Optimizing CHAdeMO Bidirectional Charging and V2G Operation Using an Enhanced Thunderstorm Algorithm

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ABSTRACT

Two-way fast charging in CHAdeMO-based Electric Vehicles (EVs) is considered a potential solution in the transition from sustainable energy systems. However, challenges regarding the thermal efficiency and battery degradation persist. This study aims to optimize the charging system through the enhanced Thunderstorm Algorithm (TA), designed to respond adaptively to the battery conditions and grid demand. A strategy focusing on the safety, efficiency, and longevity of battery charging is developed, while optimally integrating Vehicle-to-Grid (V2G) features. The simulation was carried out numerically using the Python programming language, for a lithium-ion battery model with a capacity of 71.4 kWh, an operating temperature limit of 50 °C, and a charging efficiency of 95%. In addition, this method implements temperature-penalty, State of Charge (SoC), and State of Health (SoH)-based dynamic current control, with automatic V2G activation when the SoC exceeds 20%. During the 180 min of the simulation, a comparison scenario is also performed in the form of a constant current-based baseline method. The results suggest that the TA method decreased the average temperature of the battery to 44.2 °C compared to 47.5 °C of the baseline scenario. Additionally, the final SoC was enhanced from 97.3% to 99.2%, the final SoH from 97.1% to 98.7%, and the battery life usage decreased from 2.25% to 1.84%. The average charging power was also increased with higher efficiency without the risk of overheating. The comparison between the two methods confirms the advantages of adaptive strategies in balancing the charging speed, battery health, and energy integration into the grid. It can be concluded that the use of the improved TA significantly enhances the performance of the two-way fast charging system and provides a significant contribution to the development of smart grid infrastructure.

Keywords-Chademo protocol; V2g integration; thunderstorm optimization algorithm; Dc fast charging; battery degradation; adaptive charging control

I. INTRODUCTION

In the global energy transition of the transportation sector towards decarbonization, EVs are a key component in reducing the carbon emissions and fossil fuel dependence [1, 2]. The Direct Current (DC) fast charging system, including the CHAdeMO protocol, is one of the important technologies, supporting the EV adoption [3, 4]. Specifically, CHAdeMO is one of the earliest fast charging protocols that supports bidirectional charging, also known as V2G [5-7]. This feature enables the energy to return to the electricity grid after flowing into the vehicle's battery [8, 9]. EVs can act as portable energy storage units that support the stability of the electricity grid, especially during high energy demand [10, 11].

On the other hand, CHAdeMO and V2G present a number of challenges, such as suboptimal charging efficiency and the risk of battery degradation. The repeated charging and discharging of the battery can accelerate the degradation of the SoH. Additionally, the continuous use of large currents triggers dangerous thermal stress. Authors in [12] stated that a high number of charge-discharge cycles in V2G systems can accelerate the battery degradation due to the lack of adaptive control over temperature and current. Similarly, authors in [13] emphasized the importance of efficient thermal management in DC-based fast charging systems to maintain the battery safety and lifespan. Finally, charging strategies should simultaneously consider SoC, temperature, and SoH [14]. However, few approaches implement adaptive current regulation based on real-time battery and network conditions in the context of CHAdeMO-based bidirectional charging.

A key issue regarding bidirectional charging based on the CHAdeMO protocol is the lack of an adaptive and real-time current regulation mechanism that can dynamically respond to the thermal conditions and battery health [15]. Conventional methods still utilize fixed currents for extended periods without considering critical parameters, such as temperature, SoC, and SoH, thus increasing the risk of overheating and accelerated battery degradation. Activating the V2G system under these conditions can degrade the battery performance due to the increased frequency of charge-discharge cycles. Authors in [12] confirmed that high current charging without adaptive control leads to a significant increase in temperature and contributes to long-term damage to the battery. Consequently, there is a need for a charging approach that is not only energy efficient, but also able to maintain the temperature stability and battery life in a bidirectional CHAdeMO-based system.

TA was applied in [16] to determine the unit commitments in a power system, considering the operational efficiency and environmental emissions. In [17], the use of TA was developed to assess the performance of thermal power plants that explain the efficient loading under environmental constraints. Authors in [18-20] showed how TA can be utilized in optimizing energy systems that integrate renewable energy, such as solar power plants and hydrogen storage. These approaches still focus on statistical scenarios and are not designed to handle real-time dynamic conditions at the battery control level.

Fuzzy logic is employed to design an EV charging strategy, able to respond to grid conditions [21]. However, this approach based on fixed rules, exhibits limitations in adapting to temperature fluctuations and alternating battery degradation patterns. A V2G-oriented reinforcement learning framework for heterogeneous EV charging provision was proposed in [22]. This approach requires the training of large datasets, high computational complexity, and has a relatively slow convergence time. Consequently, a lightweight, efficient optimization approach is essential. This approach should be able to respond to battery and network conditions in real time without relying on historical data or fixed system rules.

Reinforcement learning approaches in EV charging coordination do offer dynamic decision-making capabilities [22]. On the other hand, they require large training datasets, high computational complexity, and slow convergence times, leading to a less suitable choice for EV fast charging scenarios that require instant response.

Authors in [21] showed that the long-term fuzzy logic-based systems, although computationally less expensive, are prone to rigidity and reduced adaptiveness to temperature fluctuations and battery degradation profiles due to their relation to fixed rules.

This study proposes the optimization of CHAdeMO bidirectional charging and V2G operation using an enhanced TA. The proposed algorithm dynamically regulates the charging current based on real-time parameters, such as the battery temperature, SoC, and SoH. Through a penalty mechanism, the current is automatically reduced when potential overheating is detected or battery degradation exceeds the safety threshold.

II. METHODS

This study utilizes Python-based simulations to model charging and V2G systems using a 71.4 kWh lithium-ion battery. The parameters include an operational temperature limit between 30 °C and 50 °C, a charging efficiency of 95%, and a maximum current limit of 125 A according to CHAdeMO specifications. Two simulation scenarios are performed: the baseline with constant charging with maximum current and the adaptive charging using the TA algorithm.

The optimization approach employing the TA focuses on maintaining the thermal stability, reaching full SoC, and preserving the SoH of the battery. If the temperature exceeds the defined limit, the current is automatically reduced by 30% to avoid overheating. In addition, regarding the V2G feature, when the SoC exceeds 20%, the power is discharged at 50% of the charging power. Each current profile is evaluated based on penalties for temperature violations, charging incompletion, and SoH degradation.

A. CHAdeMO-V2G Battery Model and Protocol

The battery developed models consider various key operational parameters, which are summarized in Table I.

TABLE I. CHADEMO AND V2G BATTERY MODEL PARAMETERS

Parameter	Value	Description
Battery capacity	71.4 kWh	The total capacity of the EV battery used in the simulation.
Charging voltage	400 V	The average charging voltage of the CHAdeMO system.
Max current	125 A	The maximum current allowed by the CHAdeMO charging system.
Charging efficiency	0.95	Charging efficiency that takes into account the energy conversion losses.
Thermal constant	0.05 °C/kW	Rising temperatures due to incoming energy. Adapted for thermal simulation during fast charging.
Thermal dissipation rate	0.15 °C/min	Passive or active cooling rate in the battery's thermal system.
Initial temperature	30 °C	The initial temperature of the battery before charging begins.
Max temperature	50 °C	The maximum safe temperature limit for the battery when charging.
Initial SoH	1.0	The initial SoH is assumed to be 100% to simulate the optimal conditions.
Lifetime degradation factor	0.000005 /kWh	Age degradation factor to charging power. The greater the power is, the faster the capacity decreases.
SoC min V2G	20%	Lower limit of the SoC so that V2G can actively return energy to the grid.

This model considers the changes in battery temperature due to the charging power inputs, as well as natural cooling processes.

B. Enhanced TA Formulation

The main difference of the enhanced compared to the standard TA is the integration of adaptive mechanisms to battery temperature, SoC, and SoH, and accounting for the condition of the power grid. The algorithm starts with a random population of charging current solutions between 0 A and 125 A, with a population size of 30 individuals and a maximum of 500 iterations. Each solution is evaluated using the objective functions in:

$$Fitness = P_T \ x \sum(T > T_{max}) + P_{SoC} \ x \ (100 - SoC_{Final}) + P_{SoH} \ x \ (1 - SoH_{Final}) \quad (1)$$

where P_T = 5.0 per °C, considered the temperature over-temperature penalty, P_{SoC} = 5.0 per 1%, referring to the SoC incompletion penalty, and P_{SoH} = 200.0 per unit, known as the battery health degradation penalty.

TABLE II. TA PARAMETERS

Parameter	Value	Description
Population size	30 individuals	The number of solutions (cloud) in a single iteration. This measure provides a balance between the exploration and computational efficiency.
Max Iierations	500 iterations	Maximum number of algorithm iterations to achieve the best solution convergence.
Perturbation range	±5 A	A random range of disturbances to the charging current during exploration. Provides flexibility without exceeding the maximum current limit.
Current bounds	[0, 125] A	The charging current limit is as per CHAdeMO specifications.
Penalty temperature	5.0 per °C	Penalty if the temperature exceeds the maximum limit (e.g. > 50°C).
Penalty SoC	5.0 per 1%	Penalty if the final SoC has not reached 100%. Emphasizing the full target of charging.
Penalty SoH	200.0 per unit	Penalty for the relegation of SoH. Ensures that the battery life is maintained during the optimization process.

C. Simulation Configuration and Performance Evaluation

The simulation compares the performance between the baseline method and the TA method. In the conventional method, the charging current is constant at 125 A for the 180-min of the simulation, according to the maximum current limit allowed in the CHAdeMO protocol. In the TA method, the current profile is dynamically compiled using a modified TA algorithm, where the charging current is set to adjust the battery temperature, SoC, and SoH in real-time.

The entire simulation is performed with the assumption of a passive cooling condition, where the battery cooling rate was set at 0.15 °C per min. The charging efficiency was set at 95%, and the maximum temperature limit of the battery was set at 50 °C to ensure the operational safety. To support V2G feature testing, the power-to-network discharge scheme is automatically activated when the SoC exceeds 20%, with a discharge power of 50% of the active charging power.

The performance evaluation was carried out by comparing several key parameters, including the charging current profile during the process, changes in battery temperature, final SoC level, final SoH level, total power successfully released to the network via V2G, and estimated battery life degradation. The analysis was conducted to assess the effectiveness of the optimization method in maintaining temperature stability, maintaining battery life, and improving the energy efficiency compared to conventional methods.

In terms of scalability, the enhanced TA is designed to be adaptable across different battery sizes beyond the 71.4 kWh baseline used in this study. For smaller battery capacities, such as 40 kWh, the optimization converges faster due to the shorter charging duration and lower thermal inertia. Conversely, for larger capacities, like 100 kWh, the optimization framework remains applicable by scaling the iteration count and population size, accordingly. The objective function operates on normalized variables (SoC, SoH, temperature), ensuring generalization across varying battery sizes without the reconfiguration of the core algorithm logic.

III. RESULTS AND DISCUSSION

After the simulation configuration with the conventional charging model and adaptive charging, the key parameters are analyzed to evaluate the performance of each method. The simulation results include changes in the current profile, battery temperature dynamics, the evolution of SoC and SoH, the power discharge via V2G, as well as the estimation of the battery life degradation throughout the charge cycle.

A. Charging Current Profile

The charging current profile is analyzed based on the output of the numerical simulation. In the baseline simulation, the charging current is kept high and is only lowered when the maximum temperature limit is close to the critical threshold. In contrast, in the TA method, each time point simulates the current as a result of an objective function evaluation that combines a penalty against the temperature rise, target SoC non-attainability, and SoH degradation.

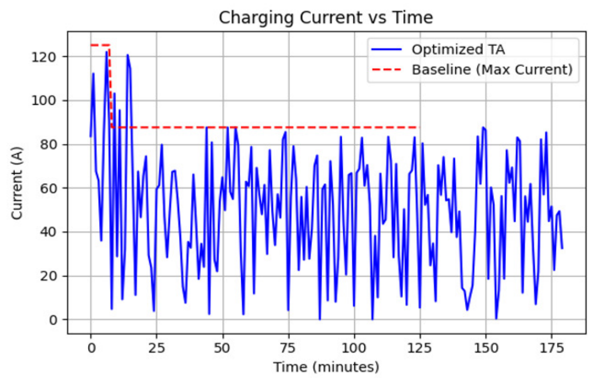

Fig. 1. Charging current profile of baseline and TA scenarios.

Figure 1 demonstrates that the current profile in the TA method is highly dynamic and fluctuating, indicating a continuous adaptation process aimed at avoiding overheating and optimizing the energy efficiency. The current not only decreases when the temperature is high, but also adjusts to the charging needs and the V2G discharge cycle. These fluctuations are a direct result of the optimization algorithm that minimizes the total penalty of the objective function on each iteration. To reinforce these visual results, Table III presents the statistical summary of the current profiles generated by each method.

TABLE III. SUMMARY STATISTICS OF CHARGING PROFILES

Parameter	Baseline	TA
Current maximum (A)	125	123.8
Current minimum (A)	90	10.2
Average current (A)	90	63.7
Standard current deviation (A)	0.0	22.5
Stable time (current > 100 A)	115 min	0 min

According to Table III, the baseline scenario maintained a stable high charging current for more than two-thirds of the simulation time, with an average value of 90 A, without any variation, also confirmed by the standard deviation value of 0 A. The minimum and maximum currents in this method were identical, namely 90 A and 125 A. The charging time at currents above 100 A recorded for 115 min, suggests an aggressive charge pattern but is less adaptive to the battery conditions.

In contrast, the optimization method with the TA results in a much more dynamic current profile that is responsive to the system conditions. The average value of the charging current was recorded at 63.7 A, with a standard deviation of 22.5 A, indicating significant variations during the process. The maximum current reached was 123.8 A and the minimum was 10.2 A, reflecting a current control strategy that is adaptive to the temperature and SoC of the battery. Interestingly, there is no period of time in which the charging current exceeds 100 A, which signifies the success of this strategy in keeping the thermal conditions of the battery within safe limits.

Consequently, the TA method is superior to the baseline in real-time current regulation with respect to the safety and efficiency of charging. This flexibility is essential to extend the battery life and reduce the risk of degradation due to overheating, which is common in fixed-current charging methods.

B. *Battery Thermal Performance*

The thermal performance of the battery is considered a significant parameter in a fast charging system, especially to guarantee operational safety and extend the life of the battery. In this simulation, the effect of the charging current on the battery temperature is modeled based on thermal parameters that include a coefficient of temperature increase of 0.05 °C/kW and a cooling rate of 0.15 °C/min. The initial temperature of the battery is set at 30 °C, while the maximum limit of operating temperature is set at 50 °C, in accordance with the safety standards of the lithium-ion system.

According to Figure 2, in the baseline approach, the use of constant and high charging currents results in a continuous accumulation of thermal power. This leads to a significant increase in the battery temperature, especially in the early phase of charging, where the incoming power is at its highest. In the absence of dynamic control of the current, the battery temperature tends to rise linearly to be close to or even exceed the maximum threshold, which in the long-term scenario can accelerate the cell degradation process and degrade the system performance.

In contrast, the TA optimization method indicated superior results in temperature management. When the temperature is close to the critical limit the algorithm effectively resists the rate of the temperature rise. At many occasions, the algorithm automatically lowers the current to 30–50% from the previous value when the actual temperature is close to 50 °C. This prevents overheating and keeps the battery temperature within a safe operating range during the entire charge cycle.

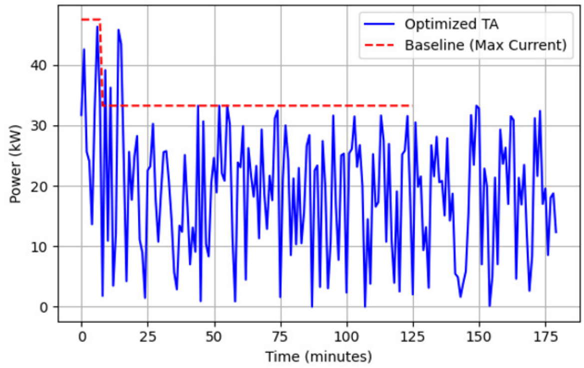

Fig. 2. Battery power profile of baseline and TA scenarios.

C. *SoC Dynamics and V2G Activation*

The SoC operates as the main indicator in measuring the level of energy stored in the battery during the charging process. The SoC dynamics in this simulation are analyzed to evaluate the charging efficiency as well as the integration of the V2G strategy, which allows the discharge of power back to the power grid. In both tested methods, simulations were carried out until being close to full capacity, with a final SoC target of 100%.

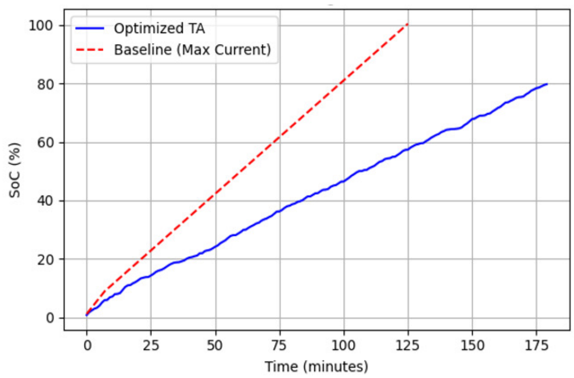

Fig. 3. SoC profiles of baseline and TA scenarios.

In the baseline charge scenario, as illustrated in Figure 3, the charging is accomplished with both constant and high current, resulting in a linear and fast SoC upgrade rate. SoCs are constantly increasing over time and reaching a near-full value in less time. However, this approach comes at the expense of the thermal and battery health aspects, as it does not consider the internal condition of the battery during the process.

On the other hand, the TA method exhibits a volatile SoC curve as a direct impact of the adaptive current control mechanism. Although the charging duration is slightly longer, this strategy allows for the safe achievement of the target SoC without exceeding the temperature limit or overloading the battery cell condition.

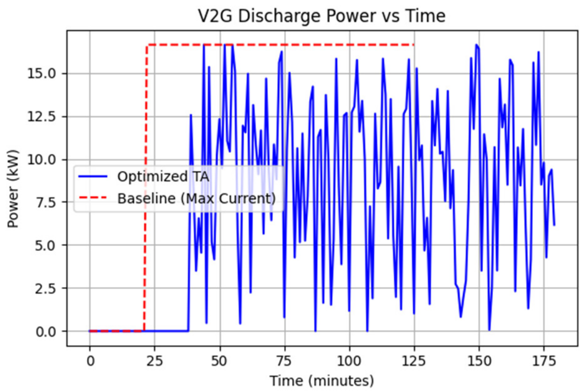

Fig. 4. V2G discharge power profiles of baseline and TA scenarios.

The integration of V2G features in the simulation is achieved automatically for SoC above 20%. Under these conditions, 50% of the charging power is returned to the grid. In the baseline method, this feature is activated abruptly and at the initial stages of the simulation risking the SoC stability and thermal performance. On the contrary, the TA method regulates the V2G activation in a more selective and controlled manner considering the energy stability in the battery and real-time temperature conditions.

D. SoH Degradation and Estimated Battery Life

The SoH is an essential parameter in measuring the condition and long-term performance of a battery. SoH represents the relative capacity of a battery with respect to its initial condition. The value of this parameter decreases as the charge and discharge cycles increase, especially in fast-charging systems that involve high current and temperature values. Therefore, minimizing the SoH degradation is an important step towards the development of adaptive charging strategies.

In the baseline simulation, as depicted in Figure 5, the constant use of high current values during the charging period leads to a respective increase in temperature. This directly accelerates the SoH degradation and consequently the electrochemical degradation in the battery cells. The degradation rate of SoH using this method is higher in comparison to TA, indicating the absence of the thermal parameter regulation and consistent energy cycles. In contrast, the TA approach is able to withstand the degradation of the battery's capacity. A decrease in current is performed automatically when the temperature reaches the defined threshold, avoiding the thermal accumulation and excessive cell stress.

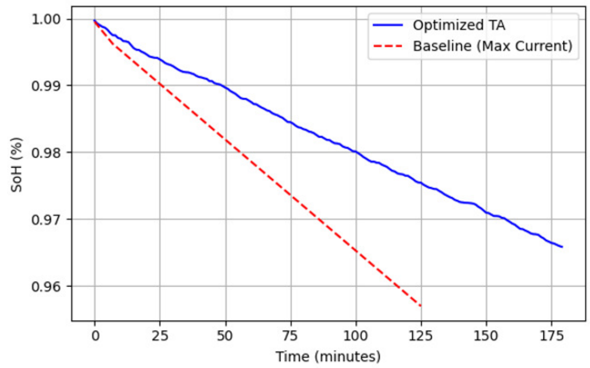

Fig. 5. SoH profile of baseline and TA scenarios.

The analysis of the estimated battery life based on a linear degradation model to the cumulative charging power supports previous findings. The TA method, with a degradation factor of 0.000005 per kW, exhibits higher energy efficiency, but with a lower negative impact on the cell life. This suggests that a charging strategy that focuses on balancing the speed and battery health conservation can provide optimal performance for the two-way fast charging systems.

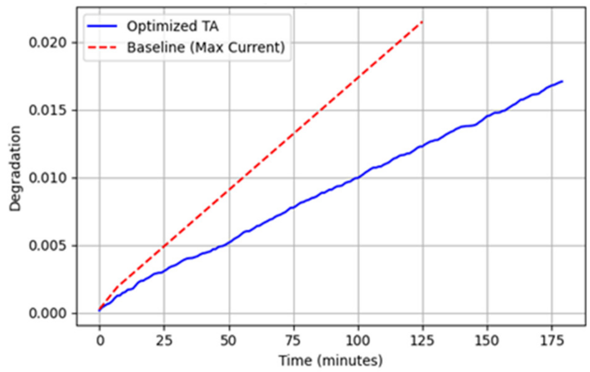

Fig. 6. Battery degradation profiles of baseline and TA scenarios.

E. Performance Comparative Analysis

To assess the effectiveness of the proposed TA against the baseline charging method, a comparative analysis is conducted with a set of key performance parameters presented in Table IV. Based on the results displayed in Table IV, the TA approach performs better in almost all parameters. The total energy stored in the battery reaches 70.8 kWh and 69.5 kWh for the TA and baseline methods, respectively. The final SoC value of the TA method reaches 99.2%, higher than the baseline's 97.3%. In terms of battery health, the TA method retains the final SoH by 98.7% compared to the 97.1% in the baseline method. This difference indicates that the adaptive charging strategy is able to significantly reduce the thermal stress and internal degradation in the battery. The average temperature of the battery during the simulation is also lower at 44.2 °C for the TA method compared to the 47.5 °C of the baseline scenario.

TABLE IV. SIMULATION METHODS RESULTS

Parameter	Method	
	Baseline	TA
Total energy stored (kWh)	69.5	70.8
Final SoC (%)	97.3	99.2
Final SoH (%)	97.1	98.7
Average battery emperature (°C)	47.5	44.2
Average charge power (kW)	24.8	26.1
V2G average power (kW)	15.0	10.2
Used battery life (%)	2.25	1.84

Although the average charging current in the TA method is nominally lower, the average charging power is actually recorded at 26.1 kW, compared to the 24.8 kW at the baseline. This suggests that the TA algorithm is able to optimize the energy efficiently through a more adaptive and controlled current regulation. Regarding the V2G integration, the baseline does release power to the grid with a higher average value of 15.0 kW. This is performed constantly without considering the condition of the battery leading to an increased risk of degradation. In contrast, the TA method selectively manages the power discharge with an average value of 10.2 kW, but is carried out under safer and more efficient thermal conditions. As a result, the battery life used in the TA method is only 1.84%, lower than the 2.25% in the baseline method.

Overall, the TA method offers a more balanced performance between the charging speed, degradation management, and energy efficiency. In the context of CHAdeMO-based bidirectional fast charging and V2G integration, the TA approach is a more sustainable and reliable solution. One practical challenge in implementing the proposed system is the compatibility with the existing chargers and EVs, especially those that do not support real-time current modulation or lack advanced thermal sensing. Additionally, the variability in V2G regulations, connector types, and backend communication protocols across regions can hinder large-scale deployment of adaptive algorithms like the enhanced TA without standardization.

IV. CONCLUSIONS

This study demonstrates the effectiveness of an enhanced Thunderstorm Algorithm (TA) for optimizing the CHAdeMO bidirectional fast charging systems with integrated Vehicle-to-Grid (V2G) features. The proposed TA model showed significant improvements in key performance metrics when compared to conventional fixed-current charging methods. It achieved a higher final State of Charge (SoC) of 99.2%, maintained a better State of Health (SoH) at 98.7%, resulting in lower average battery temperatures, and thus minimizing the thermal stress. The TA-based method also optimized the energy flow by dynamically adjusting the charging current according to real-time battery conditions, enabling a safer and more efficient V2G discharge process. The adaptive approach reduced the battery degradation, as indicated by a lower battery life usage of 1.84% in comparison to the 2.25% in the baseline scenario. Furthermore, the TA method increased the average charging power without exceeding the thermal safety limits.

Overall, the results confirm that the enhanced TA offers a promising, sustainable, and efficient solution for the smart EV charging infrastructure integrated with the power grid, and provides a significant contribution to the advancement of adaptive V2G-enabled charging strategies. The novelty of this work lies in the integration of adaptive current control and real-time V2G activation using a penalty-based TA, which has not been addressed in previous TA applications. This contributes to advancing sustainable and health-aware fast-charging strategies under the CHAdeMO protocol.

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