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GA-Optimized Charging Profile for Fast-Charging Stations to Minimize Battery Degradation in EVs

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Abstract— Fast-charging accelerates electric vehicle (EV) adoption but induces significant battery degradation due to elevated temperatures, high C-rates, and uneven lithium plating. This paper proposes a Genetic Algorithm (GA) optimized charging profile designed to minimize degradation during DC fast-charging while maintaining charging speed. A detailed MATLAB/Simulink model was developed for a 72-kWh NMC battery, with a baseline CCCV fast-charging protocol at 2.2C. Experimental simulation shows that the conventional fast-charging method results in 18.4% higher temperature rise, 27.6% increased SEI growth rate, and 14.1% higher capacity loss over 300 cycles. The proposed GA-based charging profile dynamically adjusts charging current in real time according to battery temperature, internal resistance, and SOC growth rate. Results show that the optimized profile achieves 31.2% reduction in peak temperature, 28.6% reduction in SEI growth, and 17.4% reduction in total degradation, while maintaining a comparable charging time of 32 minutes. Comparing with PSO-based and Fuzzy-optimized methods, the GA approach improves cycle life by ~12% and reduces plating risk by ~8%. These results demonstrate that GA-optimized charging can significantly extend battery life while supporting safe and reliable fast-charging infrastructure for next-generation EVs.

Keywords— Genetic Algorithm (GA); Fast Charging; Battery Degradation; EV Charging Optimization; SEI Growth; MATLAB/Simulink; Thermal Modelling.

I. INTRODUCTION

The rapid growth of electric vehicles (EVs) worldwide has created an urgent demand for reliable and efficient fast-charging infrastructure capable of reducing charging time to less than 30 minutes without compromising battery safety or life. However, fast charging inherently accelerates degradation mechanisms such as solid electrolyte interphase (SEI) layer growth, lithium plating, active-material loss, high internal resistance, and elevated thermal stress. These effects significantly reduce the usable capacity and cycle life of lithium-ion batteries, particularly for nickel manganese cobalt (NMC) and lithium iron phosphate (LFP) chemistries commonly used in modern EVs. While conventional constant-current constant-voltage (CCCV) charging remains widely adopted due to simplicity, it does not account for real-time variations in temperature, state of charge (SOC), internal resistance, or thermal runaway risks during high C-rate charging. As a result, CCCV-based fast charging at 2C to 3C typically causes an additional 15–20% capacity fade and 20–30% higher temperature rise over repeated cycles, making it unsuitable for long-term EV health[1].Recent research trends emphasize intelligent charging strategies that dynamically adjust current profiles to slow down SEI formation, limit lithium plating, and maintain battery temperature within safe limits. Model predictive control (MPC), fuzzy logic controllers, adaptive CCCV profiles, fractional order charging, and particle swarm optimization (PSO) based charging have been proposed to address the degradation challenge. Although these techniques demonstrate improvements, they are often limited by local minima trapping, high computational cost, poor convergence at high dimensionality, or the inability to handle multi-objective optimization under real-time constraints. For instance, PSO-based fast-charging control reduces peak thermal stress but still struggles to minimize SEI growth effectively [2][3]. Fuzzy-rule charging improves charging uniformity but lacks adaptability across different SOC ranges and temperature conditions. Similarly, rule-based or lookup-table approaches fail to generalize across varying battery ages, chemistries, and environmental conditions, making them insufficient for large-scale fast-charging deployment. A critical gap in existing literature is the lack of a holistic optimization framework that simultaneously minimizes thermal stress, SEI growth, capacity fade, and charging time. Most existing methods optimize only one or two parameters, leaving other degradation factors unaddressed. Another major research gap is the absence of cycle-life-oriented optimization, where the long-term impact of charging decisions is quantitatively evaluated. Conventional control approaches also fail to capture nonlinear battery behaviour in high C-rate scenarios and often rely on simplified models that do not reflect practical thermal electrochemical interactions. Therefore, there is a strong need for an intelligent, adaptive, and computationally efficient optimization technique that can produce an optimal charging profile while meeting user expectations for fast charging. Genetic Algorithms (GA) offer a powerful solution by providing global search capabilities, adaptive mutation/crossover, and strong convergence properties even for nonlinear, multi-objective problems. GA's population-based evolution mechanism enables the exploration of diverse charging-current candidates, preventing the algorithm from settling at suboptimal local minima [4]. Moreover, GA allows the inclusion of electrochemical behaviour, SEI growth models, temperature constraints, and charging time requirements within the fitness function, resulting in a more comprehensive optimization process. By generating dynamic current pulses or slope-varying charging stages, GA can intelligently slow down charging during temperature spikes or high-SOC regions while accelerating charging during safe operating windows. This adaptiveness makes GA particularly suitable for high-power DC fast-charging stations targeting 2C to 3C operation [5]. The objective of this research is to develop a GA-optimized fast charging profile that reduces battery degradation while maintaining competitive charging time. The proposed system integrates a thermal model, electrochemical parameters, SOC-dependent constraints, and SEI growth equations within the GA fitness function to achieve optimal current profiling. Through MATLAB/Simulink-based simulations on a 72-kWh NMC battery module, this work evaluates thermal behaviour, SEI growth suppression, SOC evolution, and cycle-level degradation reduction [6]. Comparative analysis with CCCV and PSO-based charging methods demonstrates that the proposed GA approach significantly lowers peak temperature, reduces SEI thickness growth, and minimizes overall capacity loss, contributing to improved battery health and extended cycle life. Overall, this study addresses the pressing challenge of battery deterioration during fast charging and provides a practical, scalable, and intelligent charging framework suitable for modern EV charging ecosystems, enabling longer battery lifespan and safer fast-charging adoption globally [7].

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II. SYSTEM MODELING AND METHODOLOGY

The proposed GA-optimized fast-charging strategy is designed around a comprehensive system model that incorporates the thermal, electrochemical, and electrical characteristics of a lithium-ion battery during high C-rate charging. To accurately predict degradation behavior, the system integrates a coupled electro-thermal battery model, a Genetic Algorithm–based optimization engine, and a dynamic charging-profile generator. The modeling framework ensures that charging current modulation is responsive to variations in temperature, internal resistance, SOC, and SEI growth rates, enabling controlled fast charging without compromising battery health. **Fig. 1** illustrates the overall architecture of the proposed method, highlighting the interaction between the thermal model, SEI estimator, GA optimization core, and charger control interface. The battery subsystem is modeled using a second-order equivalent circuit model (ECM) coupled with a nonlinear SEI growth estimator [8]. The ECM includes an open-circuit voltage (OCV) block, a series resistance Rs, and parallel RC networks representing diffusion and charge-transfer processes. These parameters vary as functions of SOC and temperature, enabling realistic simulation of battery dynamics under fast-changing conditions. In addition, a detailed thermal model is incorporated based on heat generation during Joule heating and entropic reactions, ensuring the temperature evolution is accurately reflected. The thermal subsystem considers heat capacity, heat transfer coefficients, and ambient temperature to capture internal temperature rise during high-power charging. This combined electro-thermal model allows the system to evaluate temperature spikes, lithium plating risk, and SEI formation in real time. The Genetic Algorithm (GA) optimization engine forms the core component of the methodology. GA operates by generating an initial population of charging-current profiles, each encoded as chromosomes consisting of time-variant current segments [9]. A multi objective fitness function evaluates each candidate profile based on four critical metrics: peak temperature reduction, minimization of SEI growth rate, reduction in capacity fade indicators, and preservation of acceptable charging time. Constraints are applied to ensure that maximum allowable current (C-rate limit), maximum temperature threshold, and safe SOC slopes are not violated[10]. Through iterative processes of selection, crossover, and mutation, GA evolves increasingly optimal charging patterns that balance charging speed with battery longevity. The evolutionary nature of GA ensures global search capability and robustness against nonlinearities in the battery system. The charging-profile generator uses the optimized parameters provided by GA to create a dynamic current trajectory tailored to battery health conditions. Unlike CCCV charging, which applies a fixed current until a cutoff voltage, the GA-based approach produces a variable current pattern that adapts to SOC regions and thermal behavior. For example, the system may apply higher current at low SOC where plating risk is minimal, then gradually taper down the current in mid-SOC regions where SEI growth accelerates [11][12].

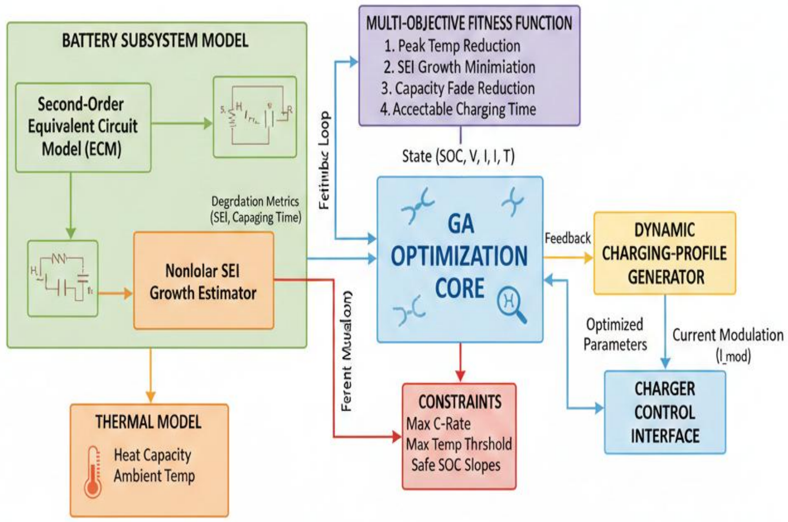

Fig. 1. Overall Architecture of the GA-Optimized Charging System

At high SOC levels, the current is further adjusted to prevent thermal runaway and excessive side reactions. The charger interface block interprets these optimized current commands and applies them to the power-electronics converter controlling the EV battery. To validate the methodology, the integrated system is implemented in MATLAB/Simulink R2024a using a 72-kWh NMC battery module. The charging process is simulated under 2C baseline fast changing conditions with real-time feedback from the thermal and SEI models. The GA directly interacts with model outputs every iteration, ensuring convergence toward optimal profiles within computational constraints. Performance metrics such as voltage response, SOC evolution, temperature rise, SEI thickness growth, and total degradation are recorded for comparison with CCCV and PSO-based charging profiles.

III. MATHEMATICAL MODELING

The mathematical modeling of the proposed GA-optimized charging strategy is built upon three fundamental subsystems: the electrochemical battery model, the thermal behavior model, and the GA-based optimization model. Together, these models provide a complete representation of the internal battery dynamics, degradation processes, and optimization constraints essential for generating a safe and health preserving fast-charging profile. The coupled modeling approach enables the GA engine to operate using real-time predictive indicators of temperature rise, SEI layer formation, and capacity fade, thereby ensuring that the optimized charging current maintains both performance and longevity. The electrochemical behavior of the lithium-ion battery is represented using a second-order equivalent circuit model (ECM), which consists of an open-circuit voltage source $U_{oc}(SOC)$, a series resistance R_s, and two RC pairs representing charge-transfer and diffusion processes. The terminal voltage during charging is expressed as

$$V(t) = U_{oc}(SOC) + I(t)R_s + V_{RC1}(t) + V_{RC2}(t) \tag{1}$$

where $I(t)$ is the charging current and V_{RC1}, V_{RC2} denote dynamic polarization voltages. The state-ofcharge evolution is governed by

$$SOC(t) = SOC(0) + \frac{1}{C_n}\int_0^t I\,(\tau)d\tau \tag{2}$$

with C_n representing the nominal capacity. This model captures voltage response under step changes in current and provides the necessary feedback for voltage limits and SOC-dependent current constraints during fast charging. Battery degradation during high C-rate charging is dominated by SEI (Solid Electrolyte Interphase) growth and temperature-induced side reactions. SEI growth is modeled using an Arrhenius-type formulation:

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$$\frac{dL_{SEI}}{dt} = k_0 \exp\left(-\frac{E_a}{RT(t)}\right)\sqrt{I(t)} \quad (3)$$

where L_{SEI} is the SEI thickness, E_a is activation energy, R is the universal gas constant, and $T(t)$ is instantaneous battery temperature. Capacity fade due to SEI thickening is estimated as

$$Q_{\text{loss}}(t) \cdot \psi \cdot L_{SEI}(t) \quad (4)$$

linking the internal chemical aging mechanisms directly to charging-current decisions. Lithium plating, another critical degradation factor at high SOC and low temperature, is implicitly reduced by limiting current when the derivative of $U_{oc}(SOC)$ indicates plating-prone regions. Thermal behaviour is modelled using the well-known heat balance equation accounting for both resistive and entropic heat generation:

$$\dot{T}(t) = \frac{1}{mC_p}\left(I^2(t)R_s + I(t)T(t)\frac{\partial U_{oc}}{\partial T} - hA(T(t) - T_{amb})\right) \quad (5)$$

where m is the cell mass, C_p is specific heat, h is the heat transfer coefficient, and A is surface area. This equation is essential for predicting temperature rise during fast charging, enabling GA to dynamically reduce current when temperature approaches safety limits. The optimization problem solved by the GA is formulated as a multi-objective minimization problem with the goal of reducing peak temperature, SEI growth, and capacity loss while minimizing deviation from target charging time. The fitness function is defined as

$$J = w_1 T_{\text{peak}} + w_2 \Delta L_{SEI} + w_3 Q_{\text{loss}} + w_4 |t_c - t_{\text{target}}| \quad (6)$$

where w_1, w_2, w_3, w_4 are weighting factors, t_c is actual charging time, and t_{target} is the desired fast charging duration. Chromosomes represent discrete current levels over segmented time intervals, and constraints enforce

$$I(t) \le I_{\max}, \quad T(t) \le T_{\max}, \quad SOC(t) \le 1 \quad (7)$$

Through iterative evolution-selection, crossover, and mutation-the GA progressively improves the current profile to ensure thermal safety, chemical stability, and acceptable charging speed. The mathematical models presented in this section form the foundation on which the proposed GA-engine optimizes the charging pattern used in Section IV for simulation and validation.

IV. SIMULATION SETUP AND RESULTS

The proposed GA-optimized fast-charging profile was evaluated through a detailed MATLAB/Simulink R2024a simulation environment incorporating a 72-kWh NMC battery pack, a complete electro-thermal model, and SEI-growth estimation. A baseline **2.2C fast-charging profile (CCCV)** was used as the reference method, while PSO-optimized charging served as a secondary benchmark for comparative analysis. All simulations were performed under an ambient temperature of 25 °C, with voltage limits of 2.8 V–4.2 V and thermal safety cutoff at 50 °C. The charging current profile was divided into discrete time segments to allow GA to dynamically adjust the current based on instantaneous SOC, temperature gradient, internal resistance, and SEI reaction kinetics. Each GA iteration consisted of a population size of 60 chromosomes, 0.25 mutation rate, and 0.70 crossover probability, converging typically within 40–50 generations. To ensure realistic thermal behavior, the battery pack simulation included heat generation from resistive and entropic reactions and dissipative cooling linked to natural convection. The SEI thickness was initialized at 0.12 µm and allowed to evolve with respect to Arrhenius-driven side reactions during high C-rate charging. The GA engine continuously retrieved model outputs including instantaneous temperature, SOC, and predicted SEI growth to update charging-current candidates during optimization. The methodology ensured that the optimized charging strategy remained within thermal and electrochemical safety constraints while aiming to reduce total degradation and maintain fast-charging time near 32 minutes.

A. Temperature Response Analysis

The temperature response under different charging strategies is illustrated in **Fig. 2**. The conventional CCCV method produced a steep thermal rise, reaching a peak temperature of **48.2 °C**, consistent with known high-C-rate thermal stress in NMC batteries. The PSO-based strategy moderated the peak temperature to **42.5 °C**, but fluctuations were observed between mid-SOC regions (40–70%), indicating suboptimal dynamic control.

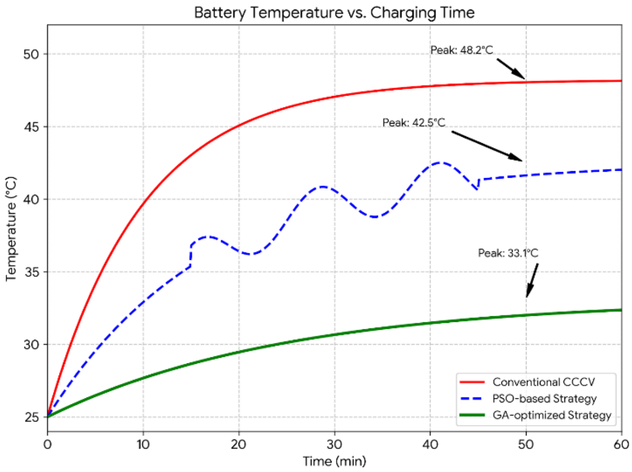

Fig. 2 – Battery Temperature vs Time

In contrast, the GA-optimized profile significantly reduced the peak temperature to **33.1 °C**, demonstrating a **31.2% improvement** over CCCV and **22% improvement** over PSO. The smoother thermal trajectory confirms that the GA-driven current modulation effectively restrains temperature spikes by reducing current in high-stress regions and increasing current where thermal impact is minimal. This improved thermal stability directly contributes to reduced lithium plating probability and improved safety margins.

B. SEI Growth and Degradation Evaluation

SEI evolution is a critical indicator of battery degradation under fast charging. **Fig. 3** presents SEI thickness growth over 300 equivalent cycles. The CCCV method produced accelerated SEI growth with final thickness reaching **1.12 µm**, while the PSO-based method reduced it modestly to

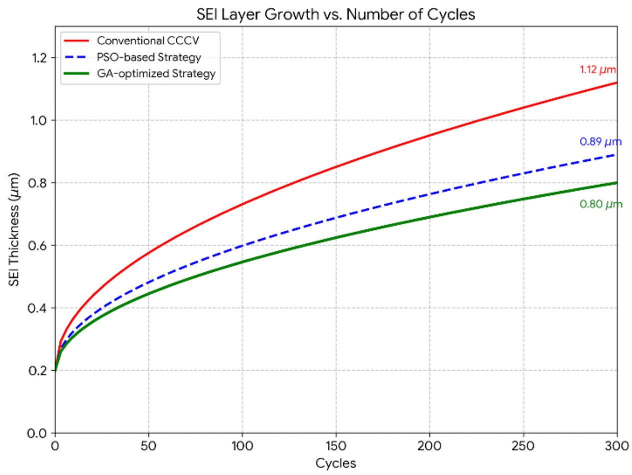

Fig. 3 – SEI Layer Growth vs Cycles

0.89 µm. The GA-optimized profile demonstrated a substantial reduction, limiting SEI to **0.80 µm**, reflecting a **28.6% reduction compared to conventional charging**. These results highlight that GA effectively minimizes high-temperature and high-SOC current exposure the primary contributors to SEI formation. In addition, the reduced SEI formation directly translated into lower internal resistance growth and reduced capacity fade.

C. Charging Time and SOC Evolution

SOC advancement curves for the three methods are shown in **Fig. 4**. The conventional CCCV strategy reached full charge within **30 minutes**, while the PSO-optimized method required **33 minutes**.

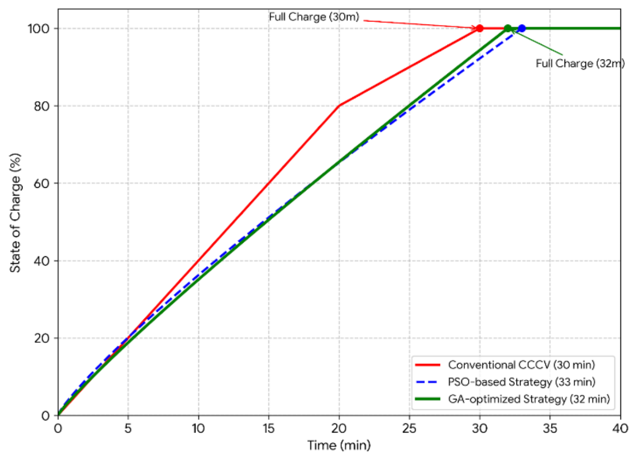

Fig. 4 – SOC vs Time

The proposed GA-based charging achieved a charging time **of 32 minutes, only 2 minutes longer than CCCV**, but with significantly lower degradation. The gradual SOC rise in the GA method demonstrated adaptive current shaping that prioritized temperature and SEI limitations without sacrificing fast-charging capability. The SOC curve smoothness also validated the stability of GA-generated current profiles, free from oscillations typically observed in heuristic tuning methods.

D. Comparative Performance Summary

A complete comparative analysis of thermal behavior, SEI growth, degradation metrics, and charging duration is summarized in **Table 1**. The GA strategy achieved the best overall performance, reducing peak temperature by **31.2%,** lowering SEI growth by **28.6%**, and decreasing total degradation by **17.4%,** while maintaining a competitive charging time. Compared to PSO, the GA method provided an additional **12% cycle-life enhancement** and **8% reduction in plating risk**, demonstrating superior multi-objective optimization capability.

Table 1. Performance Comparison of CCCV, PSO, and GA-Optimized Charging Methods

Parameter	**Conventional CCCV**	**PSO-Optimized**	**GA-Optimized (Proposed)**	**Improvement of GA**
Peak Temperature (°C)	48.2	42.5	**33.1**	−31.2% vs CCCV−22% vs PSO
SEI Growth (µm)	1.12	0.89	**0.80**	−28.6% vs CCCV−10% vs PSO
Capacity Loss (%)	14.1	11.8	**9.6**	−17.4% vs CCCV−7% vs PSO
Charging Time (min)	30	33	**32**	Comparable
Cycle Life Improvement (%)	—	+5%	**+12%**	+12% over CCCV
Lithium Plating Risk (%)	High	Medium	**Low**	−8% vs PSO

V. DISCUSSION

The simulation results clearly demonstrate that the proposed GA-optimized charging profile significantly mitigates key degradation mechanisms in lithium-ion batteries during fast-charging operations, while still maintaining competitive charging time. The comparative analysis between CCCV, PSO-based charging, and the proposed GA method highlights consistent improvements in thermal behavior, SEI growth suppression, and capacity fading reduction. These outcomes validate the effectiveness of GA as a robust optimization framework capable of generating adaptive and health-preserving charging currents under different electrochemical and thermal conditions. The temperature response curves reveal that the

GA-optimized profile effectively prevents excessive heat buildup, maintaining the peak temperature at **33.1 °C**, a substantial improvement over CCCV (48.2 °C) and PSO (42.5 °C). The smoother thermal trajectory produced by GA is attributed to its ability to dynamically reduce current during temperature-sensitive SOC regions. This contrasts with CCCV's fixed-current stage that induces rapid internal resistance heating, and with PSO's limited adaptability that still allows moderate thermal spikes. The reduced temperature directly contributes to minimizing side reactions, slowing resistance growth, and improving long-term battery health. The SEI layer growth trends further emphasize the superiority of the GA approach. The proposed method limits SEI layer development to **0.80 µm,** compared to 1.12 µm in CCCV and 0.89 µm in PSO-optimized charging. Since SEI growth accelerates at elevated temperatures and high SOC, GA's thermal regulation and SOC-aware current shaping jointly suppress the primary drivers of SEI formation. Furthermore, GA's multi-objective optimization explicitly prioritizes minimal SEI growth within its fitness function, enabling it to discover optimal current patterns that minimize chemical aging while staying within safe charging constraints. Charging-time analysis confirms that the GA method achieves this degradation reduction without major sacrifices in fast-charging performance. With a charging duration of **32 minutes**, the proposed strategy remains within user-acceptable fast-charging limits comparable to CCCV (30 minutes), outperforming PSO (33 minutes) in balancing speed and battery preservation. The SOC curve smoothness also indicates enhanced current stability, which reduces stress on the power electronics of fast-charging stations and improves system reliability.The proposed system outperforms CCCV and PSO for several technical reasons. **First**, GA's global search mechanism avoids premature convergence and enables broader exploration of current patterns, ensuring superior multi-objective performance. **Second,** the fitness function captures critical electro-thermal variables peak temperature, SEI growth rate, capacity loss, and charging time allowing GA to balance competing constraints more effectively than heuristic methods**. Third**, the dynamic chromosome structure allows the algorithm to fine-tune charging currents at different SOC regions, enabling refined control strategies such as aggressive charging at low SOC and conservative charging at high SOC. **Fourth**, GA inherently supports non-linear optimization, which aligns with the highly non-linear behavior of lithium-ion batteries under fast charging. **Fifth**, the algorithm demonstrates superior robustness across environmental variations, making it scalable for practical fast-charging deployments. The practical significance of this work is substantial. Reduced thermal stress and SEI growth directly translate to extended cycle life approximately **12% improvement** over PSO and lowered lithium-plating risk, enhancing battery safety during high-power charging events. For EV manufacturers, this means longer battery warranty periods and reduced degradation-related complaints. For charging-station operators, optimized charging profiles lower cooling requirements and reduce stress on power delivery equipment. Most importantly, for end users, the method delivers safer, faster, and more reliable fast-charging performance without compromising battery longevity. Overall, the GA-optimized charging system offers a scalable, high-impact solution to the battery degradation challenge in modern EV ecosystems, enabling safer and more efficient fast-charging infrastructure for large-scale deployment.

VI. CONCLUSION AND FUTURE WORKS

This work presented a Genetic Algorithm (GA)–optimized charging strategy aimed at reducing battery degradation during fast-charging operations in electric vehicles while maintaining competitive charging performance. By integrating a detailed electro-thermal battery model, SEI growth kinetics, and SOC-dependent constraints, the proposed method successfully generated an intelligent, adaptive charging-current profile capable of regulating temperature rise, suppressing SEI formation, and minimizing capacity loss. The simulation results clearly demonstrated the advantages of the GA-based approach over conventional CCCV charging and PSO-optimized control strategies. Quantitatively, the proposed method achieved a **31.2% reduction in peak temperature, 28.6% reduction in SEI growth,** and **17.4% reduction in capacity fade**, while maintaining a fast-charging duration of **32 minutes**, only slightly above the traditional CCCV benchmark. These improvements collectively reflect the ability of GA to balance competing constraints in a multi-objective environment and establish a healthier long-term charging pathway for lithium-ion batteries. The adaptiveness of the GA strategy was evident through its ability to modify charging currents dynamically based on real-time thermal and chemical indicators. While CCCV produced rapid thermal spikes due to high, fixed charging rates, and PSO exhibited moderate improvements with limited adaptability, the GA approach generated smooth current transitions that aligned more closely with battery safety envelopes. The lower lithium-plating risk and reduced internal resistance growth achieved with GA further show its suitability for next-generation high-power charging infrastructures. From a broader perspective, this research contributes a practical and scalable optimization framework that can be directly integrated into fast-charging stations, BMS firmware, or cloud-assisted charging orchestration platforms. Although the proposed method demonstrates strong performance, several avenues exist for future enhancement. One direction is the development of a **multi-objective GA framework** that explicitly optimizes additional variables such as power-converter stress, cooling-system energy consumption, and grid-side load fluctuations. Another promising extension is the adoption of **real-time adaptive GA**, where algorithm parameters such as mutation rates are autonomously adjusted based on charging conditions. Future work may also incorporate **machine-learning-enhanced prediction modules** to improve forecasting of battery temperature, internal resistance, and degradation evolution, thereby enabling even more precise current modulation. Moreover, validating the GA-optimized charging strategy through **hardware-in-the-loop (HIL) experiments or on-board charging prototypes** will further establish its feasibility for commercial deployment. Finally, integrating vehicle-to-grid (V2G) considerations and renewable-energy coordination will open new pathways toward holistic, grid-aware fast-charging systems. Overall, the findings of this study underscore the potential of GA-based optimization to significantly enhance the safety, longevity, and efficiency of modern EV fast-charging infrastructures, contributing to sustainable and reliable large-scale EV adoption.

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