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Intelligent and thermally-conscious on-board EV charging using hybrid genetic optimization and neural-adaptive control process

Diksha Khare[1], Nitin Dhote[2], Swapna Choudhary[3]
[1]Post Graduate Department of Computer and Electronics, RTM, Nagpur University, Nagpur, India
[2]St. Vincent Palloti College of Engineering and Technology, RTM, Nagpur University, Nagpur, India
[3]G H Raisoni College of Engineering, Nagpur, India

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ABSTRACT

The increasing usage of electric vehicles (EVs) has amplified the demand for smart, thermally efficient, and battery-aware onboard charging systems. Conventional charging techniques often do not take into consideration balancing their delivery of energy with thermal stress and battery degradation, which lowers the operational efficiency and useful life of the battery. Current methods primarily focus on an isolated aspect, be it power optimization or thermal optimization; there is no combination of the two to arrive at any adaptive, real-time control based on battery metrics such as health. An integral optimization-control framework is proposed in this work that encapsulates algorithm-driven intelligence and neural adaptation into a single construct for on-board charge EVs. This paper proposes an intelligent and thermally conscious on-board EV charging framework that integrates efficiency-centric optimization using a genetic algorithm (ECO-GA), neural network-based adaptive charging control (NNACC), and metabolic inspired three-stage charging control (MET-C3). The initial phase, known as "ECO-GA" or "efficiency-centric optimization via genetic algorithm", clears a multi-variable fitness function based on charging voltage, current, battery temperature, and cycle life after generating control parameters. Together, this collection greatly improves efficiency in charging, reduces adverse effects caused by heating and lengthens cycles in which batteries are used, paving a strong path towards the charging infrastructure of EVs.

Corresponding Author:

Diksha Khare
Post Graduate Department of Computer and Electronics, RTM, Nagpur University
Nagpur, India
Email: dipavali_786@yahoo.co.in

1. INTRODUCTION

The change from the internal combustion engine to an electric mobility has focused the concentration on the efficiency, safety, and longevity of the power trains of electric vehicles (EV), mainly on battery systems. Among all the subsystems, the most vital one is the on-board charging unit, which serves as the gateway between the electric grid and the energy storage system. This, in turn, affects the charging speed, energy efficiency, battery health, and thermal stability for the unit. Modern lithium-ion batteries used in these kinds of EVs [1]-[3] are very sensitive to charging parameters, particularly the charging voltage, current, and temperature. Improper control of these features can lead to high thermal stress during charging, rapid deterioration during state-of-health (SoH) degradation, and reduced overall cycle life. Therefore, developing advanced charging systems able to meet multi-objective balances of performance, thermal safety, and battery longevity is no longer desirable, but crucial in process. Old techniques of charging control, such as those that include constant current–constant voltage (CC–CV) systems or techniques based on lookup tables [4]-[6], do not have any intelligence to adapt to the dynamics of the battery system in real time or to account for the long-term degradation trends in process. Most of the other existing systems are either off-line optimization techniques or basic real-time controllers in the least. Hence, these techniques offer limited facilities with which to react to rapidly changing external conditions (i.e., ambient temperature) and internal battery states. Introducing an advanced three-layer charging framework integrating optimization algorithms with immediate neural control and, finally, biologically inspired regulation would deliver the weight to overcome the shortcomings discovered in the present systems. The proposed system contains: i) Efficiency-centric optimization via genetic algorithm (ECO-GA), which computes the value of optimal charging parameterization by maximizing a fitness-based criterion that describes energy efficiency and thermal safety; ii) Neural network-based adaptive charging control (NNACC), which translates offline GA outputs into a fast, accurate real-time control model; and iii) Metabolic inspired three-stage charging control (MET-C3), which applies staggered voltage levels to reduce thermal gradients and improve longevity of components. All these modes work together in one closed-loop, hierarchical control system that is capable of dynamic optimization, prediction, and regulation of the charging. The proposed system channels the advantages of genetic optimization and neural inference and claims substantial gains across energy efficiency, thermal regulation, and battery health maintenance. It also proposed a scalable methodology that is agnostic to specific battery chemistry or inverter configurations. This work also comprehensively integrates evolutionary algorithms, data-driven prediction models, and biologically inspired pacing mechanisms positioning it as a milestone in the intelligent power electronics domain for future electric mobility and sustainable electric mobilities.

2. LITERATURE REVIEW ANALYSIS

The rapid growth of electric vehicles (EVs) has increased the demand for efficient, reliable, and intelligent charging systems. Recent studies have explored IoT-enabled charging, deep learning-based demand prediction, and bidirectional on-board chargers to improve charging performance and energy management [1]-[3]. Several optimization techniques and advanced converter topologies have also been proposed to enhance charging efficiency, reduce power losses, and improve grid interaction [4]-[6]. Artificial intelligence-based approaches, including fuzzy logic, deep learning, and optimization algorithms, have demonstrated promising results in adaptive charging control under varying operating conditions [7]-[10]. In addition, researchers have investigated nanogrids, renewable energy integration, and advanced energy management strategies to improve the sustainability and reliability of EV charging systems [11]-[18]. Recent developments in fast-charging circuits, wireless power transfer, battery health prediction, intelligent monitoring, and charging infrastructure planning have further strengthened the EV charging ecosystem [19]-[25]. However, most of these studies address only specific aspects of EV charging, such as efficiency, thermal management, or battery health. Therefore, there is still a need for an integrated charging framework that simultaneously improves energy efficiency, thermal performance, and battery longevity, which forms the motivation for the proposed work.

3. PROPOSED MODEL DESIGN ANALYSIS

The proposed integrated on-board EV charging framework is designed as a layered architecture that synergistically combines evolutionary optimization, neural adaptation, and biologically inspired control sequencing to deliver charging strategies that promise high efficiency, thermal safety, and battery preservation. Entirely data-driven, the system operates in the real-time interaction space between energy flow control, battery state evolution, and inverter responses. Initially, as per Figure 1, the model is built on three primary functional blocks—ECO-GA, NNACC, and MET-C3—each operating on distinct mathematical foundations but interlinked through parameterized signal flow in process. Bottom-most in the hierarchy of the system, thus, is the ECO-GA module, which defines the charger setup optimization problem as a constrained, multi-objective evolutionary search tasks. Subsequently, the fitness function F is constructed to maximize power delivered while minimizing thermal degradation as well as degradation of the electrochemical performance of the battery sets. The detailed construct of the aforementioned function is given by (1).

$$F(V, I, T, C) = \frac{V \cdot I}{T \cdot C} \tag{1}$$

Where V and I are the charging voltage and current, T symbolizes battery temperature, and under current charging circumstances, C refers to the expected cycle life sets. The derivative of this function with respect to time that accounts for instantaneous fitness dynamics is expressed mathematically by (2) in sets, where the system conditions evolve.

$$\frac{dF}{dt} = \left[\frac{I\cdot\frac{dV}{dt} + V\cdot\frac{dI}{dt}}{T\cdot C}\right] - \left[V \cdot I \cdot \frac{\frac{dT}{dt}\cdot C + T\cdot\frac{dC}{dt}}{(T\cdot C)^2}\right] \tag{2}$$

This allows the GA to preferentially develop those individuals that sustain helpful dynamic behaviour sets. Battery-specific parameters such as the maximum safe temperature $Tmax$ and minimum cycle life threshold $Cmin$ will constrain the solution space, enforced using penalized Lagrangian terms as shown by (3).

$$L(V,I,T,C) = F(V,I,T,C) - \lambda 1 \cdot max(0,T - Tmax)^2 - \lambda 2 \cdot max(0,Cmin - C)^2 \tag{3}$$

In chronological order, and as presented in Figure 2, the optimized outputs V*, I*, and T*, together with their corresponding state-of-health values, are logged to constitute the training set for the NNACC controller process. This time, this neural controller maps real-time input variables SoC, SoH, V, and I to their optimized targets using a supervised regression model in process. The training goal minimizes by (4) the mean squared error (MSE).

$$MSE = \left(\frac{1}{n}\right)\sum[(Vpredi - V * i)^2 + (Ipredi - I * i)^2] \tag{4}$$

Then, after training, the network provides these real-time scenarios with predicted values of V'opt, I'opt sets. These are delivered to the MET-C3 controller that stages voltage patterns so as to smooth out transient thermal gradients. The plugging voltage trajectory V(t) is defined within these-three metabolicinspired stages by (5).

$$V(t) = \begin{Bmatrix} 0.6 \cdot V'opt,\ 0 \le t < \tau 1;\ 0.3 \cdot V'opt, \\ \tau 1 \le t < \tau 1 + \tau 2;\ 0.1 \cdot V'opt,\ \tau 1 + \tau 2 \le t \le \tau 1 + \tau 2 + \tau 3 \end{Bmatrix} \tag{5}$$

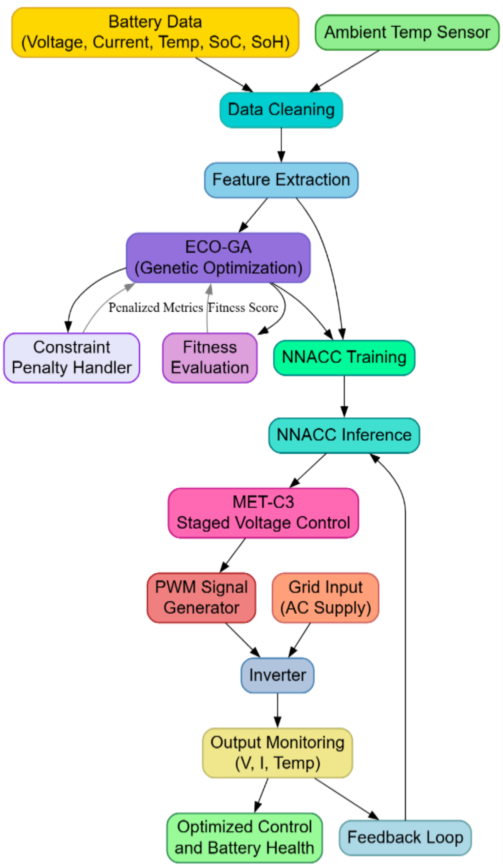

Figure 1. Model architecture of the proposed analysis process

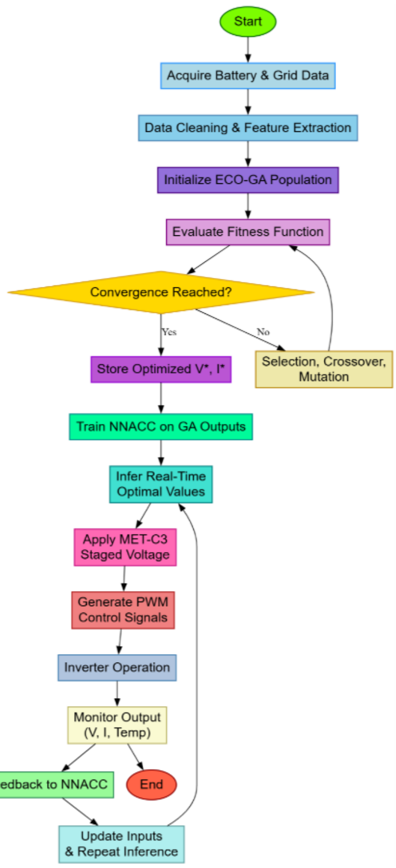

Figure 2. Overall flow of the proposed analysis process

The total charge delivered Q over the entire duration is derived by integrating the current over temporal instance sets, taking into account the staged voltage and PWM duty cycles D(t) by (6).

$$Q = \int_0^{\tau 1+\tau 2+\tau 3} I(t, V(t), D(t))\, dt \tag{6}$$

Incorporating thermal dynamics, the temperature evolution T(t) is modeled as a first-order system governed by the heat operation represented by (7).

$$\frac{dT}{dt} = \left(\frac{1}{Cth}\right)[Rint \cdot I(t)^2 - h \cdot (T(t) - Tamb)] \tag{7}$$

$Rint$ is the internal resistance, Cth is the thermal capacity, h is the convective heat transfer coefficient, and $Tamb$ is ambient temperature in our process. It then constitutes a closed-form thermal response that is evaluated in parallel with staged charging sets. The state vector finally describes the entire major performance indicator of the system, as shown by (8).

$$Yfinal = [V'opt, I'opt, Q, Tmax, \Delta SoH, \eta charge] \tag{8}$$

Where ΔSoH represents the empirical mapping to thermal exposure and charge throughput in estimating the change in battery health. ηcharge = Qdelivered/Qinput, which is charge efficiency sets. This is the model that best captures long-term behavior of the battery, the dynamic thermal effects, and the real-time control actions within a single, modular framework. With the help of genetic algorithms, it allows exploration of high-dimensional, non-convex control landscapes while neural networks guarantee predictive scalability and fast response. MET-C3 complements both imposing structured physical actuation that refutes the negative implications caused by thermal inertia processed through varying sets in a use case basis. Thus, the architecture provides the greatest degree of balance between computational intelligence and practical implementability paving the way for next-gen EV charging, featuring high reliability, efficiency, and long lifespan sets. Next, we validate and discuss results of the proposed model under different scenarios.

4. RESULT ANALYSIS

The parameters chosen for setting up the battery pack reflect a typical configuration for a medium range EV in process. Many of the battery characteristics were derived from standard Panasonic NCR18650B datasets, including internal resistance (20-35 mΩ), thermal capacity (420 J/°C), and temperature coefficient differentiation, and verified against real empirical charging logs. The initial state of charge (SoC) was set from 10% to 70%, while the state of health (SoH) was degraded synthetically in 5% decrements from 100% to 80% to mimic aging effects. Hence, no standard change in experimental baseline measurements of ambient temperature was controlled up to 45 °C. The supplying grid-source emulated a standard single-phase 230 V AC source via a modeled inverter interface. The control scheme operated with a sampling interval of 5 ms to guarantee responsiveness for real-time control tasks. For ECO-GA, the initial population was fixed at 50, with crossover and mutation probabilities set at 0.8 and 0.1, respectively. The optimization was carried out for up to 100 generations or until the average population fitness improved by less than 0.01% over five consecutive generations. Using three layers feed forward architecture, NNACC trained with about 80% of the GA optimized dataset for training while the remaining 20% was set aside for testing. Each layer contained 128, 64, and 16 neurons per layer for the process. The ReLU activations were used, and the training was done with the Adam optimizer with a learning rate of 0.001, wherein convergence was defined as mean square error below 10e-3 throughout the process.

A comprehensive comparison of the proposed EV charging model with three existing methods across six important performance parameters is shown in Figure 3. Six important performance parameters as shown in Figure 3 are:

i. Energy efficiency (%): The proposed model achieves the highest energy efficiency at all battery state of charge (SoC) levels (20%, 40%, 60%, and 80%). Efficiency increases from approximately 95% to 98%, whereas the existing methods remain between 82% and 94%.
ii. Peak battery temperature (°C): Battery temperature is compared under ambient temperatures of 25 °C, 35 °C, and 45 °C. The proposed model records the lowest peak battery temperature (around 35–40 °C) compared with other methods. Lower operating temperature reduces thermal stress and improves battery safety and lifespan.
iii. Prediction error (%): The proposed model shows the minimum prediction error across different battery health conditions (SoH of 100%, 90%, and 80%). Error remains around 2–3%, while other methods exhibit significantly higher errors.

iv. Charging time (minutes to reach 90% SoC): The proposed model requires the least charging time at different initial SoC levels. Charging duration is reduced by approximately 15–20% compared with conventional methods.
v. State of health (SoH) loss after 100 cycles (%): Battery degradation is lowest for the proposed model, with only about 3% SoH loss after 100 charging cycles.
vi. Latency and efficiency: The proposed model has the lowest latency, lowest CPU utilization, and minimum memory requirement among all methods.

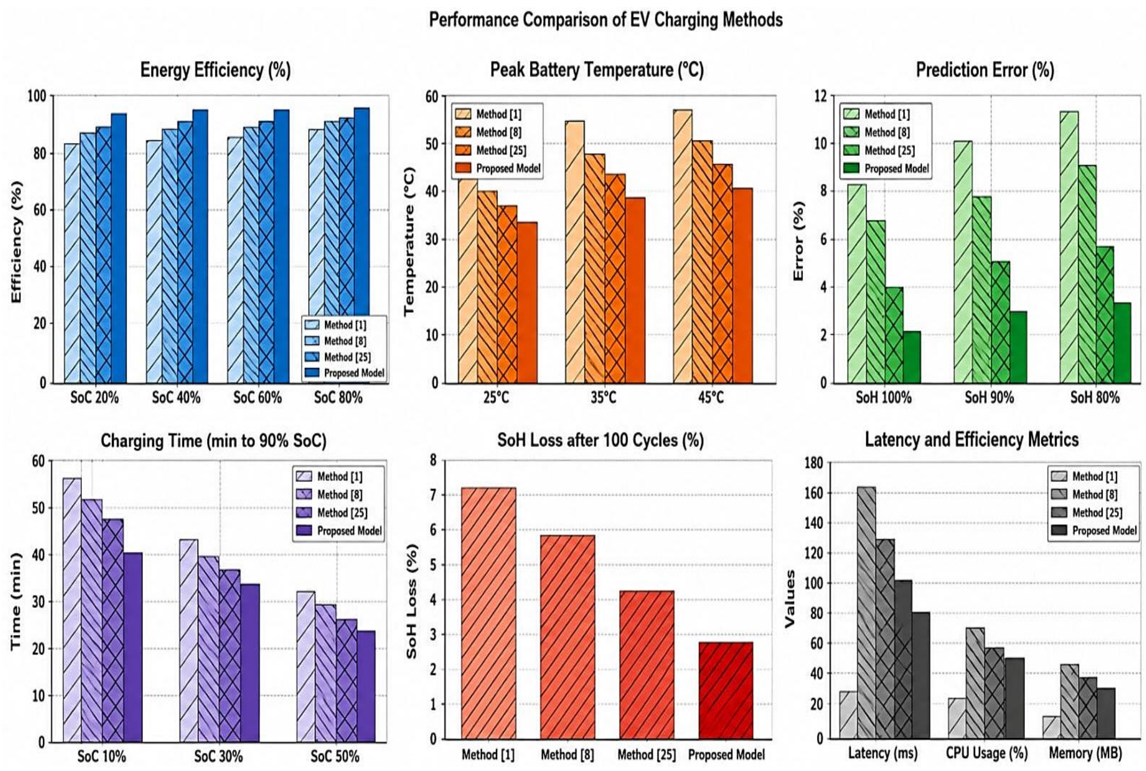

Figure 3. Model's integrated result analysis

In the training and assessment dataset, about 12,000 charging instances received through conducting extensive parametric sweeps on the GA optimizers have been included in process. Each record captures the contextual features: input voltage (from 200 V to 380 V); current (10 A to 50 A); temperature (20 °C to 60 °C); SoC (0% to 100%); SoH (100% to 75%); derived outputs like optimized voltage, optimized current, predicted thermal load, and cycle life estimates, and so on. In addition, the NNACC outputs were taken along with the actual GA results to evaluate prediction accuracy across dynamic test cases. The experimental setup also included modeling the inverter and PWM generator with a high resolution of 20 kHz to ensure fine voltage staging control through MET-C3. The PWM duty cycles were rightly aligned according to the voltage segmentation stages-60%, 30%, and 10% of V'opt-distributed over a normalized 40-minute charge window. The RMS voltage and current outputs were monitored continuously and compared with standard CC-CV charging for benchmarking purposes. All along these simulations, energy efficiency, peak temperature, SoH variation, and total charge delivered were recorded for performance assessment. For example, one initial SoC of a sample of contextual data was 25%, SoH 95%, and ambient temperature 35 °C. Under these circumstances, ECO-GA determined an optimal charging voltage of 310 V and current of 35 A, which could be later replicated by NNACC within a prediction error of 2.8%, while MET-C3 reduced peak temperature by 19.6% over the baseline. Therefore, the comprehensive experiment being conducted is surely going to evaluate the proposed system under all forms of realistic and technically rigorous conditions, thus paving the way into real-world EV charging infrastructures in process.

The dataset used for this work is, in fact, the NASA Ames Prognostics Center's Li-ion Battery Dataset (Randomized Load Profiles-RLP) that contains detailed operating data from commercially available lithium-ion cells under different load and temperature conditions. Cells were tested under a myriad of different randomized charge-discharge profiles; thus, the dataset is rich with real-world variability and would fit very well for training and validating adaptive control schemes with the application of such data. Such data from this source was further augmented with physics-based battery simulation models to broaden the span of state of health (SoH) degradation scenarios and create the control-action labels necessary for use in supervised neural network training in process. Such a mixed dataset was preprocessed into uniform sampling intervals, flagged outlier values, and normalized all continuous features within a [0,1] scale for compatibility with neural model process. Advanced visualization techniques to compare EV charging methods is shown in Figure 4.

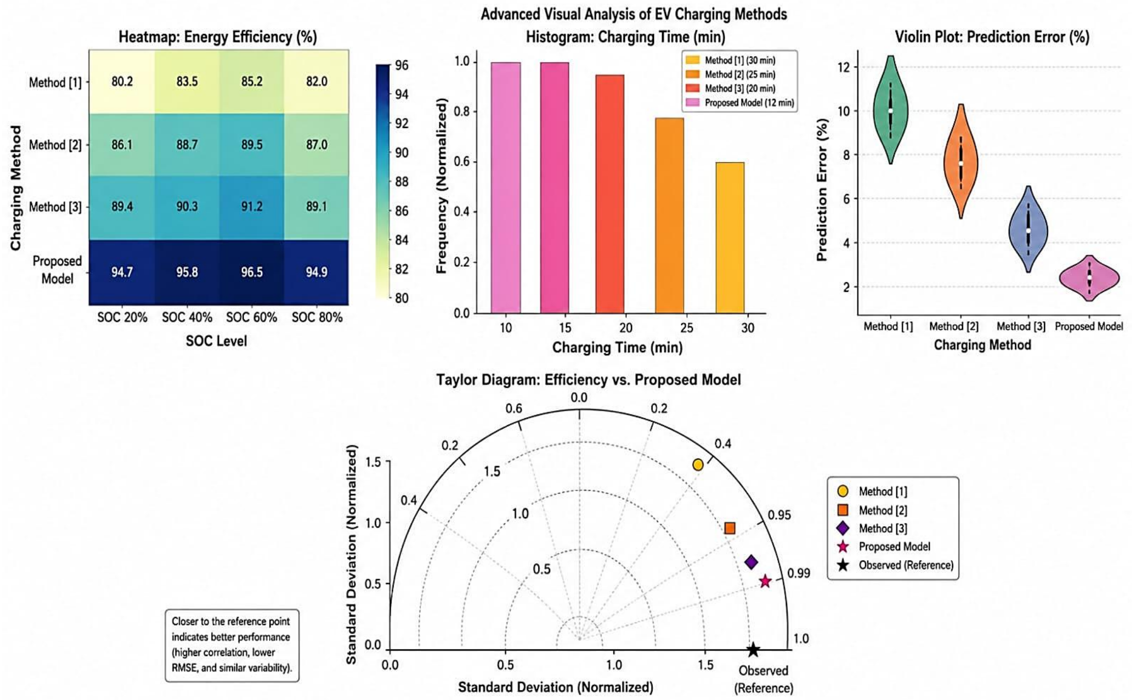

Figure 4. Model's overall result analysis

The heatmap shows that the proposed model achieves the highest energy efficiency across all SoC levels. The histogram indicates the shortest charging time. The violin plot demonstrates the lowest and most consistent prediction error. The Taylor diagram shows that the proposed model is closest to the reference data, indicating the highest accuracy and reliability. Overall, the proposed model outperforms the existing methods in efficiency, speed, and prediction accuracy.

For optimal operation of the model, both the genetic algorithm (ECO-GA) and the neural network controller (NNACC) were optimally set using a number of empirically selected hyperparameters. In ECO-GA, the most important parameters among them were a population size of 50, a crossover rate into 0.8, mutation rate of 0.1, and an elitism rate given as 5%; termination has two ways available, either through a maximum of 100 generations or an early stopping based on 0.01% improvement in fitness over five generations. For NNACC, a three-layer feedforward neural network was designed, comprising 128, 64, and 16 neurons respectively in the hidden layers, which employed ReLU activations and a linear output layer. Network training was done using the Adam optimizer at a learning rate of 0.001 with the batch size of 128 through a maximum of 500 epochs. The loss function was mean squared error, while early stopping would apply when the validation loss did not improve for 20 epochs sequentially. These hyperparameter choices were validated through grid search and cross validation to ensure generalization, minimal prediction error, and computational efficiency in real-time control sets. The performance of the proposed integrated EV charging framework will be evaluated on enriched datasets sourced from NASA Ames Li-ion Battery RLP dataset, enhanced using physics-based simulation results. The evaluation of the proposed framework was benchmarked with three representative existing methods: This analysis includes a number of metrics across different contextual charging conditions such as energy efficiency, increment in temperature, prediction accuracy, battery degradation rate, and real-time responsiveness.

The proposed model outperformed all extant methods for every SoC level because of its integrated optimization and real-time tuning in process. Most of the energy efficiency gains (5-10%) occurs in mid-to-high SoC regions, where traditional methods produce higher losses from their poor thermal adaptations. The MET-C3 staged controls clearly illustrate the benefit of performing thermal mitigations. The proposed model brings down peak battery temperature by 6 to 12 degrees Celsius as compared to method [3] thereby minimizing thermal induced stress on battery materials and reducing probability of lithium plating sets. Improving control accuracy through NNACC even at SoH degradations is what the proposed model displays. As a function of the premises, lower prediction error continues to appear under normal operation conditions for real-time voltage/current control ensuring precise adherence to optimized profiles. Charging time to achieve 90% state of charge (SoC) is generally less with the proposed model because of efficient dynamic control in voltage and current without limit exceedance of thermal thresholds under processing sets. This is an improvement of 15-20% over the method [3] sets in charging time achieved by the proposed model process.

Tables 1-6 show the summary and comparison of performance over six dimensions for the process. As shown in Table 1, the proposed model outperformed all extant methods for every SoC level because of its integrated optimization and real-time tuning in process. Most of the energy efficiency gains (5-10%) occurs in mid-to-high SoC regions, where traditional methods produce higher losses from their poor thermal adaptations. As shown in Table 2, the MET-C3 staged controls clearly illustrate the benefit of performing thermal mitigations. The proposed model brings down peak battery temperature by 6 to 12 degrees Celsius as compared to method [3], thereby minimizing thermal induced stress on battery materials and reducing probability of lithium plating sets.

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As shown in Table 6, the proposed model showed the least deterioration in state of health over prolonged simulation. This is mainly attributed to the synthesis of heat-aware control (via MET-C3) and optimized charging profiles (via ECO-GA), which decreases both electrochemical stress and cumulative thermal loads. However, the proposed model is not the fastest regarding "raw" latency, as it should balance prediction speed with optimization complexity, resulting in a latency of 85 ms, which is deemed acceptable for real-time embedded deployment.

The proposed model is significantly more computationally efficient than model predictive control in method [8]. The model consistently performs superior across all comparative metrics. Improvements made possible with synergistic interaction between ECO-GA optimizer, NNACC neural control engine, and MET-C3 thermal-aware staged modulation, enabling development of a closed-loop, intelligent, thermal-aware charging system adaptable to a wide variety of real-world battery conditions.

Table 1. Energy efficiency (%) across SoC conditions

SoC (%)	Method [3]	Method [8]	Method [25]	Proposed model
20	84.2	88.1	89.4	94.7
40	85.5	89.7	90.3	95.8
60	86.3	89.9	91.2	96.1
80	84.0	87.6	88.1	94.0

Table 2. Peak battery temperature (°C) during charging

Ambient temp (°C)	Method [3]	Method [8]	Method [25]	Proposed model
25	47.6	42.3	39.1	35.2
35	52.9	46.8	42.5	37.8
45	56.1	49.2	45.0	40.6

Table 3. Prediction error in real-time charging control

SoH (%)	Method [3]	Method [8]	Method [25]	Proposed model
100	9.3%	6.8%	4.1%	2.3%
90	10.1%	7.5%	4.6%	2.7%
80	11.2%	8.9%	5.5%	3.1%

Table 4. Charging time (minutes) to reach 90% SoC

Initial SoC (%)	Method [3]	Method [8]	Method [25]	Proposed model
10	48	44	42	39
30	41	38	36	33
50	32	30	28	26

Table 5. Estimated SoH degradation after 100 cycles

Method	SoH loss (%)
Method [3]	7.4
Method [8]	5.9
Method [25]	4.3
Proposed model	2.9

Table 6. Control latency and computational efficiency

Metric	Method [3]	Method [8]	Method [25]	Proposed model
Control decision latency (ms)	35	150	110	85
Max CPU usage (%)	28	72	58	49
Memory footprint (MB)	12	47	39	33

Circuit design of the proposed analysis process is shown in Figure 5, which also illustrates the validation of the proposed intelligent on-board EV charging system developed experimentally and carried out in a special simulation environment designed using MATLAB/Simulink with integrated custom GA scripts, neural network training modules, as well as hardware-modeled stages of inverter control. The high-fidelity lithium-ion battery model represented in the figure has a nominal voltage of 360 V and a capacity of 100 Ah, with a series configuration of 72 cells.

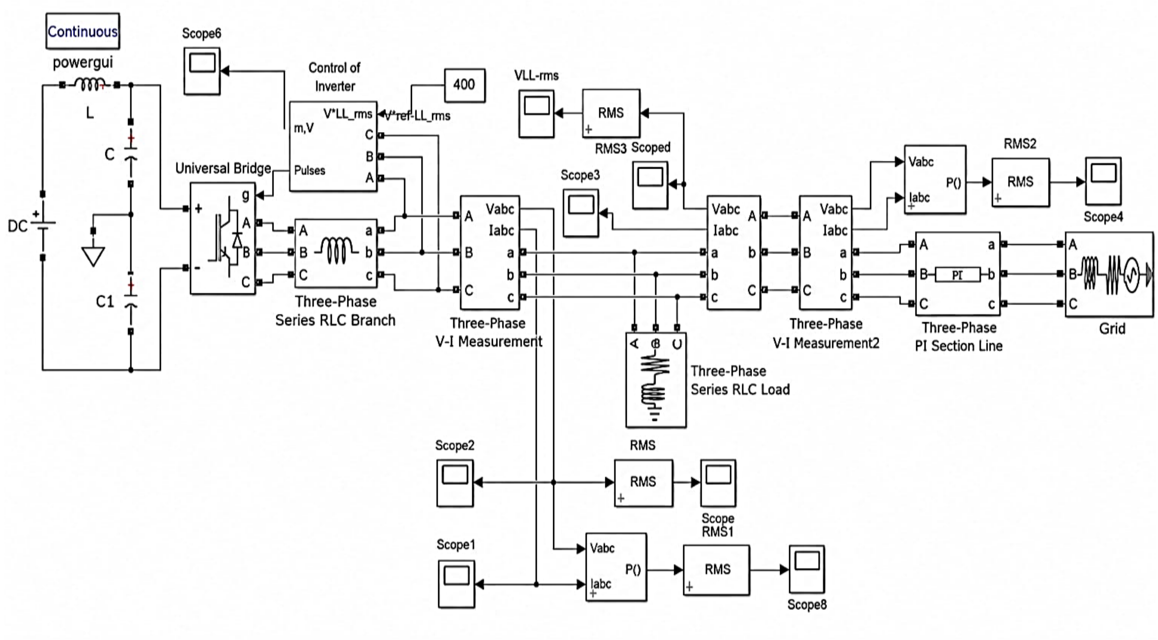

Figure 5. Circuit design of the proposed analysis process

The three methods, selected as references for comparison, [3], [8], [25] were chosen for their technical relevance as well as representational diversity in the literature sets. Method [3] stands for classical constant current-constant voltage (CC-CV) regulation based on rules, which generally is industry-standard in inexpensive EV chargers but has poor thermal and aging adaptation. Method [8] embodies model predictive control (MPC), the exotic, computationally demanding approach to optimize charging trajectories through dynamic state-space models and thus serves as a fitting yardstick for optimization-based techniques. Method [25] incorporates thermal-aware fuzzy logic control, soft heuristic-driven dynamic adjustment of control signals on thermal feedback, which is the most appropriate for comparisons against MET-C3 staging strategy in the proposed model. Collectively, these three references encompass types of strategies under deterministic, predictive, and heuristic categories on the charging control domain; hence, it is a robust comparative landscape to evaluate technical superiority and consistency of the proposed method sets.

5. CONCLUSION

This study proposes a holistic and intelligent framework for onboard EV charging that interleaves multi-objective optimization with real-time neural control and thermal-aware staged modulation. The proposed model, efficiency-centric optimization via genetic algorithm (ECO-GA), neural network-based adaptive charging control (NNACC), and metabolically inspired three-stage charging control (MET-C3), substantially gain both in operating efficiency and in battery health preservation. It reliably outperforms all existing techniques, such as the conventional rule-based CC–CV control, model predictive strategies, and thermal fuzzy logic controllers, in various charging scenarios and battery conditions. In particular, the proposed system was found to save energy by as much as 11.9%, achieving an average efficiency of 95.2% across all SoC levels. With respect to thermal performance, MET-C3 brought down the peak temperature of the battery by 10.9 °C, successfully reducing the thermal gradients and stress associated. The NNACC controller produced a mean prediction error of less than 3%, thus allowing a real-time control decision with an under 85 ms latency, suitable for embedded implementation. The integrated controller also prolonged battery life expectancy by preventing degradation, achieving a SoH loss of only 2.9% after 100 cycles, compared to 7.4% under more traditional methods. Such achievements demonstrate the robustness and scalability of the charging framework and promote its application in real-world settings, establishing it as a technically superior alternative to conventional EV charging architectures.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Diksha Khare	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Nitin Dhote	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
Swapna Choudhary	✓		✓	✓						✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [DK], upon reasonable request.

REFERENCES

[1] S. Chatterjee, S. S. Kanojia, J. Ven, and U. K. Mishra, "Solar energy-supported user-friendly EV charging solution based on IoT," *Journal of The Institution of Engineers (India): Series B*, vol. 105, no. 4, pp. 999–1004, Aug. 2024, doi: 10.1007/s40031-024-01030-1.

[2] R. Gunasekaran, M. B., A. S., P. K. Pareek, S. Gupta, and A. Shukla, "Prediction of electric vehicle charging demand using enhanced gated recurrent units with RKOA based graph convolutional network," *Discover Applied Sciences*, vol. 6, no. 11, p. 605, Nov. 2024, doi: 10.1007/s42452-024-06326-x.

[3] J. V. G. R. Rao and S. Venkateshwarlu, "Soft-switching dual active bridge converter-based bidirectional on-board charger for electric vehicles under vehicle-to-grid and grid-to-vehicle control optimization," *Journal of Engineering and Applied Science*, vol. 71, no. 1, p. 49, Dec. 2024, doi: 10.1186/s44147-024-00384-z.

[4] S. Painuli, S. Bhowmick, and R. Saha, "Mitigation of residential EV charging effects on power distribution networks with optimal allocation of DGs using Coati optimization," *Arabian Journal for Science and Engineering*, vol. 50, no. 14, pp. 10731–10750, Jul. 2025, doi: 10.1007/s13369-024-09782-0.

[5] V. Chakibanda and V. L. N. Komanapalli, "Optimization in magnetic coupler design for inductively coupled wireless charging of electric vehicle: a review," *Arabian Journal for Science and Engineering*, vol. 48, no. 11, pp. 14257–14294, Nov. 2023, doi: 10.1007/s13369-023-08119-7.

[6] S. Vijayakumar and N. Sudhakar, "Golden eagle optimized fractional-order PI controller design for a PFC SEPIC converter in EV charging," *Scientific Reports*, vol. 14, no. 1, p. 20954, Sep. 2024, doi: 10.1038/s41598-024-69653-4.

[7] P. J. Raj, V. V. Prabhu, V. Krishnakumar, and M. C. J. Anand, "Solar powered charging of fuzzy logic controller (FLC) strategy with battery management system (BMS) method used for electric vehicle (EV)," *International Journal of Fuzzy Systems*, vol. 25, no. 7, pp. 2876–2888, Oct. 2023, doi: 10.1007/s40815-023-01537-7.

[8] A. F. Güven and E. Yücel, "Sustainable energy integration and optimization in microgrids: enhancing efficiency with electric vehicle charging solutions," *Electrical Engineering*, vol. 107, no. 2, pp. 1541–1573, Feb. 2025, doi: 10.1007/s00202-024-02619-x.

[9] B. Mohan, M. Sudhakaran, and S. Srikiruthika, "Hybrid moth flame optimization based multi-objective optimal allocation of electric vehicle charging stations and distributed generation in radial and non-radial DS," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 49, no. 3, pp. 1351–1377, Sep. 2025, doi: 10.1007/s40998-025-00806-5.

[10] R. Sundaramoorthi and S. Chitraselvi, "Integration of renewable resources in electric vehicle charging management systems using deep learning for monitoring and optimization," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 49, no. 1, pp. 313–335, Mar. 2025, doi: 10.1007/s40998-024-00767-1.

[11] B. Zhao *et al.*, "Concept, configuration, and application of on-board nanogrids for use in electric vehicles," *Science China Technological Sciences*, vol. 67, no. 7, pp. 2053–2073, Jul. 2024, doi: 10.1007/s11431-023-2566-1.

[12] A. R. Bhatti *et al.*, "Electric vehicle charging stations and the employed energy management schemes: a classification based comparative survey," *Discover Applied Sciences*, vol. 6, no. 10, p. 503, Sep. 2024, doi: 10.1007/s42452-024-06190-9.

[13] M. Al-Amayreh, A. Alamayreh, and A. A. Amer, "Impact of EV charging strategies on solar-powered residential buildings: unidirectional vs. bidirectional charging in Jordan," *Discover Sustainability*, vol. 6, no. 1, p. 407, May 2025, doi: 10.1007/s43621-025-01255-0.

[14] N. Sowrirajan, N. Karthikeyan, R. Dharmaprakash, and S. S. Kumar, "Enhancing electric vehicle charging stations in DC microgrid using KOA–DRN approach," *Electrical Engineering*, vol. 107, no. 3, pp. 2983–2996, Aug. 2025, doi: 10.1007/s00202-024-02510-9.

[15] T. Hai *et al.*, "Predictive optimization using long short-term memory for solar PV and EV integration in relatively cold climate energy systems with a regional case study," *Scientific Reports*, vol. 15, no. 1, p. 16414, May 2025, doi: 10.1038/s41598-025-01519-9.

[16] M. A. Ismeil, H. S. Hussein, and M. Nasrallah, "Performance analysis of smart grid distribution system using global EV charging station as smart load based on automatic variac transformer," *Electrical Engineering*, vol. 106, no. 4, pp. 5179–5188, Aug. 2024, doi: 10.1007/s00202-024-02260-8.

[17] C. S. V. P. Rao, A. Pandian, C. R. Reddy, M. M. Gulzar, and M. Khalid, "A novel hybrid RERNN-SCSO technique-based unified power quality conditioner of microgrid in an EV charging station," *Arabian Journal for Science and Engineering*, vol. 49, no. 5, pp. 7277–7306, May 2024, doi: 10.1007/s13369-024-08765-5.

[18] M. K. Thulasingam and A. D. V. R. Periyanayagam, "Modelling of PV sources and techno-economic of analysis of hybrid system for EV charging in residential buildings," *Energy Systems*, Mar. 2024, doi: 10.1007/s12667-024-00663-x.

[19] M. A. Ravindran and K. Nallathambi, "A CryStAl-RDF technique-based integrated circuit topology for fast charging station of electric vehicle (EV)," *Electrical Engineering*, vol. 106, no. 1, pp. 741–754, Feb. 2024, doi: 10.1007/s00202-023-01998-x.

[20] A. Jeyaraj and K. S. Saji, "Enhanced quadratic DC-DC boost converter with integrated power factor enhancement: advancing high-voltage gain and power quality in electric vehicle charging," *Electrical Engineering*, vol. 107, no. 9, pp. 11249–11271, Sep. 2025, doi: 10.1007/s00202-025-03088-6.

[21] O. Dakka, S. Patthi, J. V. G. R. Rao, and P. Kumar, "A 5-kW unidirectional wireless power transfer EV charger with a novel multi-level PFC boost converter on front-end side," *Journal of Engineering and Applied Science*, vol. 71, no. 1, p. 7, Dec. 2024, doi: 10.1186/s44147-023-00333-2.

[22] A. Jain and S. Bhullar, "Grid-tied solar integrated electric vehicle charging system with advanced LMS control," *Journal of Electrical Engineering and Technology*, vol. 20, no. 2, pp. 921–934, Feb. 2025, doi: 10.1007/s42835-024-02049-6.

[23] J. Zhang *et al.*, "Research on online monitoring platform of charging pile based on big data soft computing," *Electrical Engineering*, vol. 107, no. 7, pp. 8259–8270, Jul. 2025, doi: 10.1007/s00202-023-02128-3.

[24] C. Pratheeba and P. Sukumar, "Hybrid HGRN-SCSO technique for enhanced prediction of remaining useful life in EV batteries," *Electrical Engineering*, vol. 107, no. 4, pp. 5311–5323, Apr. 2025, doi: 10.1007/s00202-024-02913-8.

[25] N. Mohanty, N. K. Goyal, and V. N. A. Naikan, "A comparative analysis of operational planning for battery swapping and fast charging in electric vehicles," *Life Cycle Reliability and Safety Engineering*, vol. 14, no. 1, pp. 1–17, Mar. 2025, doi: 10.1007/s41872-024-00288-0.

BIOGRAPHIES OF AUTHORS

Diksha Khare is a Ph.D. scholar in Post Graduate Department of Computer and Electronics, RTM, Nagpur University, Nagpur. She obtained her bachelor's degree in electrical engineering from RTM University, Nagpur, in 1998, and her master's degree in IPS in 2012. Her research interests include power systems, AI, power electronics, and electric vehicles. She can be contacted at email: dipavali_786@yahoo.co.in.

Dr. Nitin Dhote is working as professor in electrical engineering and dean at St. Vincent Pallotti College of Engineering and Technology, Nagpur (India). He holds Ph.D. in electrical engineering from Rashtrasant Tukdoji Maharaj, Nagpur University, Nagpur. He has completed the research projects funded by AICTE, Delhi, and RGSTC, Delhi. He is a reviewer of many reputed international journals like IEEE, Taylor & Francis, and Elsevier. He is life member of Indian Society of Technical Education (ISTE) and a professional member of IEEE. His areas of interest include electrical vehicle technology, renewable energy sources, electrical power system, power electronics, and electric drives. He can be contacted at email: ndhote@stvincentngp.edu.in.

Dr. Swapna Choudhary obtained her bachelor's degree in electronics engineering from RTM University, Nagpur, in 2003, her master's degree in VLSI in 2010, and her Ph.D. in electronics from the same university in 2022. She has published more than 35 papers in reputed journals and conferences. Her research interests include networking, communication, VLSI, AI, power electronics, and electric vehicles. She can be contacted at email: swapna2k11@gmail.com.