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RESEARCH ARTICLE

An Implementation of Quasi-Newton Algorithm for Fast-Charging Lithium-Ion Battery (LIB) Optimization in Electric Vehicle Application

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Abstract

Lithium-Ion Battery (LIB) is still an effective alternative technology in maximizing the efficiency of electric vehicles (EV). The application of EVs has had a significant impact in order to reduce the issue of global problems - reducing carbon gas emissions. The LIB charging mechanism with the fast-charging method is an alternative to the application of EVs on a more massive scale. However, the dynamics of the battery where the battery work function can decrease over time will affect battery performance. In addition, fast-charging efforts at LIB with maximum speed have the impact of increasing the risk of battery temperature and the existence of a larger gap in battery degradation. This paper proposes the application of Limited-Memory-Broyden-Fletcher-Goldfarb-ShannoBound Constrained (L-BFGS-B) algorithm for Lithium-Ion Battery (LIB) fast-charging optimization as an innovative solution approach in dealing with the complex LIB fastcharging dynamics. The research shows that this approach is able to maintain battery health (SoH) and capacity with only a decrease in SoH of about 2 percent and battery capacity retained at 98 percent of the initial capacity. The Quasi-Newton L-BFGS-B method is highly applicable in extending battery life and enhancing overall charging efficiency.

Keywords: Quasi-Newton 1, Fast-charging 2, Lithium-Ion Battery 3

1. Introduction

The issue of environmental problems related to global warming and the reduction of energy sources due to the rapidly growing number of fossil fuel vehicles makes the application of Electric Vehicles (EV) an alternative solution to challenges in the world of the transportation industry in meeting the parameters: efficiency, performance, automation and emission reduction [1], [2]. Batteries are still an effective technology in increasing the efficiency of electric vehicles [1]. Lithium-Ion Battery (LIB) is an important part of innovation for the issue of energy crisis in transportation systems due to the limited existence of fossil fuels and sources. The low application of LIB in EVs is due to limitations in terms of capacity, management of charging and discharging batteries as the main power supplier in EVs is a challenge that must be resolved [3]. Charging LIB with the fast-charging method is an optimal alternative to charging batteries in EVs [4].

The fast-charging method is expected to expand the use of EVs to replace conventional vehicles. However, there are generally three things to consider when it comes to charging batteries using the fast-charging method. Charging too fast can cause the battery temperature to rise significantly, which will result in battery degradation. Conversely, charging too slowly can reduce the efficiency of time and energy utilization. Furthermore, too low or too high a voltage during the charging process can accelerate battery damage. Based on research [5], fast-charging efforts on LIBs at maximum speed have the impact of increasing the risk of battery temperature and a greater chance of battery degradation. In addition, fast-charging can reduce battery life and limit overall system performance. Therefore, there is a need for research related to the optimal fast-charging of LIBs to ensure optimal performance, long life, and battery safety.

This research is focused on finding innovative solutions to complex fast-charging problems by considering several key factors that affect battery performance, including State of Charge (*SoC*), terminal voltage (*Vt*), battery temperature (*Tc*), and State of Health (*SoH*). *SoC* is a parameter of the battery charge level. Vt is the voltage at the battery terminals. *Tc* is the temperature of the battery. And *SoH* is a battery health parameter that represents the current battery capacity relative to its initial capacity.

In this study, a Quasi-Newton Limited-Memory-Broyden-Fletcher Goldfarb Shanno-Bound Constrained (L-BFGS-B) approach is proposed to find the optimal solution of a objective function modeled in [5]. This approach is expected to handle fast-charging optimization problems with many variables and constraints. The L-BFGS-B algorithm has been proven to be effective in terms of accuracy and computational efficiency in various optimization applications.

2. Fast-charging System of Lithium-Ion Battery (LIB)

The application of fast-charging in LIBs has a significant role in the development of widespread application of EVs. The system of fast-charging makes it easy for EV users to recharge the battery quickly in a shorter time. In its application, fast-charging presents technical challenges that need to be further examined and addressed. One of the challenges faced in implementing a fast-charging system is the increase in battery temperature, which can damage battery cells and shorten battery life. For this reason, this research discusses the fast-charging system on LIB by considering electro-thermal and battery degradation.

2.1 The Quasi-Newton L-BFGS-B

The Quasi-Newton Limited-memory Broyden-Fletcher-Goldfarb-Shanno Bound (L-BFGS-B) method is a variation of the Quasi-Newton Broyden-Fletcher-Goldfarb Shanno (BFGS) algorithm that efficiently handles large-scale optimization problems with variable constraints. L-BFGS-B performs its task by only storing the updates of m vector pairs. This method does not store the entire iteration history thus significantly reducing the memory requirements of the computation process. In the application of this research, L-BFGS-B is proposed because of its advantages that can handle the LIB fast-charging problem, where in its application the charging current must be kept within a certain range in an effort to maintain safety and battery life. This study does not explicitly explain the mathematical formulation in the calculation of the Hessian matrix and its gradient. This is because L-BFGS-B is a complex method where the calculation of the Hessian matrix and its gradient is not done directly, but is updated iteratively based on gradient information and position changes between iterations.

2.2 The Algorithm of Fast-charging System in Lithium-Ion Battery (LIB)

The battery model used in this study is a battery model based on [6] with reference to the A123 LiFePO4 2500 mAh battery datasheet. This battery model considers electrical and thermal dynamics, including changes in State of Charge (*SoC*), voltage, and temperature during the battery charging process. Figure 1 shows the Simulink block diagram of the A123 LiFePO4 2500 mAh battery model.

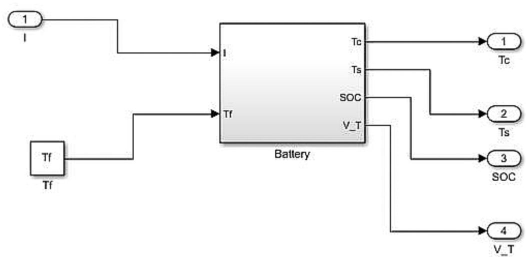

Figure 1. Block Diagram of A123 LiFePO4 Battery Simulation Model [6]

The model block diagram above considers several aspects of the battery, including chemical aspects, electrolytes, electrodes and electrochemical reactions that occur in the battery. The input or input of this block diagram consists of two parameters, namely current (I) and reference temperature (Tr). The output or output of the block diagram is in the form of State of Charge (*SoC*) parameters, battery core temperature (Tc), battery surface temperature (Ts), and terminal voltage (VT) [6]. Figure 2 is a further description of the Lithium-Ion Battery (LIB) electro-thermal model block diagram [6].

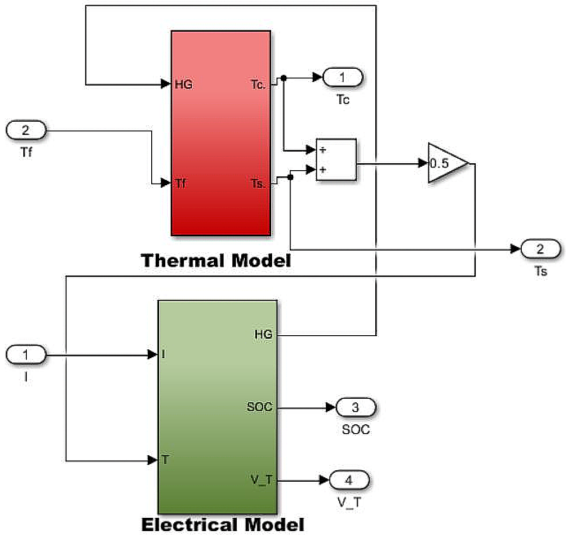

Figure 2. Electro-Thermal Model [6]

Figure 2 represents an integration model for the battery system which is composed of two main parts, namely the electrical model and the thermal model. This battery model is used to describe the battery behavior and the relationship between electrical aspects and thermal aspects that affect each other under battery charging conditions. In Figure 2 there is a Heat Generation (*HG*) block that represents the concept of heat generation in the battery resulting from internal chemical reactions and internal resistance in the battery during the charging and discharging process. The State of Charge (*SoC*) block represents the percentage of the battery capacity. The *VT* block represents the terminal voltage measured at the battery terminals. The Core Temperature (*Tc*), Surface Temperature (*Ts*), and Ambient Temperature (*Tf*) blocks represent the core temperature inside the battery cell, the temperature on the battery surface, and the ambient temperature around the battery, respectively. The electrical model and thermal model influence each other. The *HG* block in the electrical model impacts *Tc* in the thermal model, this is because the electrical processes that occur in the battery produce heat energy. Furthermore, *Tc* in the thermal model impacts the electrical model through changes in battery parameters, namely on internal resistance or on open circuit voltage conditions.

Electrical Model is a model that represents the effect of electrical aspects on battery performance. Figure 3 below is a block diagram of the electrical model [6].

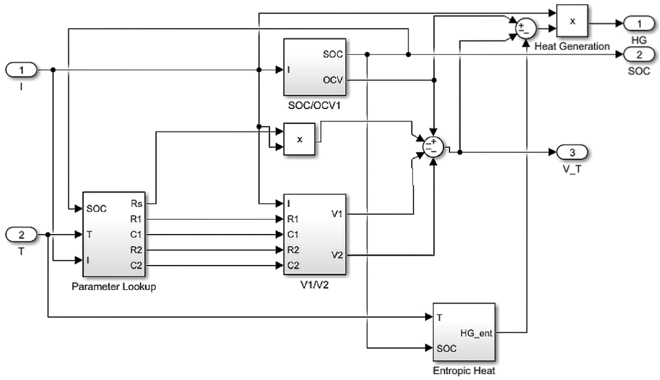

Figure 3. Electrical Model [6]

In Figure 3 the SOC/OCV1 block represents the relationship between State of Charge (*SoC*) and Open Circuit Voltage (OCV). State of Charge is the percentage charge level of the battery. OCV is the battery voltage when no current is applied to the battery. The rate of change of *SoC* with respect to time is shown in equation (1). The increase or decrease in *SoC* depends on the current entering or leaving the battery.

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

Equation (2) describes the mathematical equation of terminal voltage (*VT*) which is affected by the relationship between *SoC* and OCV. The terminal voltage (*VT*) is the sum of the OCV voltage, the voltage of the RC (resistor-capacitor) equivalent circuit model component, and the voltage of the series resistance *Rs*.

$$V_t(t) = V_oC(S_o, t) + V_{p1}(t) + V_{p2}(t) + R_s(t)I(t) \tag{2}$$

Furthermore, the Parameter Lookup block contains battery model parameters including internal resistance (*Rs*), polarization resistance (*Rp*1 and *Rp*2) and polarization capacitance (*Cp*1 and *Cp*2). The mathematical equations that represent voltage changes in the RC (resistor-capacitor) equivalent circuit model components are shown in equation (3) and equation (4).

$$\frac{dV_{p1}}{dt} = -\frac{V_{p1}}{R_{p1}(t)C_{p1}(t)} + \frac{I(t)}{C_{p1}(t)} \tag{3}$$

$$\frac{dV_{p2}}{dt} = -\frac{V_{p2}}{R_{p2}(t)C_{p2}(t)} + \frac{I(t)}{C_{p2}(t)} \tag{4}$$

Then, the Thermal Model is a model that describes the influence of thermal aspects on battery performance. Figure 4 is a block diagram of the thermal model [6].

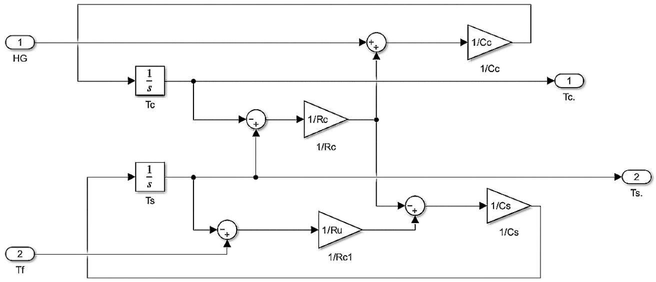

Figure 4. Thermal Model [6]

Figure 4 represents the change in core temperature (*Tc*) and surface temperature (*Ts*) over time as a result of heat generation (*HG*) in the battery. The heat generated by *HG* causes *Tc* to increase. Things that affect the rate of increase in *Tc* include core heat capacity (*Cc*) and thermal resistance (*Rc*) between the core and surface of the battery. The heat coming from the battery core is flowed to the battery surface (*Ts*). Factors that affect the rate of increase in *Ts* include surface heat capacity (*Cs*) and thermal resistance (*Rc*) between the core and surface of the battery. Furthermore, equation (5) and equation (6) describe the mathematical model of the battery surface temperature (*Ts*) and the average temperature between the battery core and surface (*Ta*) changing over time.

$$\frac{dTs(t)}{dt} = -\frac{ts(t)}{RuCs} - \frac{2Ts(t)}{RcCs} + \frac{2Ta(t)}{RcCs} + \frac{Tf}{RuCs} \tag{5}$$

$$\frac{dTa(t)}{dt} = \left(\frac{Cs - Cc}{RcCcCs} - \frac{1}{2RuCs}\right) Ts(t) + \left(\frac{Cc - Cs}{RcCcCs}\right) Ta(t) + \frac{H(t)}{2Cc} + \frac{Tf}{2RuCs} \tag{6}$$

Equation (7) below describes the overall heat generation $H(t)$ generated in the battery. The heat generated comes from the internal resistance of the battery, where when current flows through the battery, the internal resistance will convert some of the electrical energy into heat. In addition, the heat generated also comes from chemical reactions in the battery which are influenced by the battery temperature.

$$H(t) = I(t)\left[V_{p1}(t) + V_{p2}(t) + R_s(t)I(t)\right] + I(t)\left[Ta(t) + 273\right] En(SoC, t), \tag{7}$$

Equation (8) below describes the relationship between the battery core temperature (*Tc*), the average temperature between the core and surface (*Ta*), and the battery surface temperature (*Ts*).

$$Tc(t) = 2Ta(t) - Ts(t) \tag{8}$$

This research applies a multi-objective model approach for the purpose of optimizing battery fast-charging. The objective function in this study aims to measure the quality of the applied fastcharging strategy. (9) is the objective function in this study [5]

$$J_t = \omega_1 C_{soc} + \omega_2 C_{volt} + \omega_3 C_{heat} + \omega_4 C_{soh} + \omega_5 C_{smooth} \tag{9}$$

(9) consists of C_{SoC},C_{volt},C_{heat},C_{SoH},and C_{smooth} which are represented by (10), (11),(12), (13), and (14), respectively [5]

$$C_{SoC} = |SoC_{tar} - SoC_t| \tag{10}$$

In (10) C_{SoC} represents the cost associated with S_oC deviation from the desired S_oC target [5]

$$C_{volt} = \begin{cases} 0 & ifV_{tar_low} < V_t \quad < V_{tar\_upp} \\ \tau_1 \left| V_t - V_{tar\_upp} \right| & ifV_t > V_{tar\_upp} \\ \tau_1 \left| V_t - V_{tar\_low} \right| & ifV_t < V_{tar\_low} \end{cases} \tag{11}$$

In (11) C_{volt} represents the cost associated with deviating the terminal voltage from the safe voltage range [5]

$$C_{heat} = \begin{cases} 0 & ifT_{a,t} < T_{tar} \\ \tau_2 \left| T_{a,t} - T_{tar} \right| & ifT_{a,t} > T_{tar} \end{cases} \tag{12}$$

In (12) C_{heat} represents the Charge associated with increasing the battery temperature above the target temperature [5]

$$C_{SoH} = \tau_3 \, |\Delta SoH_t| \tag{13}$$

In (13) C_{SoH} represents the cost associated with battery degradation (decrease in SoH) [5]

$$C_{smooth} = \left| I_t - I_{t-1} \right| \tag{14}$$

In (14) C_{smooth} represents the cost associated with sudden changes in charging current, which aims to produce a smoother charging profile.

Furthermore, the Quasi-Newton L-BFGS-B algorithm is used to find the optimal solution of the multiobjective model function of the proposed fast-charging system. It iteratively updates the charging current value to minimize the objective function.

Figure 5 is a flow chart illustrating the workflow of the proposed fast-charging system. The system begins with the initialization process. The initialization process contains the process of reading the battery class and objective function as well as the required initial parameters. Next, enter the battery data input section to obtain SoC, Vt and Tc parameter data. Then, enter the battery charging cycle section. In this cycle, there is an optimization process using the Quasi-Newton L-BFGS-B method to find the optimal objective function value, where this objective function describes the optimal current for fast charging the battery by minimizing battery degradation. In the next process, there is decision making, if it has found the optimal objective function value then the process is complete. Conversely, if it has not found the optimal objective function, it will return to the optimization process until it finds the optimal objective function value.

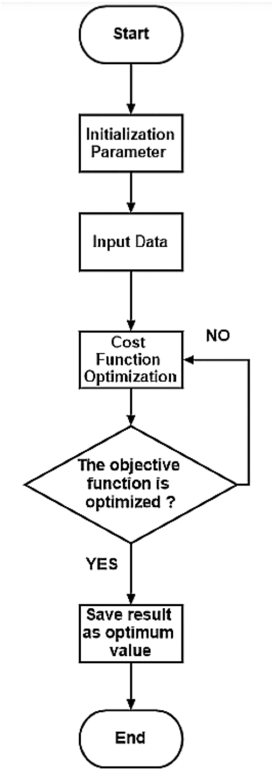

Figure 5. Overview of the proposed model architectures

2.3 Result and Discussion

In this study, a battery fast charging test of at least one thousand cycles was conducted to illustrate the dynamics of the battery. The test results using the Quasi-Newton LBFGS-B algorithm were obtained as shown in Figure 6.

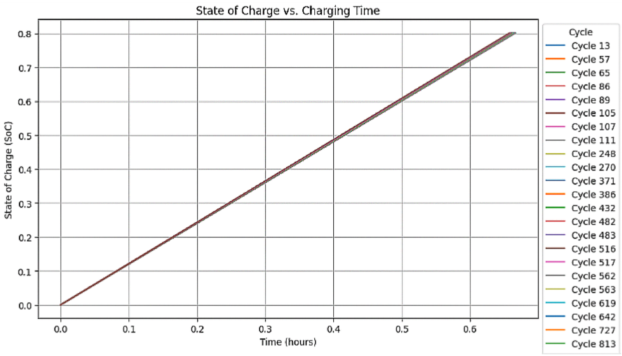

Figure 6. SoC vs Charging Time

Figure 6 shows that the proposed algorithm is able to make the system reach the expected target SoC (State of Charge) of 0.8 in a relatively constant time for the entire cycle which is within 0.6 hours. In this study the proposed algorithm is also able to minimize battery degradation. This can be seen in Figure 7.

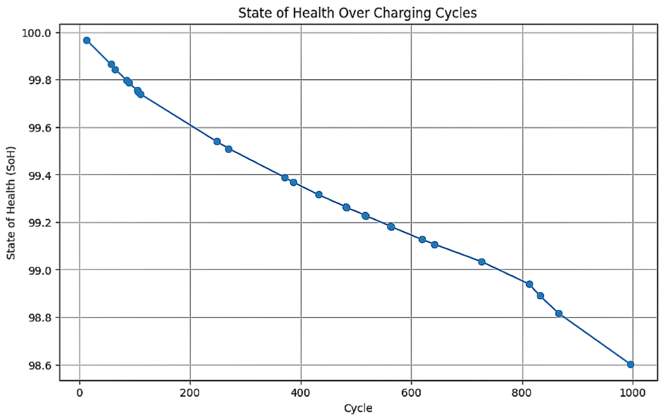

Figure 7. SoH vs Cycle

From Figure 7, there is a decrease in battery SoH which is only around the value of 2 percent, this shows that the Quasi-Newton Limited-Memory BFGS Bound (LBFGS-B) algorithm applied successfully maintains battery health so that the decrease in battery capacity can be significantly suppressed. The battery capacity that shows a decrease in degradation can be seen in Figure 8.

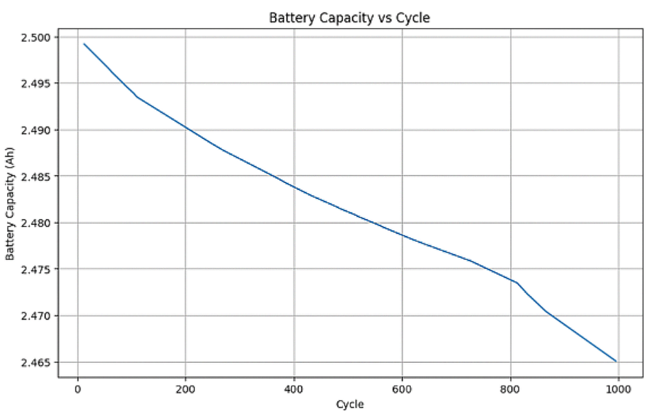

Figure 8. Battery Capacity vs Cycle

Based on Figure 8, it can be seen that the battery capacity from the full capacity value of 2500 Ah is reduced to around 2400 Ah. This shows a typical phenomenon in batteries, where the battery capacity decreases with time and usage. After 1000 cycles, the battery still has a capacity of about 98 percent, indicating a fairly good performance in terms of capacity retention. The results also show that the proposed method is able to maintain the battery capacity for a longer period while taking into account battery degradation and safety.

Furthermore, in this research, a comparative study is conducted to strengthen the argument of the superiority of the proposed Quasi-Newton L-BFGS-B optimization method. The comparative study is conducted using a conventional optimization method, namely the Gradient Descent method. The Gradient Descent method was chosen as a comparison because the method has been widely used in various optimization applications. The following Figure 9 shows the SoH vs Cycle of the optimization results with the Quasi-Newton L-BFGS-B method and the Gradient Descent method.

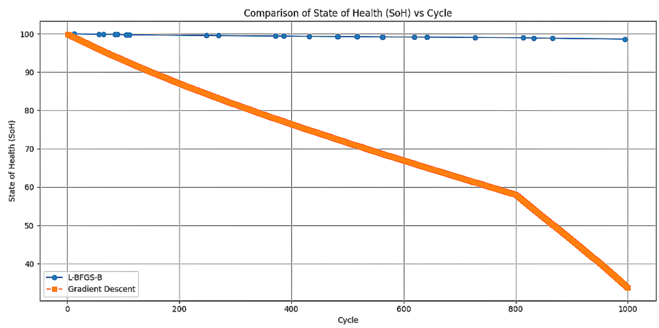

Figure 9. Comparison of SoH vs Cycle

Based on Figure 9, it can be seen that the Quasi-Newton L-BFGS-B method provides much better performance in maintaining battery health (SoH) compared to the conventional method in this case Gradient Descent. It can be seen that throughout 1000 cycles, the SoH curve for Quasi-Newton L-BFGS-B is maintained at around 98 percent. While the SoH for Gradient Descent shows a very significant drop to 35 percent after 1000 cycles. Moreover, Figure 10 shows the battery capacity comparison for 1000 cycles of the Quasi-Newton L-BFGS-B method compared to the Gradient Descent method.

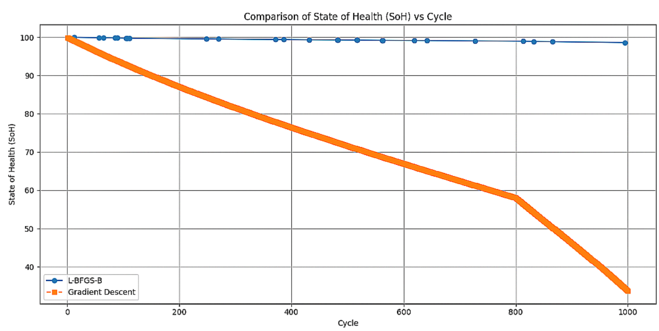

Figure 10. Comparison of Battery Capacity vs Cycle

From Figure 10, it can be seen that the Quasi-Newton L-BFGS-B method is able to maintain the battery capacity with very high performance compared to the conventional method, in this case the Gradient Descent method. The graph shows that the battery capacity for the Quasi-Newton L-BFGS-B is able to be maintained at around 2.4 Ah for 1000 cycles. While the battery capacity for Gradient Descent has decreased very significantly to 1 Ah after 1000 cycles.

The overall experimental outcomes indicate that the Quasi-Newton L-BFGS-B method is effective in maintaining battery health and reducing battery degradation. This shows that the Quasi-Newton L-BFGS-B method is highly applicable in extending battery life and enhancing overall charging efficiency.

3. Conclusion

From this research, a Quasi-Newton L-BFGS-B algorithm is proposed to find the optimal current of LIB fast charging in an attempt to maintain battery life and reduce potential battery degradation. The results show that this approach is able to maintain battery health (SoH) and capacity with only a decrease in SoH of about 2 percent and battery capacity is maintained at 98 percent of the initial capacity. The Quasi-Newton L-BFGS-B method is highly applicable in extending battery life and enhancing overall charging efficiency. The Quasi-Newton L-BFGS-B method has significant potential to be applied to LIB fast charging applications in both electric vehicle applications and other electronic devices.

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