



Original Research Article

Advanced PI-Optimized Constant Current–Constant Voltage Control for Electric Vehicle Battery Charging and Discharging

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ABSTRACT

The increasing adoption of electric vehicles (EVs) has heightened the demand for reliable and efficient battery charging strategies that minimize degradation while ensuring user convenience. Although conventional Constant Current–Constant Voltage (CC–CV) control is widely used, its conventional implementation often results in prolonged charging times and potential stress on the battery. This study addresses this limitation by developing and evaluating an optimized EV battery charging system using a Direct Current to Direct Current (DC–DC) boost converter under the Constant Current–Constant Voltage profile to enhance efficiency, reduce charging duration and preserve battery State of Health (SoH). A dynamic MATLAB/Simulink model was developed to incorporate realistic lithium-ion battery dynamics and control parameters. Three metaheuristic optimization algorithms namely Teaching–Learning-Based Optimization (TLBO), Sine Cosine Algorithm (SCA) and Adaptive Sparrow Decision Algorithm (ASDA) were employed for optimal tuning of PI controller gains (Kp and Ki). The optimized controllers were evaluated against a conventional baseline controller under varying initial State of Charge (SoC) conditions 30%, 50% and 70%. Simulation results demonstrated that all approaches achieved complete charging to 100% SoC while maintaining SoH above 98.5%. The optimized controller exhibited competitive charging performance and stable SoH preservation, with only marginal differences observed among the algorithms. The findings confirm that optimization improves the robustness and adaptability of CC–CV control for full-cycle EV battery operation and provides practical insight for intelligent battery management system design.

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1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has been driven by advances in lithium-ion batteries (LIBs) and the global need for sustainable transportation (Khurana et al.,2023). LIBs offer high energy density and long cycle life, but their safety, durability and performance depend on effective charging

and discharging control (Zhang et al., 2022). The Constant Current–Constant Voltage method is widely used for its simplicity, faster charging and protection against overcharging (Chen et al., 2023). However, uncontrolled discharge may lead to deep discharge, voltage instability and capacity loss (Ali et al., 2022). Most existing studies focus on charging strategies while optimized discharging remains underexplored despite its crucial role in sustaining performance and range (Ali et al., 2022). Furthermore, conventional CC–CV models often rely on rigid algorithms that cannot adapt to variations in temperature, load, and state-of-charge (Khurana et al., 2023).

Recent research has explored adaptive and multistage CC–CV methods, reconfigurable topologies, and physics-informed models, demonstrating faster charging, improved safety, and better battery health management (Li et al., 2020; Berliner et al., 2022). Optimization and intelligent control approaches, including model predictive control, fuzzy logic, and neural networks, have also reduced thermal stress, enhanced state-of-charge estimation, and prolonged battery lifespan (Zhou and Li, 2023; Rahim and Abu-Bakar, 2023; Gao et al., 2024). MATLAB/Simulink has become the dominant simulation platform for dynamically modeling and validating CC–CV strategies, enabling real-time evaluation and performance optimization without relying solely on physical prototypes (Olatunde and Yin, 2024; Zhao and Li, 2023). Despite these advances, gaps remain, particularly in developing optimized PI-based CC–CV controllers that balance efficiency, safety, and cost-effectiveness while addressing both charging and discharging phases (Jiang et al., 2023; Li et al., 2020; Rahim and Abu-Bakar, 2023; Zhao and Li, 2023).

To address these limitations, this study implemented an optimized PI-based CC–CV control strategy in MATLAB/Simulink for electric vehicle batteries. The approach integrates a dynamic DC–DC boost converter model, implements a metaheuristic-tuned PI controller and evaluates system performance against conventional PI control using metrics such as charging time, SoC and state-of-health (SoH). This comprehensive framework aims to enhance charge efficiency, shorten charging time, extend battery lifespan and support sustainable EV adoption through intelligent battery management systems. Figure 1 illustrates Constant Current/Constant Voltage (CC/CV) charging profile.

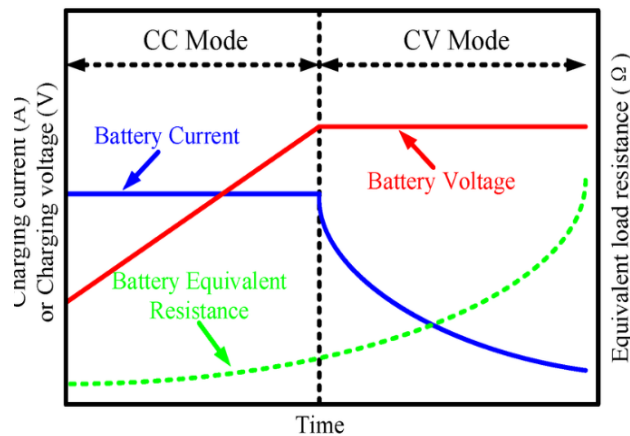


Figure 1: Constant Current/Constant voltage charging profile (Patel and Singh, 2024).

2. METHODOLOGY

2.1. System Model

In modeling the DC–DC boost converter, several simplifying assumptions were applied. The filter capacitor's equivalent series resistance (ESR) and parasitic inductance were considered negligibly small, while conversion losses during the switching process were neglected. The switching devices, which are the MOSFET and diode, were assumed to be ideal, and a small-signal model was employed for system linearization. The converter was further assumed to operate under steady-state conditions in continuous conduction mode (CCM). Figure 2 shows the basic DC-DC boost Converter circuit.

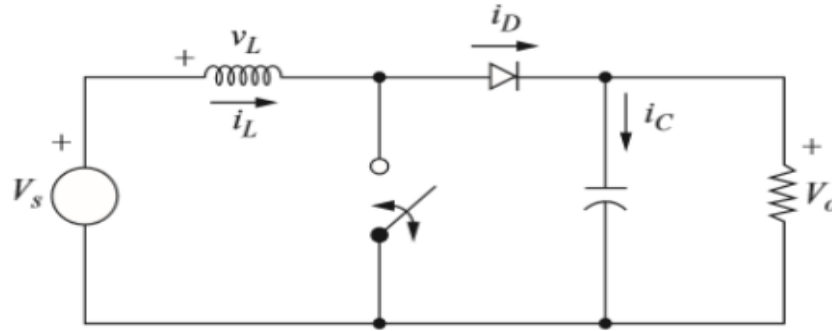


Figure 2: The basic boost converter circuit (Hwang et al., 2020)

When the switch is turned ON, the diode becomes reverse-biased since its anode is connected to ground. In this state, the inductor charges as its current increases, storing energy in its magnetic field, while the capacitor continues to supply the load. Conversely, when the switch is turned OFF, the diode is forward-biased as its anode connects to the positive rail of the DC source. The inductor current cannot drop abruptly due to its inherent polarity reversal; instead, it behaves as an ideal source in series with the DC supply, discharging to provide energy to both the load and the capacitor. Figures 3 and 4 describe the boost converter Circuit during ON & OFF conditions, respectively.

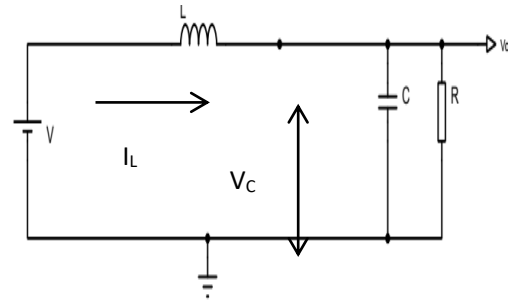
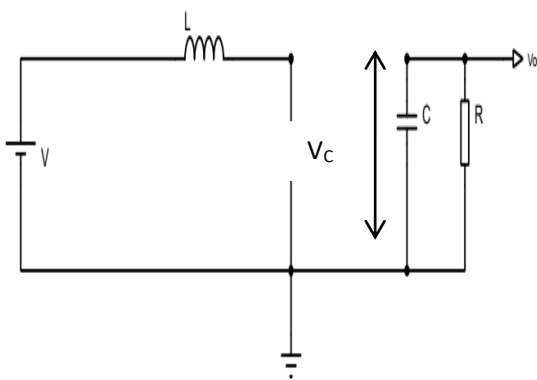


Figure 3: Boost converter circuit during ON condition

Figure 4: Boost converter circuit during OFF condition

2.2. Battery Parameters

The battery parameters used for simulation are presented in Table 2.

Table 2: Battery parameters specifications

Value	Parameters
Lithium-ion (Li-ion)	Cell type
400V	Nominal Voltage
400V	Maximum Voltage (CV cutoff)
250V	Minimum Voltage (Discharge)
50Ah	Rated Capacity
1C (50A)	Charging Current (CC phase)
45°C	Thermal Cutoff Temperature
100mΩ	Internal Resistance
30% - 100%	SoC Operating Range

2.3. PI Controller Tuning

The proportional (K_p) and integral (K_i) gains for both PI controllers were carefully adjusted to deliver a well-balanced system response, one that reacted quickly to changes while avoiding excessive overshoot or instability. The tuning process began with basic empirical methods such as trial-and-error to establish a working baseline, followed by gradual refinement. A step-by-step tuning strategy was applied; the inner current control loop was tuned first and stabilized with its parameters held constant while tuning the outer voltage loop afterward. If the blocks are replaced by their respective transfer functions, then the control structure will be as shown in Figure 5.

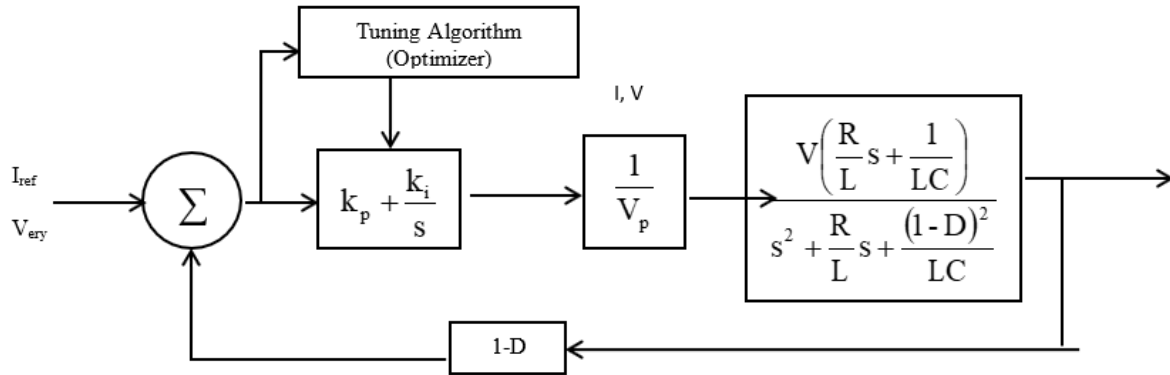


Figure 5: The complete control structure of the DC-DC boost converter

The design values are as follows: inductance ($L=100\mu\text{H}$), Capacitance ($C=10000\mu\text{F}$), internal resistance ($R=100\text{m}\Omega$), max. Voltage ($V_p=400\text{V}$) and duty cycle ($D=0.5$). The transfer function is obtained by using the design values. The transfer function for the DC-DC boost converter is expressed as:

$$\frac{V_0(s)}{d(s)} = \frac{V \left(\frac{R}{L}s + \frac{1}{LC} \right)}{s^2 + \frac{R}{L}s + \frac{(1-D)^2}{LC}} \quad (1)$$

The optimization problem was formulated as a constrained minimization problem where the decision variables were the PI controller parameters, K_p and K_i . The single objective function which minimizing error indices was based on the Integral of Time-weighted Absolute Error (ITAE) which was selected for its effectiveness in penalizing both large initial errors and small errors that persist over time. The objective function was mathematically expressed as:

$$\text{Min ITAE} = \int_0^t |e| dt \quad (2)$$

$$\text{Subject to } K_i^{\min} \leq K_i \leq K_i^{\max}$$

$$K_p^{\min} \leq K_p \leq K_p^{\max}$$

where: $e(t)$ is the tracking error, K_p is the proportional gain and K_i is the integral gain.

2.4. Computational Intelligence Techniques

Computational intelligence (CI) methods were applied to optimize PI controller gains for EV battery charging and discharging system. Traditional tuning methods may be inadequate for nonlinear systems with competing objectives such as fast charging, voltage stability, and battery health preservation. To address these challenges, advanced metaheuristic optimization techniques were employed. Techniques covered include the Teaching Learning-Based Optimization (TLBO), Adaptive Sparrow Decision Algorithm (ASDA), and the Sine Cosine Algorithm (SCA). These algorithms have demonstrated promising results in improving control performance, minimizing charging time, and ensuring battery safety.

3. RESULTS AND DISCUSSION

The open-loop simulation results verified that the developed model achieved a seamless transition between the constant current (CC) and constant voltage (CV) operating modes, maintaining voltage stability and effective current regulation throughout the process. This validated configuration provided the baseline platform for integrating and evaluating the optimized closed-loop PI control strategies.

3.1. Deployment of Optimized PI Controllers

The PI controller was implemented in a closed-loop configuration to regulate the duty cycle of the boost converter. The controller gains (K_p and K_i) were optimized using the three selected metaheuristic techniques, which are: ASDA, SCA, and TLBO. The optimization objective was to minimize the ITAE criterion while ensuring fast settling time and minimal overshoot. Table 3 presents the optimized PI gains obtained for each control strategy

Table 3: Obtained optimal PI gains for the controllers

Controller Type	K_p	K_i
Unoptimized	0	0.0049289
SCA	1.7922	51.5219
ASDA	1.7910	90.5438
TLBO	1.7725	56.0916

3.2. Evaluation and Validation of the Optimized System

The performance of the optimized controllers was evaluated against the conventional PI controller using charging time, SoC, and SoH as performance indicators.

3.2.1. State of charge performance

The State of Charge (SoC) performance was examined to assess the ability of each controller to achieve complete battery charging under the CC–CV strategy. The SoC profiles indicate the charging behavior of the battery from the selected initial SoC conditions to full charge. Figure 6 shows the SoC profile for ASDA. The ASDA controller achieved complete charging while maintaining a smooth SoC progression throughout the charging cycle. The ASDA achieved full charge at $t = 5756.625$ seconds, which is identical to the performance recorded for the SCA algorithm. The charging curve reflects stable controller behaviour and acceptable dynamic response under the CC–CV operating conditions.

Figure 7 shows the SoC profile for TLBO. The TLBO controller also achieved complete charging to 100% SoC with a smooth progression and stable response. The battery was fully charged from 30% SoC at $t = 5735.704$ seconds, but it outperformed both SCA and ASDA. The charging pattern indicates effective controller performance and acceptable convergence during operation. The SoC progression was relatively smooth, suggesting reasonable convergence and acceptable control stability. The discharge phase began after full charge and followed the uniform discharge time of 2947.699 seconds. Figure 8 shows the SoC profile for SCA. The SCA controller produced a gradual and stable SoC trajectory, reaching full charge successfully. Its charging response was comparable to those of the other optimized controllers and the discharge phase lasted 2947.699 seconds. Figure 9 shows the SoC profile for Conventional PI.

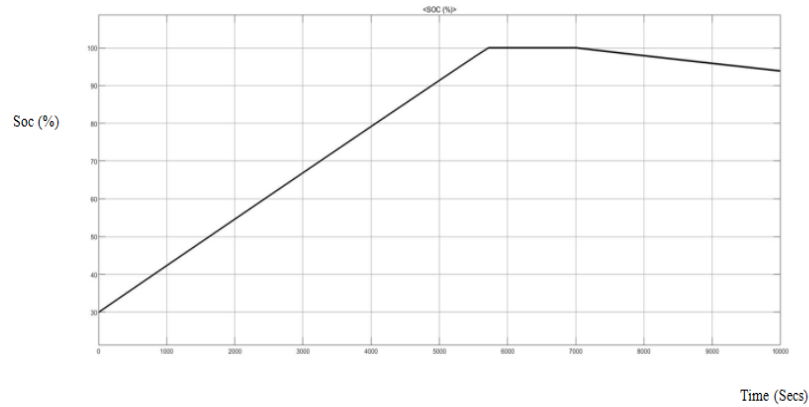


Figure 6: SoC vs Time (ASDA)

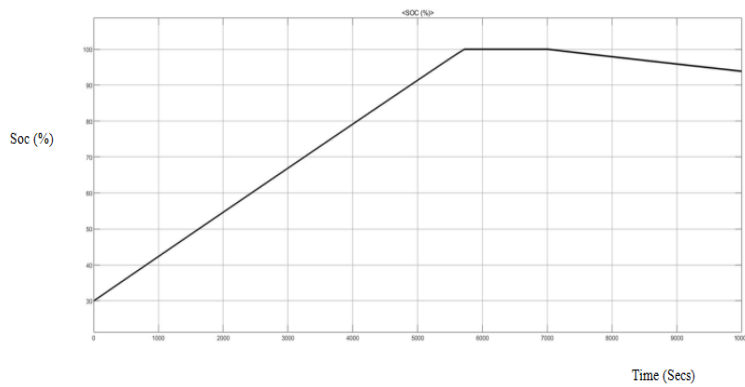


Figure 7: SoC vs Time (TLBO)

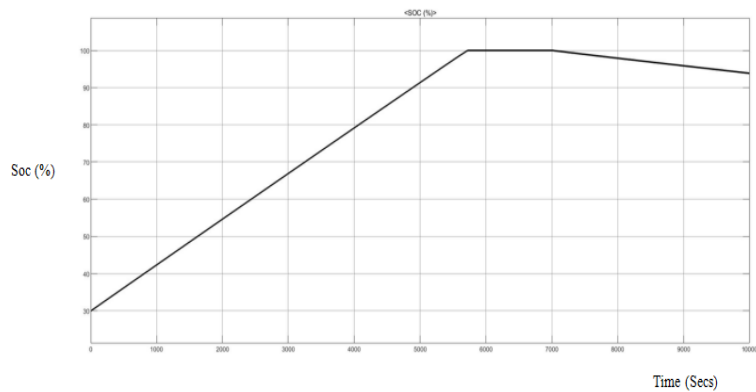


Figure 8: SoC vs Time (SCA)

The Conventional controller shows a steady increase from 30% to 100%, achieving full charge at $t = 5735.704$ seconds. This reflects stable current and voltage regulation under the CC–CV charging profile, despite the lack of adaptive tuning. After a brief hold period, the battery enters the discharge phase, lasting 2947.699 seconds. It serves primarily as a baseline for evaluating the improvements brought by computational intelligence-based controller.

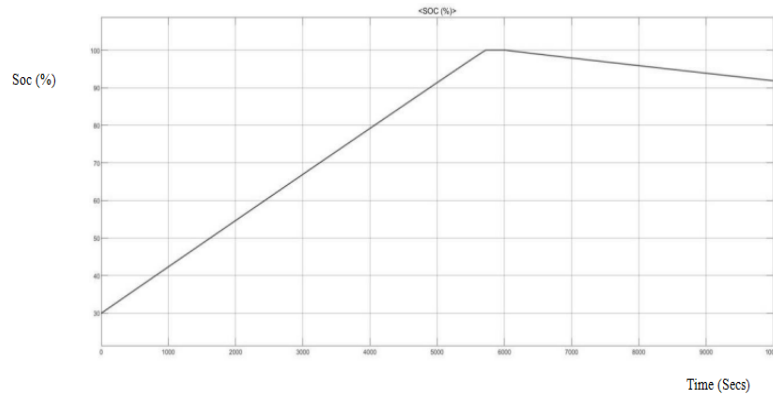


Figure 9: SoC vs time (Conventional)

3.2.2. State of health vs time trends

This subsection presents the State of Health (SoH) trends observed during the charging process under the different control strategies. SoH performance is important for evaluating the extent to which each controller preserves battery integrity and minimizes degradation. Figure 10 shows that all control strategies maintained closely similar SoH profiles throughout the charging process. In all cases, the SoH remained above 98.5%, indicating minimal battery degradation during charging. This result suggests that the optimized controllers improved control behaviour without imposing additional electrochemical stress on the battery.

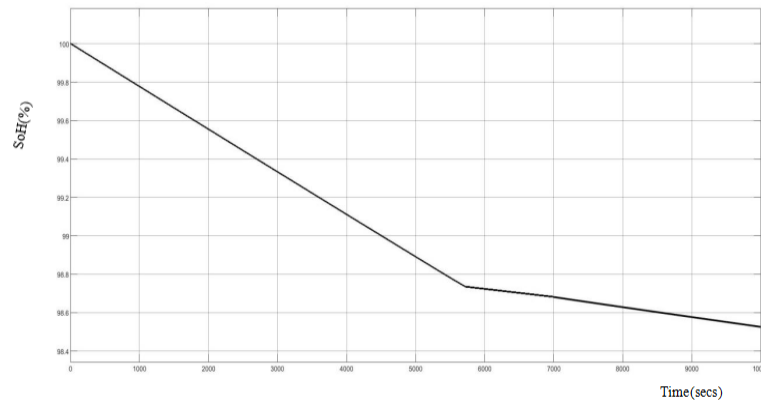


Figure 10: SoH vs time

This consistent outcome across all methods indicates minimal degradation of the battery throughout the charging process, demonstrating that the optimized algorithms, while varying in terms of charging speed and control dynamics, were equally effective in minimizing stress on the battery cells during the CC–CV charging phases. The absence of variation in SoH among the control strategies suggests a high level of efficiency in voltage and current regulation, thus contributing to sustained battery health. These findings imply that the integration of intelligent algorithms does not compromise SoH and aligns closely with the performance of the conventional method, which reinforces their suitability for electric vehicle applications.

3.2.3. Discharging performance

To support full-cycle battery operation, the discharge behavior of the battery was also observed following the charging phase. The discharge profiles indicated a stable reduction in SoC after full charge, with no abrupt instability or abnormal response under the tested control configurations.

The discharge phase followed a generally consistent pattern across the controllers, suggesting that the optimized control framework is applicable not only to charging regulation but also to maintaining stable battery operation during discharge. Although the observed differences among the controllers during discharge were limited, the inclusion of discharge analysis strengthens the practical relevance of the framework for EV battery applications.

3.3. Comparative Performance Evaluation

Table 4 presents the comparative performance of the Conventional baseline controller and three optimized controllers at initial SoC levels (30%, 50%, and 70%). The analysis focuses on charging time, final SoC, and State of Health (SoH) outcomes.

Table 4: Comparative performance evaluation

Algorithm	Initial SoC (%)	Charging Time (s)	Final SoC(%)	SoH (%)
Conventional PI	30	5735.704	100	98.53
	50	4145.746	100	98.82
	70	2486.053	100	99.12
TLBO	30	5735.704	100	98.53
	50	4138.773	100	98.82
	70	2506.974	100	99.12
SCA	30	5756.625	100	98.53
	50	4124.826	100	98.82
	70	2506.974	100	99.12
ASDA	30	5756.625	100	98.53
	50	4145.746	100	98.82
	70	2548.815	100	99.12

The results presented in Table 4 show that all control strategies successfully achieved full charging to 100% SoC while maintaining SoH within a narrow and acceptable range of 98.53% to 99.12%. This indicates that the optimization methods did not compromise charging completeness or battery health. With respect to charging time, the differences among the optimized algorithms were relatively small and varied depending on the initial SoC level. At 30% SoC, the baseline controller and TLBO produced the shortest charging time, while SCA and ASDA required slightly longer durations. At 50% initial SoC, SCA recorded the shortest charging time, followed closely by TLBO, whereas ASDA performed similarly to the baseline controller. At 70% initial SoC, the baseline controller recorded the shortest charging time while the optimized methods remained close in performance.

The results indicate that no single optimization algorithm consistently outperformed the others across all operating conditions. However, the optimized controllers demonstrated competitive charging behavior and improved tuning flexibility while maintaining stable SoH performance. Therefore, the primary contribution of the optimization framework lies in enhancing controller robustness and adaptability rather than delivering a uniformly dominant charging-time reduction under all conditions.

4. CONCLUSION

This study presented an optimized PI-based CC–CV control framework for electric vehicle battery charging and discharging using a DC–DC boost converter in MATLAB/Simulink. The framework incorporated three metaheuristic optimization techniques: TLBO, SCA and ASDA for tuning the PI controller gains and evaluating their influence on battery charging performance. Simulation results showed that all controllers successfully achieved complete charging to 100% SoC while preserving battery State of Health above 98.5%. Although the charging-time improvements among the optimized controllers were relatively modest and condition-dependent, the optimized strategies demonstrated stable and competitive performance across different initial SoC levels. The inclusion of discharge behaviour further supports the applicability of the framework for full-cycle EV battery operation.

In conclusion, the study confirms that optimization can improve the adaptability and practical effectiveness of PI-based CC–CV battery control systems. The developed framework provides a useful basis for intelligent battery management system design and future enhancement of EV charging and discharging strategies.

5. ACKNOWLEDGEMENT

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6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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