robustness.

2.2. Thermal Model of a Li-ion Battery

Some researchers have shown that Li-ion batteries have a safe operating window of -10 to 50 °C [14], while others have identified their optimal operating temperature range to be between 20 and 30 °C [15]. Operating temperatures outside of this range may affect battery performance and safety.

Another major safety concern for such batteries is the risk of thermal runaway, where internal components of the battery experience thermal stresses and start to malfunction due to heat accumulation and temperature rise, eventually resulting in conditions that cause further rise in temperature and thermal runaway. Since battery performance is highly dependent on temperature, it is important to limit the rise of temperature during battery operations. Battery thermal models have been found to be very useful for such purpose, because such models can be used to predict the expected temperature rise of a battery during charge/discharge operations.

Different types of battery thermal models, suitable for different applications, have been proposed in the literature [16]. Each of these is associated with a different level of complexity, accuracy and computational cost. These models can be divided into three main categories, namely, lumped parameter models (LPM), finite element models (FEM), and analytical numerical models (ANM). The LPM models are useful for fast simulation, but suffer from limited accuracy, whereas FEM models are rather slow to execute, but offer high accuracy. The ANM models, on the other hand, offer a good trade-off between simulation accuracy and speed. In view of above, we chose an ANM model in this study.

A popular thermal ANM model can be described by the following equations [17]:

$$C_c\dot{T}_c = Q + \frac{T_s - T_c}{R_c} \quad (4)$$

$$C_s\dot{T}_s = \frac{T_f - T_s}{R_u} - \frac{T_s - T_c}{R_c} \quad (5)$$

$$Q = I(V_{OCV} - V_T) + IT_c\frac{dV_{ocv}}{dT_c} \quad (6)$$

where C_C and C_S denote the heat capacities of the core and the surface, whereas T_C and T_S denote their temperatures; T_f denotes the temperature of ambient air, and T_C and R_u denote the thermal resistances used to model the heat exchange between the "core and surface" and "surface and ambient air", respectively. Also, Q denotes the heat produced during chemical reactions in the battery and modeled by equation (6), where I denote the charge current, V_{OCV} is the open circuit voltage, V_T is the cell voltage and $\frac{dV_{ocv}}{dT_c}$ denotes the entropy coefficient.

3. MCC CHARGE PATTERN OPTIMIZATION PROBLEM

A MCC charge pattern simply consists of N gradually decreasing constant current charge levels, I_k, $1 \leq k \leq N$, of unequal durations, $\Delta t_k = t_k - t_{k-1}$, $1 \leq k \leq N$, respectively. The charge pattern optimization problem can be stated as follows:

Find optimal values of {N; Δt_k, I_k, $1 \leq k \leq N$} *that minimize the total charge time, t_N, subject to the constraints,*

$$\sum_{k=1}^{N} \Delta T_k \leq \Delta T_{max} \quad (7a)$$

$$\sum_{k=1}^{N} \Delta SOC_k = 1 \quad (7b)$$

where ΔT_k and ΔSOC_k denote the temperature-rise and SOC gain during the k^th stage of charge, and ΔT_{max} denotes the maximum allowable rise in core temperature of the battery.

The above problem is difficult to solve unless some simplifying assumptions are made. Thus, most researchers assume that N is known a priori, and the allowable values of charge current levels, I_k, are assumed to be known fractions or multiples of C-rate charge current, such as 0.5C, 1C, 1.5C, etc. [1], [10]-[12]. So, a simplified version of the above problem becomes:

Find optimal values of {t_k, I_k, $1 \leq k \leq N$} *that minimize the total charge time, t_N, subject to the constraints (7)*

An optimal solution to the above problem can be found by using either a multi-objective optimization algorithm, such as minmax or goal programming or an evolutionary optimization method, such as genetic algorithm (GA) [18]. In fact, GA has been the algorithm of choice by several researchers [1], [10]-[12]. However, it should be borne in mind that the solutions so obtained are really not optimal, but only quasi-optimal because: i) N is assumed to be known a priori, ii) (as indicated by other researchers), MCC profile may not be an optimal charge profile after all, and iii) a solution given by GA is not guaranteed to be optimal at all because basically it is a random search technique conducted in an organized way.

4. A SIMPLIFIED MCC CHARGE PATTERN OPTIMIZATION SCHEME

In view of above, we propose to use a quasi-optimal search strategy that is much faster, easy-to-implement, and can provide a near-optimal solution. To simplify the problem, we add an additional constraint related to temperature-rise in each stage and therefore, constraint (7a) is modified to the following simplified form:

$$\Delta T_k \leq \Delta T_{k,max} \quad (8)$$

where $\Delta T_{k,max}$ denotes the maximum temperature-rise allowed for the kth stage. With prior knowledge of $\Delta T_{k,max}$, $1 \leq k \leq N$, the above optimization problem reduces to finding the optimal values of successive stage-to-stage transition times, $\{t_k, 1 \leq k \leq N\}$, which only requires successive one-dimensional searches for each stage. For instance, a simple Interval-Halving method [18] for stage k may consist of the following steps:

Step 1. For stage k, first compute an upper bound for t_k as: $t_{k,max} = \frac{1-\sum_{j=1}^{k-1} \Delta SOC_j}{I_k}$

Step 2. Using a battery thermal model, compute the expected temperature-rise, $\Delta T(t_{k.max})$, at time $t_{k,max}$, If $\Delta T(t_{k.max}) < \Delta T_{k,max}$, let $t_k = t_{k,max}$ and proceed to the next stage; else go to Step 3.

Step 3. Compute the expected temperature-rise at $(t_{k,max}/2)$. If $\Delta T(t_{k.max}/2) < \Delta T_{k,max}$, choose the reduced search interval as: $(t_k, t_{k,max}/2)$, else choose it to be: $(t_{k,max}/2, t_{k,max})$, and go back to Step 2.

Our simulation results indicate that the search for optimal values of t_k requires only a few iterations for each stage. The number of iterations can be reduced even further by using a golden section search method [18].

Remark

It may be pointed out that the solution obtained above can be improved further by picking the best one from M separate solutions obtained by starting from M randomly chosen constraints $\{\Delta T_{k,max}, 1 \leq k \leq N\}$. This is a well-known method of finding a near-optimal solution [18] to any optimization problem.

5. SIMULATION RESULTS

The proposed quasi-optimal search strategy was simulated for an integrated electro-thermal battery model for A123-26650 Li-ion battery [19]. Although many simulations were carried out to study the performance of the proposed optimization algorithm under different scenarios, the results of only three studies are shown below.

Sample Simulation Results

Three sample MCC charge pattern optimization simulation results for a five-stage, a six-stage, and a seven-stage are shown in Figures 3-11 below. In all cases, the battery is assumed to be fully discharged to start with and the initial temperature of the battery core is assumed to be 25 °C. Also, the simulations in all cases were stopped at SOC = 1. Figures 3-5 show the current levels, temperature-rise, and battery voltage for a six-stage charge pattern, where ΔT_{max} was chosen to be 9 °C. The values of $\Delta T_{k,max}$ (in ^oC) and charge current levels for this simulation were chosen to be as follows:

$\{\Delta T_{k,max}$ (*in* ^oC), $1 \leq k \leq 5\} = \{2\ \ 2\ \ 2\ \ 2\ \ 1\}$;

Charge currents (in C-rate),
I_k, $1 \leq k \leq 6$ = {3.5C 3C 2.5C 2C 1.5C 1C}.

In this case, it took approximately 1750 secs to completely charge the battery.

Also, Figures 6-8 show similar results for a six-stage charge pattern, where ΔT_{max} was chosen to be 7 °C. The values of $\Delta T_{k,max}$ (in ^oC) and charge current levels for this simulation were chosen to be as follows:

$\{\Delta T_{k,max}$ (*in* ^oC), $1 \leq k \leq 5\} = \{1\ \ 1\ \ 1\ \ 2\ \ 2\}$;

Charge currents (in C-rate),
I_k, $1 \leq k \leq 6\}$ = {3C 2.5C 2C 1.5C 1.2C 1C}.

In this case, it took approximately 2330 secs to completely charge the battery.

A comparison of the above two simulations shows the trade-off between ΔT_{max} and total charge time, t_N, namely, a decrease of ΔT_{max} results in a longer charge time and vice versa.

Finally, keeping the optimal operating temperature range in mind, Figures 9-11 show the results for a seven-stage charge pattern, where

ΔT_{max} was chosen to be 5 °C. The values of $\Delta T_{k,max}$ (in °C) and charge current levels for this simulation were chosen to be as follows:

$\{\Delta T_{k,max}\ (in\ ^oC),\ 1 \leq k \leq 5\} = \{1\ \ 1\ \ 0.5\ \ 0.5\ \ 1\ \ 1\}$;

Charge currents (in C-rate),
$I_k,\ 1 \leq k \leq 7 = \{2.5C\ 2C\ 1.7C\ 1.5C\ 1.2C\ 1C\ 0.5C\}$.

In this case, it took approximately 2750 secs to completely charge the battery.

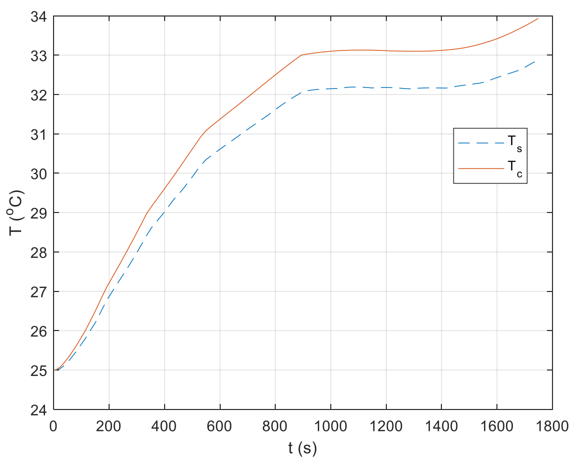

Figure 3: Temperature rise of battery core (Tc) and surface (Ts) for ΔTmax = 9 °C (From 25 °C - 34 °C)

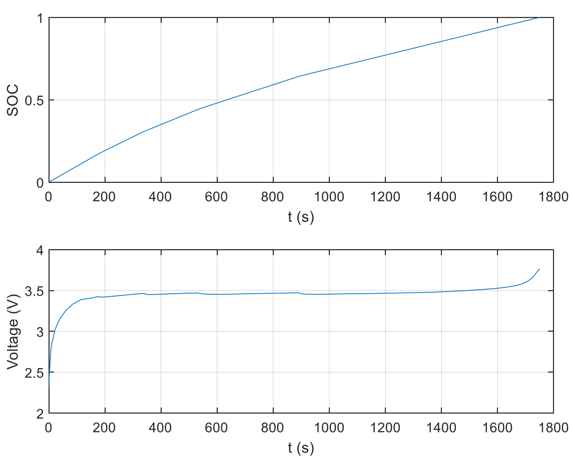

Figure 4: SOC and VOC for ΔTmax = 9 °C (From 25 °C to 34 °C)

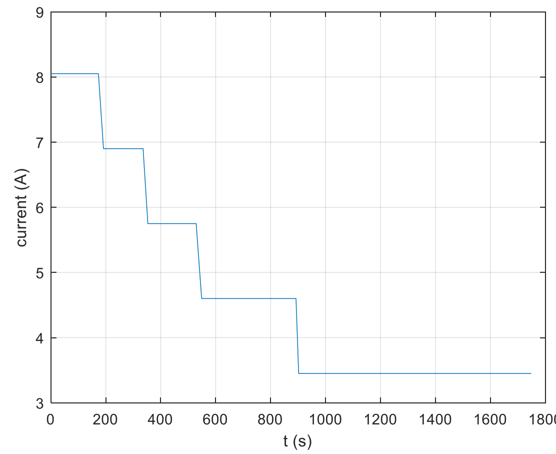

Figure 5: Optimum charge pattern for ΔTmax = 9 °C (From 25 °C to 34 °C)

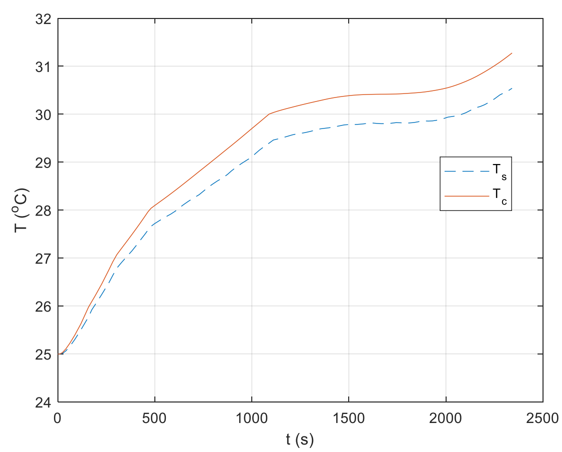

Figure 6: Temperature rise of battery core (Tc) and surface (Ts) for ΔTmax = 7 °C (25 °C - 32 °C)

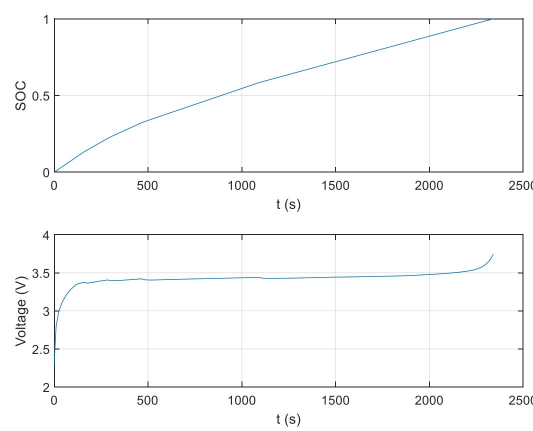

Figure 7: SOC and VOC for ΔTmax = 7 °C (From 25 °C to 32 °C)

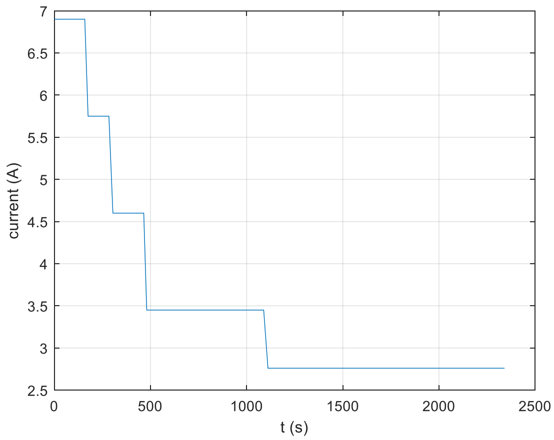

Figure 8: Optimum charge pattern for ΔTmax = 7 °C (From 25° C to 32 °C)

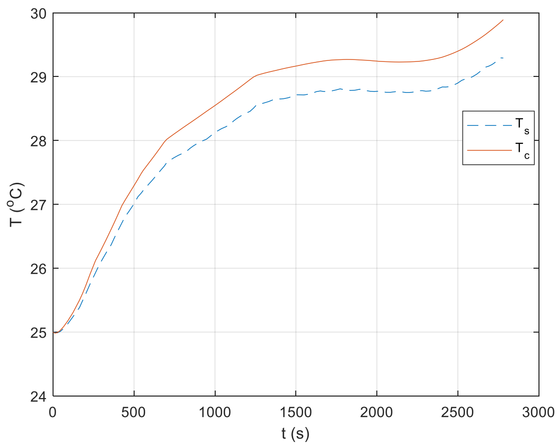

Figure 9: Temperature rise of battery core (Tc) and surface (Ts) for ΔTmax = 5 °C (25 °C - 30 °C)

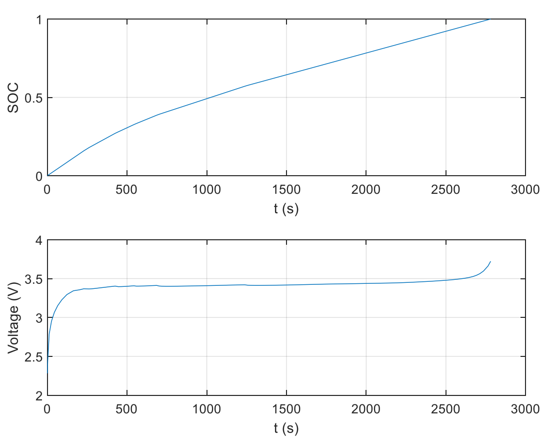

Figure 10: SOC and VOC for ΔTmax = 5 °C (From 25 °C to 30 °C)

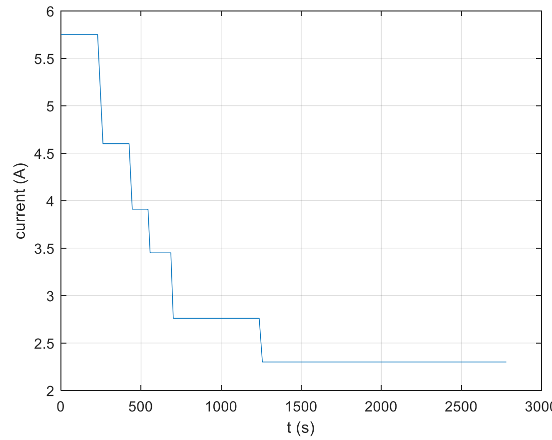

Figure 11: Optimum charge pattern for ΔTmax = 5 °C (From 25° C to 30 °C)

6. CONCLUSION

A fast and safe quasi-optimal MCC charge pattern optimization strategy for Li-ion batteries has been proposed and studied here. Simulation results obtained from an integrated electro-thermal model of a 2.3 AH A123-26650 Li-ion battery indicate that the proposed charging strategy performs as expected and can serve as a useful, easy-to-implement alternative to existing computationally intensive optimal charge strategies proposed by other researchers. Further improvement of the proposed search strategy by incorporating additional battery-stress issues as well as non-MMC charge patterns are currently under investigation.

7. REFERENCES

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