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Hybrid deep learning-based adaptive charging for electric vehicle batteries

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ABSTRACT

Electric vehicles (EVs) require intelligent charging strategies that enable fast charging while limiting battery temperature rise and aging to improve safety and service life. Conventional charging methods, including constant current-constant voltage (CC–CV), pulse charging (PC), constant power charging (CPC), multi-stage constant current (MSCC), and fuzzy logic charging (FLC), often fail to achieve an optimal balance between charging speed, thermal performance, and battery degradation. This paper proposes a hybrid deep learning and whale optimization algorithm (WOA)-based adaptive charging strategy for lithium-ion batteries. A deep learning model predicts battery temperature and state of health (SOH) from charging current, voltage, state of charge (SOC), charging time, and ambient temperature. The predicted battery states are incorporated into a multi-objective WOA to determine an optimal charging current profile that minimizes charging duration, temperature rise, battery aging, and converter stress. Simulation results show that the proposed method reduces charging time from 11,400 s to 10,300 s and decreases the average battery temperature from 39.0 °C to 28.1 °C compared with the conventional CC–CV method. Furthermore, the optimized charging profile reduces current ripple and thermal loading in the DC-DC charging converter, improving converter efficiency, EV drive system reliability, and battery lifespan.

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1. INTRODUCTION

Electric vehicles (EVs) rely heavily on lithium-ion batteries for their performance, safety, and driving range. Although fast charging improves charging convenience, it can increase battery temperature, accelerate degradation, reduce state of health (SOH), and impose additional stress on the charging converter. Hence, an adaptive charging strategy is required to balance charging time, thermal behavior, battery aging, and converter performance [1]–[5]. Conventional approaches such as constant current–constant voltage (CC–CV), pulse charging (PC), constant power charging (CPC), and multi-stage constant current (MSCC) generally employ predefined charging profiles. Their limited adaptability makes it difficult to respond to the nonlinear behavior of lithium-ion batteries. AI and deep learning methods have been applied for predicting battery temperature,

state of charge (SOC), and SOH [6]–[10], while optimization techniques such as PSO, GWO, MFO, and WOA have been used to obtain improved charging profiles under operating constraints [11]–[15].

However, existing studies commonly address battery-state prediction and charging optimization as separate tasks. Recent intelligent charging approaches include DDPG-based charging [16], deep reinforcement learning for fast charging [17], urgency-aware charging [18], reinforcement-learning-based energy management [19], and intelligent fast-charging strategies [20]. These methods do not explicitly combine temperature and SOH prediction with WOA-based optimization while jointly considering charging time, thermal response, battery aging, and converter performance. This motivates an integrated approach for coordinated battery and converter management [9], [12], [15].

This paper proposes a hybrid deep learning–WOA-based adaptive charging strategy for EV batteries. The proposed framework predicts battery temperature and SOH and uses these predictions to optimize the charging-current profile through WOA. The main contributions are: i) Simultaneous prediction of battery temperature and SOH; ii) Prediction-guided WOA optimization of charging current; and iii) Performance assessment using charging time, battery temperature, SOH, and DC–DC converter efficiency.

2. METHOD

This paper proposes a hybrid deep learning and whale optimization algorithm (WOA)-based adaptive charging strategy for lithium-ion batteries in electric vehicles. The framework combines deep learning-based battery state prediction with WOA to generate an optimal charging current profile that minimizes charging time, temperature rise, battery aging, and converter stress. By adaptively regulating the charging current according to the predicted battery conditions, the proposed method improves charging efficiency and extends battery lifespan.

Figure 1 presents the overall architecture of the proposed framework. Battery operating parameters, including charging current, battery voltage, SOC, ambient temperature, and charging time, are supplied to the deep learning model to predict battery temperature and SOH. The predicted battery states are then provided to WOA, which generates the optimal multi-stage charging current profile while satisfying the battery operating constraints. The battery input vector is defined as in (1).

$$X = [I, V, SOC, T_{amb}, t] \tag{1}$$

Where I is the charging current, V is the battery voltage, SOC is the state of charge, T_{amb} is the ambient temperature, and t is the charging time. The deep learning model predicts battery temperature and SOH as in (2).

$$[T_b, SOH] = f(X) \tag{2}$$

Where T_b is battery temperature and f(X) represents the trained deep learning model. A normalized battery aging index is calculated as in (3).

$$A_{battery} = 1 - (SOH/100) \tag{3}$$

Where $A_{battery}$ represents the battery aging index; a lower value indicates better battery health. The charging problem is formulated as a multi-objective optimization problem as in (4).

$$J = w_1 T_{\{charge\}} + w_2 \Delta T + w_3 A_{\{battery\}} + w_4 I_{\{stress\}} \tag{4}$$

Where J is the overall objective function; T_{charge}, ΔT, $A_{battery}$, and I_{stress} represent charging time, battery temperature rise, battery aging index, and converter current stress, respectively, while w1 to w4 are their corresponding weighting factors. The WOA updates the candidate charging-current solution according to (5).

$$X(k+1) = X*(k) - A \cdot D \quad \text{where} \quad D = |C \cdot X*(k) - X(k)| \tag{5}$$

Where X(k) is the current candidate solution at iteration k, X∗(k) is the best solution obtained so far, and A and C are WOA coefficient vectors controlling the search process. The charging constraints are defined as in (6).

$$0 \le \text{Ic} \le 2\ \text{A}, \text{Tb} \le 40 \circ \text{C}, \text{Vb} \le 4.2\ \text{V}, \ SOC_final = 100\% \tag{6}$$

Where Ic is the charging current, and Vb is the battery voltage. The weighting factors were selected as w1 = 0.30, w2 = 0.30, w3 = 0.20, and w4 = 0.20 for charging time, temperature rise, battery aging, and converter current stress, respectively. The optimized charging profile is finally applied to the battery charger while satisfying the constraints in (6).

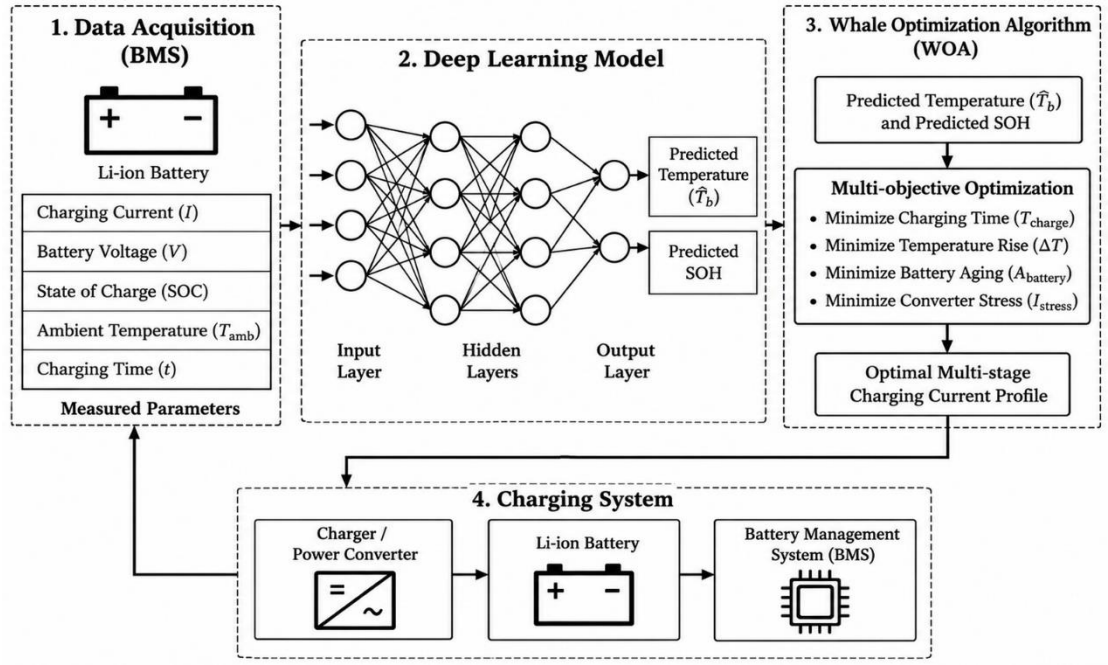

Figure 1. Overall architecture of the proposed hybrid deep learning and WOA-based adaptive charging framework

2.1. Battery data preparation

The proposed adaptive charging framework was implemented using a lithium-ion battery model in MATLAB/Simulink under different charging conditions. Battery operating parameters, including charging current, battery voltage, SOC, ambient temperature, and charging time, were obtained from the simulated battery model and used as input features. The corresponding battery temperature and SOH were considered as target outputs. A dataset of 1200 samples was generated using a 10 s sampling interval over the charging period. Before model training, all input variables were normalized using Min–Max normalization to improve convergence and prediction accuracy.

2.2. Deep learning model training

The normalized dataset was divided into 70% training, 15% validation, and 15% testing subsets to evaluate the prediction capability of the proposed deep learning model. A feedforward neural network comprising five input neurons, two hidden layers (16 and 8 neurons), and two output neurons was employed to estimate battery temperature and SOH. The network was trained using the Adam optimizer with the ReLU activation function, while the mean squared error (MSE) was adopted as the loss function. Training was performed for 200 epochs with an initial learning rate of 0.001. Model performance was evaluated using the root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The trained model was subsequently integrated with the whale optimization algorithm to generate the adaptive charging current profile.

$$MSE = \left(\frac{1}{N}\right)\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

2.3. WOA-based charging optimization

The predicted battery temperature and SOH were supplied to the whale optimization algorithm (WOA) to determine the optimal multi-stage charging current profile. A population of 30 whales was initialized within the 0–2 A current range and optimized for a maximum of 100 iterations. The objective weights were 0.30, 0.30, 0.20, and 0.20 for charging time, temperature rise, battery aging, and converter current stress, respectively. Battery temperature and voltage were constrained to 40 °C and 4.2 V, respectively, with the final SOC set to 100%. Optimization terminated at the maximum iterations or upon convergence of the objective function. The resulting charging profile was applied for performance evaluation.

2.4. Simulation settings

The proposed framework was developed using MATLAB/Simulink. Simulations were performed under identical operating conditions for all charging strategies to ensure a fair comparison. Charging was carried out from 20% to 100% SOC at an ambient temperature of 25 °C. The performance of the proposed hybrid deep learning–WOA strategy was compared with five benchmark charging strategies, namely CC–CV, PC, constant power charging (CPC), MSCC, and fuzzy logic charging (FLC). These methods were selected as benchmark charging strategies for comparative evaluation of the proposed framework. The battery specifications and the configuration of the proposed deep learning model are summarized in Tables 1 and 2, respectively. The simulation model in Figure 2 integrates the lithium-ion battery, BMS measurements, deep learning prediction, WOA optimization, and a bidirectional DC–DC converter. Battery operating parameters are used to predict temperature and SOH, and WOA determines the optimal charging-current profile. All charging strategies are evaluated under identical simulation conditions.

Table 1. Battery specifications

Parameter	Value
Battery type	Lithium-ion
Nominal voltage	3.7 V
Rated capacity	2.6 Ah
Initial SOC	20 %
Final SOC	100 %
Ambient temperature	25 °C
Maximum charging current	2 A
Cut-off voltage	4.2 V

Table 2. Deep learning model parameters

Parameter	Value
Input features	5 (current, voltage, SOC, ambient temperature, and charging time)
Hidden layers 0	2 Neurons
Hidden layers 1	16 Neurons
Hidden layers 2	8 Neurons
Output variables	2 (Battery Temperature, SOH)
Activation function, optimizer	ReLU, ADAM
Loss function	Mean squared error (MSE)
Learning rate, epochs	0.001, 200
Training, validation, testing	70%, 15%, 15%

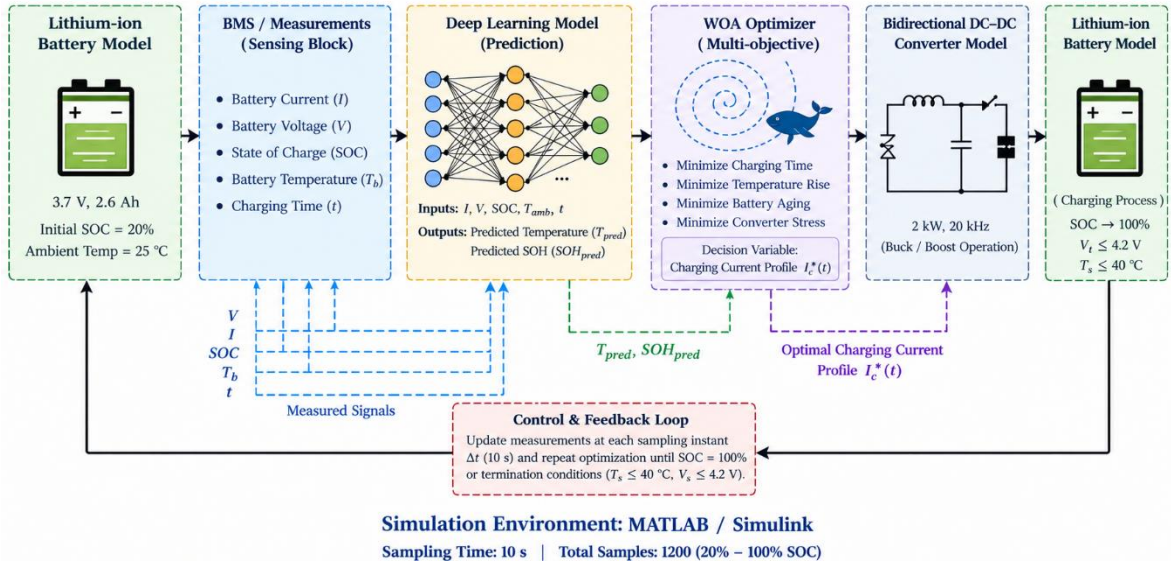

Figure 2. Simulation setup of the proposed hybrid deep learning–WOA-based adaptive EV battery charging system

2.5. Performance evaluation

The proposed charging strategy was evaluated using charging time, average battery temperature, SOH, battery aging index, converter efficiency, converter current ripple, and converter current stress. The optimized charging profile was applied to a bidirectional DC–DC converter implemented in MATLAB/Simulink to assess its impact on charging and converter performance. The simulation results and comparative analysis are presented in the following section.

3. RESULTS AND DISCUSSION

3.1. Battery temperature prediction

The proposed deep learning model was evaluated by comparing predicted and measured battery temperatures. As shown in Figure 3(a), the predicted temperature closely follows the measured profile, while the training and validation losses in Figure 3(b) converge smoothly. The model achieved an RMSE of 0.18 °C, MAE of 0.13 °C, MSE of 0.032, and of 0.995, confirming its suitability for battery temperature prediction and subsequent WOA-based charging-current regulation [21]–[23].

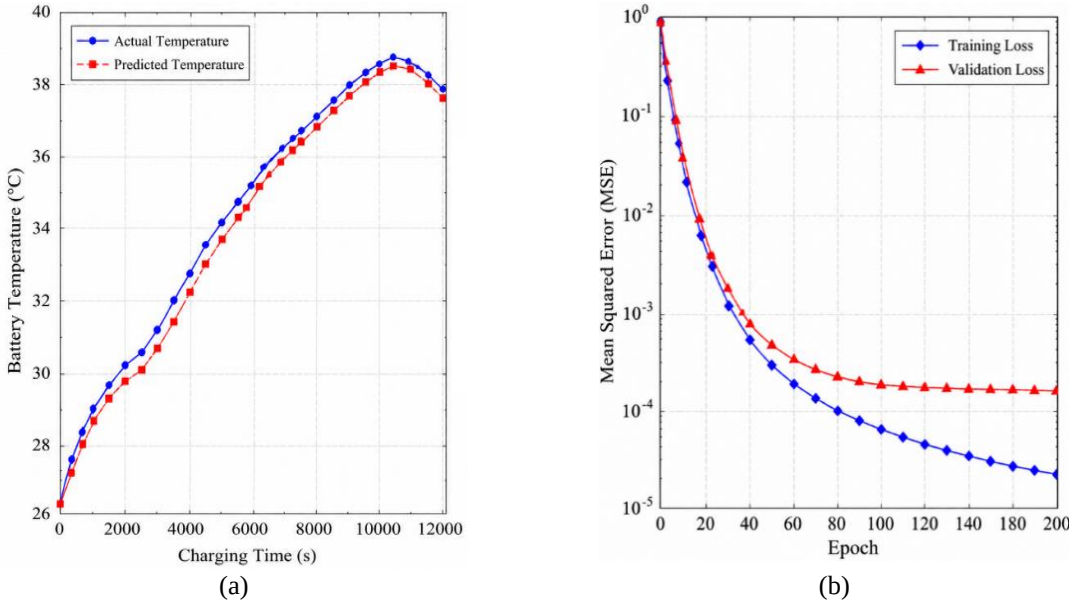

Figure 3. Battery temperature prediction performance of the proposed deep learning model: (a) actual vs. predicted battery temperature and (b) training and validation loss

3.2. WOA convergence analysis

The convergence performance of WOA was evaluated using the objective function defined in section 2. As shown in Figure 4, the fitness value decreases rapidly initially and converges after approximately 60–70 iterations. The convergence indicates effective optimization of the charging-current profile while considering charging time, temperature rise, battery aging, and converter stress [24]–[26].

3.3. Adaptive charging current profile

Figure 5 compares the charging-current profiles of the proposed hybrid deep learning–WOA strategy and conventional CC–CV charging. The proposed method adaptively regulates the current according to the predicted battery temperature and SOH, reducing thermal stress while maintaining fast charging. The smoother current profile also reduces converter current stress and improves DC–DC converter operation [27]–[29].

3.4. Battery temperature analysis

Figure 6 compares the temperature profiles of the charging strategies. The average temperatures are 39.0 °C, 35.6 °C, 33.1 °C, 31.1 °C, 29.6 °C, and 28.1 °C for CC–CV, PC, CPC, MSCC, FLC, and the proposed strategy, respectively. Thus, the proposed method reduces the average temperature from 39.0 °C to 28.1 °C, corresponding to a 27.95% reduction compared with CC–CV. The reduction is attributed to adaptive current regulation, which limits heat generation during thermally sensitive charging conditions [27]–[30].

3.5. State of health (SOH) analysis

Figure 7 shows the SOH obtained with the different charging strategies. The values are 82.0%, 84.3%, 86.9%, 89.0%, 91.5%, and 95.0% for CC–CV, PC, CPC, MSCC, FLC, and the proposed strategy, respectively. Compared with CC–CV, the proposed strategy improves SOH from 82.0% to 95.0%, corresponding to a 15.85% improvement. The higher SOH is associated with the reduced thermal loading and adaptive charging-current regulation shown in Figures 4 and 5 [28]–[30].

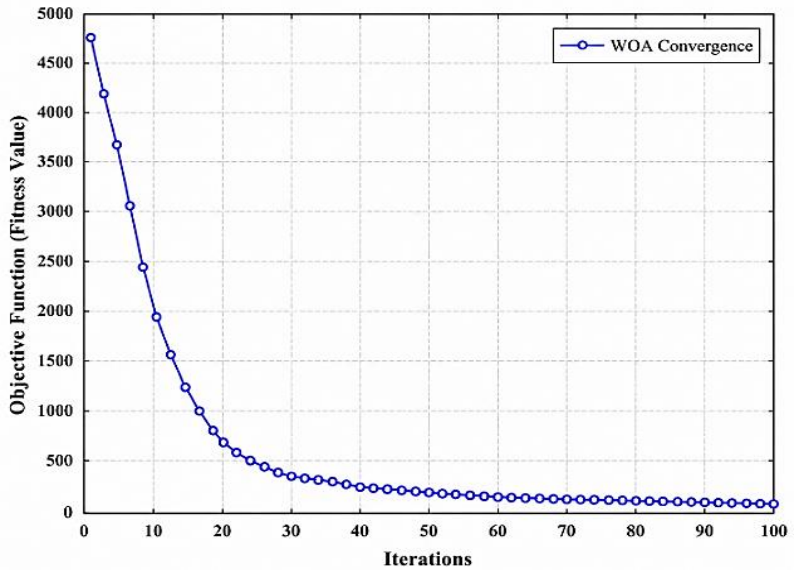

Figure 4. WOA convergence

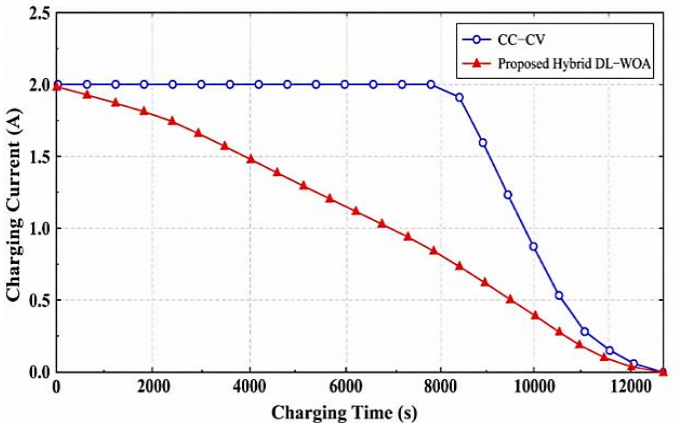

Figure 5. Comparison of charging current profiles and conventional CC-CV charging

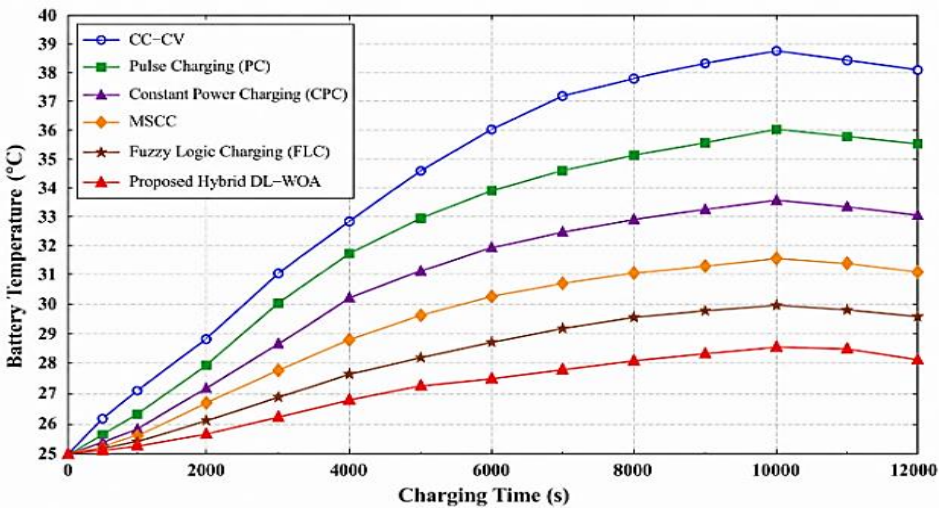

Figure 6. Comparison of battery temperature profiles under different charging methods

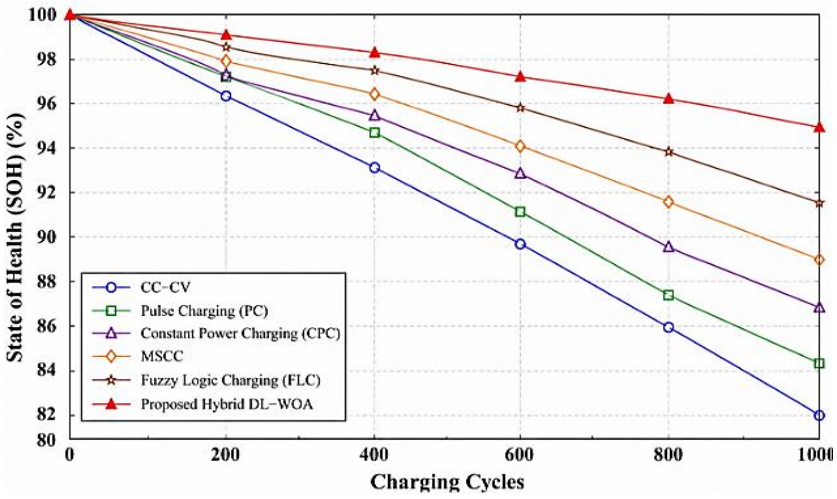

Figure 7. Comparison of SOH under different charging methods

3.6. Power converter performance analysis

Figure 8 compares converter efficiency for the different charging strategies. The efficiencies are 92.8%, 93.6%, 94.3%, 95.0%, 95.8%, and 97.1% for CC–CV, PC, CPC, MSCC, FLC, and the proposed strategy, respectively. The proposed method improves converter efficiency from 92.8% to 97.1%, corresponding to a 4.63% relative improvement. This improvement is attributed to the smoother charging-current profile, which reduces abrupt current variations and associated converter loading [29], [30].

Table 3 compares the charging strategies. The proposed hybrid deep learning–WOA achieves the shortest charging time (10,300 s), lowest temperature **(**28.1 °C), highest SOH (95.0%), and converter efficiency (97.1%). Compared with CC–CV, these correspond to 9.65% faster charging, 27.95% lower temperature, 15.85% higher SOH, and 4.63% higher efficiency, demonstrating a balanced multi-objective charging performance.

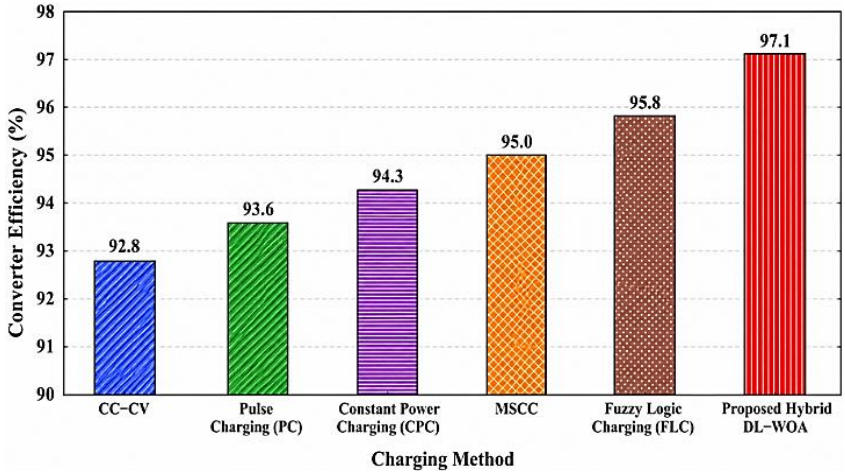

Figure 8. Comparison of converter efficiency under different charging methods

Table 3. Performance comparison of different charging methods

Charging method	Charging time (s)	Average temperature (°C)	SOH (%)	Converter efficiency (%)
CC–CV	11400	39.0	82.0	92.8
Pulse charging	11120	35.6	84.3	93.6
Constant power charging	10980	33.1	86.9	94.3
MSCC	10780	31.1	89.0	95.0
Fuzzy logic charging	10580	29.6	91.5	95.8
Proposed hybrid DL–WOA	10300	28.1	95.0	97.1

4. CONCLUSION

This paper presented a hybrid deep learning–whale optimization algorithm (WOA)-based adaptive charging strategy for lithium-ion batteries in electric vehicles. The deep learning model predicted battery temperature and SOH, while WOA optimized the charging current by considering charging time, temperature, battery aging, and converter current stress. Compared with conventional CC–CV charging, the proposed strategy reduced charging time from 11,400 s to 10,300 s and average battery temperature from 39.0 °C to 28.1 °C, corresponding to 9.65% faster charging and 27.95% lower average temperature. The SOH increased from 82.0% to 95.0%, representing a 15.85% improvement, while converter efficiency increased from 92.8% to 97.1%, an absolute improvement of 4.3 percentage points (4.63% relative improvement). These results demonstrate that the proposed method provides a balanced improvement in charging speed, thermal performance, battery health, and converter efficiency. Future work will focus on real-time hardware implementation and experimental validation using practical EV battery charging platforms.

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The authors confirm that the research was carried out independently without financial influence.

AUTHOR CONTRIBUTIONS STATEMENT

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

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Mallareddy Adudhodla	✓		✓	✓			✓			✓	✓		✓	
T. Sathish Kumar	✓	✓			✓	✓			✓		✓		✓	
R. Kalaivani	✓			✓	✓		✓		✓	✓		✓		✓
P. Kavitha	✓	✓	✓		✓		✓			✓		✓		

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

All authors have reviewed and agreed to this conflict of interest statement.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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