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Optimization of EV battery charging for temperature control

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ABSTRACT

Electric vehicles (EVs) offer a sustainable mode of transportation; however, excessive battery temperature rise during charging degrades performance, limits lifespan, and affects the safe operation of power converters and EV drive systems. To address this problem, a back propagation neural network (BPNN) based temperature prediction model is integrated with four nature-inspired optimization techniques (NIOTs): whale optimization algorithm (WOA), moth flame optimization (MFO), modified particle swarm optimization (MPSO), and grey wolf optimization (GWO), to optimize multi-stage charging current profiles. Among the evaluated methods, WOA achieves the best performance, reducing charging time by approximately 10% (11400 s to 10300 s) and average temperature rise by nearly 50% (3.9 °C to 1.9 °C) compared to the conventional constant current–constant voltage (CC-CV) strategy. The optimized charging currents directly support improved DC-DC converter operation and stable EV drive performance by limiting thermal stress and current transients. Overall, accurate thermal-aware charging enhances charging efficiency, ensures safe converter operation, and contributes to reliable and long-life EV battery and drive system performance.

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1. INTRODUCTION

Electric vehicles (EVs) are emerging as a dominant solution for clean and energy-efficient transportation, with lithium-ion batteries forming the backbone of modern EV power electronics, converters, and electric drive systems. Batteries not only supply propulsion energy but also support auxiliary loads across platforms ranging from two-wheelers and commercial fleets to public transport systems. However, the charging process remains a critical bottleneck, as thermal rise during charging adversely affects converter duty cycles, drive reliability, and long-term battery health. The widely adopted constant current–constant voltage (CC-CV) method [1], though simple and robust, often results in higher temperature rise, inefficient current regulation, and extended charging duration, thereby limiting overall EV performance.

To overcome these limitations, several advanced charging strategies have been reported in the literature, including PSO-optimized multistep charging [2], adaptive pulse charging [3], fuzzy-logic-based control [4], and flexible multi-stage constant current (MSCC) methods [5]. These approaches improve charging efficiency and thermal behavior; however, they introduce challenges related to optimal current selection, computational burden, and integration with real-time converter and drive systems. Predictive control techniques have also been explored to mitigate temperature rise [6], but their implementation complexity restricts practical deployment. In contrast, backpropagation neural networks (BPNNs) have demonstrated strong capability in modeling nonlinear battery thermal dynamics with moderate computational effort [7], while recent studies highlight the benefits of combining machine learning and optimization for improved EV battery performance [8].

Despite these advances, a clear research gap exists in the form of systematic, comparative investigations of nature-inspired optimization techniques with direct relevance to temperature-aware charging and converter-drive system integration. Motivated by this gap, this work proposes a unified BPNN-based predictive charging framework combined with multiple nature-inspired optimization techniques (NIOTs), including whale optimization algorithm (WOA), moth flame optimization (MFO), modified particle swarm optimization (MPSO), and grey wolf optimization (GWO). The framework benchmarks these methods against conventional CC-CV charging to identify optimal charging currents that balance thermal safety, charging efficiency, and operational reliability. By explicitly linking accurate state of charge (SOC) and temperature prediction to stable converter operation and efficient EV drive performance, the proposed approach contributes toward safer, faster, and more sustainable electric mobility [9].

2. METHODOLOGY IMPLEMENTED

The outline of the suggested pricing method is shown in Figure 1. Using data from battery charging, a BPNN is trained to create a temperature rise prediction model. Using input factors like charging current (I) and SOC, the model predicts an increase in battery temperature. The BPNN-based model is presented here, together with information on neural network architecture, data gathering, training, and validation. Later parts present a comparative examination of different NIOTs for the defined objective function.

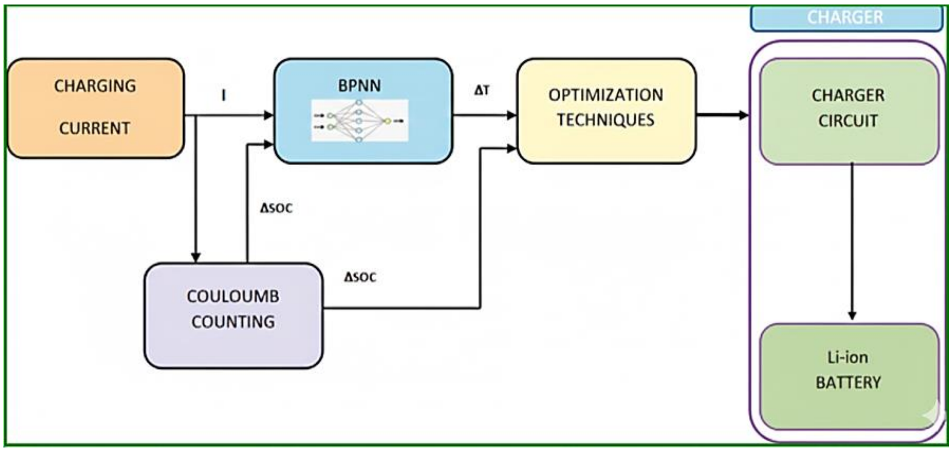

Figure 1. An outline of the proposed technique

2.1. Design and implementation of the BPNN model

A BPNN was employed to establish the relationship between battery operating conditions and temperature behavior during charging. In this supervised learning approach, the network learns from labelled input–output data and iteratively adjusts its internal weights to minimize prediction error. During training, the predicted output is compared with the target value, and the resulting error is propagated backward through the network to update the connection weights. This optimization process continues over multiple training cycles until the prediction accuracy reaches a satisfactory level [10], [11].

The developed BPNN architecture consists of an input layer with two neurons, a hidden layer containing six neurons, and a single output neuron. Charging current (I) and battery SOC are selected as the input variables, while battery temperature rise serves as the output variable. Experimental data were collected using a FENIX 18650 lithium-ion cell, the specifications of which are presented in Table 1. Prior to each charging test, the battery was discharged until its open-circuit voltage reached the prescribed lower operating limit. To eliminate the influence of ambient temperature fluctuations, all experiments were conducted within an isothermal chamber maintained at 25 °C.

Five charging rates ranging from 0.6 C to 1.0 C, with increments of 0.1 C, were considered for dataset generation as given in Table 2. Throughout the constant-current charging stage, the battery surface temperature was recorded at two-minute intervals. A total of 400 data samples were obtained from the experiments, of which 335 samples were used for network training, and 35 samples were reserved for validation as given in Table 3. Since the charging duration varies with charging current, the collected datasets represent different charging profiles. Model performance was evaluated using the mean squared error (MSE) criterion. The comparison between measured and predicted temperature values is illustrated in Figure 2, where the maximum prediction deviation remained within approximately 0.07–0.08 °C, indicating satisfactory modelling accuracy.

Table 1. Specifications of Fenix-ARB-L18-2 600

Battery model	Fenix 18650 ARB-L18-2600 mAh
Capacity	2600 mAh
Nominal voltage	3.6 V
Cut-off voltage	2.6 V
Charging current	1 A (Maximum 2 A)
Dimensions	69 × 18.6 mm
Weight	50 g
Recommended charging temperature	0 – 45 °C
Recommended discharging temperature	-20 – 60 °C

Table 2. Number of training datasets used for the BPNN model

C-rate	Number of training datasets
1 C	70
0.9 C	76
0.8 C	78
0.7 C	68
0.6 C	73

Table 3. Number of validating datasets used for the BPNN model

C-rate	Number of validation datasets
1 C	7
0.9 C	7
0.8 C	7
0.7 C	7
0.6 C	7

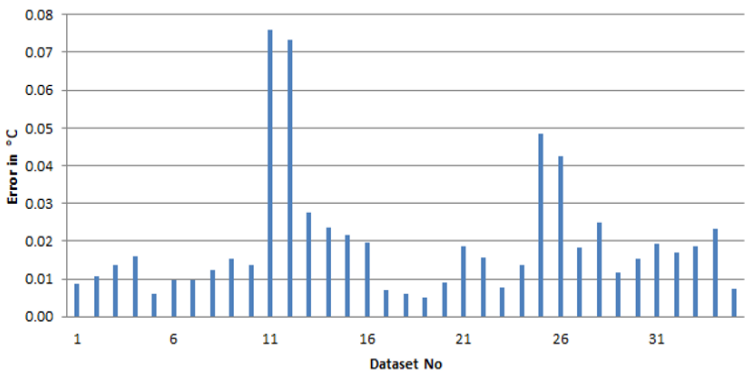

Figure 2. Results of the BPNN model

3. NATURE-INSPIRED OPTIMIZATION TECHNIQUES (NIOT)

The NIOTs have emerged as effective approaches for addressing complex optimization tasks because of their capability to explore extensive solution spaces while adapting to dynamic operating conditions. In the present study, these optimization techniques were utilized to identify an optimal charging current profile for lithium-ion batteries with the dual objective of enhancing charging efficiency and minimizing battery temperature rise. To accomplish this, an objective function was developed by incorporating both the change in state of charge (ΔSOC) and the associated increase in battery temperature (ΔT). A weighting parameter, α, was introduced to balance the contribution of these two performance measures according to the optimization requirements. The objective function adopted in this study is represented as (1).

$$Minimize\left\{\alpha\left(\frac{1}{n}\sum_{i=1}^{n}\left(1-\frac{SOCfinal-SOC_i}{SOCfinal-SOC_{initial}}\right)\right)+(1-\alpha)\frac{1}{m}\sum_{i=1}^{m}(|T_{desired}-T_i|)\right\} \quad (1)$$

In this formulation, α represents the weighting factor assigned to the SOC improvement component of the objective function. The first term quantifies the mean increase in SOC obtained from the selected SOC measurement points, whereas the second term estimates the average variation in battery temperature based on the recorded thermal data. The variables n and m denote the total number of SOC measurements and temperature observations, respectively, included in the optimization procedure. By integrating both charging efficiency and thermal characteristics into a unified objective function, the proposed optimization approach achieves an effective balance between maximizing battery charging performance and limiting undesirable temperature elevation.

3.1. Whale optimization algorithm

The WOA simulates the hunting strategy of humpback whales by integrating prey encirclement, spiral updating, and stochastic exploration, thereby achieving an effective balance between exploration and exploitation during optimization [12]-[15]. Whales move around the best solution using adaptive coefficients, shrink their search radius during exploitation, or follow a spiral path to simulate natural helix movement. A 50% probability decides whether shrinking or spiral actions are used. For exploration, whales update their positions relative to randomly selected agents, helping them escape local optima. This switch between global search and local refinement enables WOA to maintain balance throughout optimization.

3.2. Moth flame optimization

The MFO algorithm initializes moths as candidate solutions and evaluates their fitness to determine attraction strength toward the current best solution (flame) [16]–[19]. Moths then update their positions using a distance-based attraction mechanism with randomness, while an additional exploration step ensures diversity and prevents premature convergence. Through these repeated steps, MFO efficiently explores the search space and improves the quality of solutions.

3.3. Modified particle swarm optimization

The MPSO enhances classical PSO by adapting inertia weight, controlling particle velocity, and tuning parameters dynamically for improved convergence [20]–[22]. Particles update their positions using their personal best and global best information, while velocity clamping ensures stability. The incorporation of adaptive adjustments and local search helps MPSO maintain a better exploration–exploitation balance, reducing stagnation and improving optimization performance.

3.4. Modified grey wolf optimization

The MGWO algorithm starts by ranking wolves into alpha, beta, delta, and omega categories and updating positions based on their distances to these leader wolves using modified coefficients [23]–[25]. Wolves move toward the nearest dominant wolf to refine search direction, while added local search and adaptive parameter updates enhance exploration and prevent entrapment in local optima. Multiple runs help determine optimized charging currents and compare results with traditional charging approaches such as CC-CV. In order to prevent local optima, NIOTs employ random parameters, which results in solution unpredictability. After 50 runs of 100 iterations, the average optimized charging current (OCC) is determined for each NIOT 50, 100, 200, and 300 particle counts are used to calculate final OCCs. The optimization outcomes are also benchmarked using the traditional CC-CV method.

4. COMPUTATIONAL PARAMETER CONFIGURATION AND FINDINGS

To ensure effective results, each NIOT is run 25 times with 100 iterations, and the average OCC is calculated. The study also compares the conventional CC-CV method. Table 4 shows results for Tc (s), energy loss (J), and CS (Ah). Table 5 lists OCCs for each case. MPSO is preferred for its lowest Tc, aligning with the study’s objective. After Python-based simulation, real battery tests are conducted, and charge performance metrics (CPM) are evaluated to confirm OCC optimality.

Table 4. Performance parameters obtained from simulation

Technique	Time for charging Tc (s)	Charging storage CS (Ah)	Loss of energy (J)
WOA	9,950	3.405	3566.79
MFO	9,720	3.320	2860.24
MPSO	9,800	3.369	2960.03
GWO	9,909	3.392	3088.43
0.6 C CC-CV	11,449	2.2936	3118.50

Table 5. OCC obtained using different NIOTs

Technique	I1	I2	I3	I4	I5	Cut-off (V)
WOA	1.232	0.802	0.3122	0.2005	0.1202	3.6
MFO	1.180	0.732	0.3725	0.2570	0.1385	3.6
MPSO	1.165	0.720	0.3809	0.2628	0.1102	3.6
GWO	1.193	0.736	0.3706	0.2829	0.1352	3.6
0.6 C CC-CV	1.6	-	-	-	-	3.6

5. EXPERIMENTAL VERIFICATION

To enable practical validation, a real-time monitoring setup as shown in Figure 3 is developed using an ESP32-based embedded system. A lithium-ion 18650 battery configuration is interfaced with temperature and current sensors to measure operating conditions during charging. Although the proposed model is developed for a single cell, the hardware setup represents a multi-cell configuration for practical implementation. The ESP32 module enables real-time acquisition of current and voltage data, which can be further utilized for SOC estimation using computational algorithms.

The experimental procedure commenced by applying the required charging current levels according to the charging current patterns listed in Table 6. Subsequently, the battery was charged, and the corresponding CPMs along with the charging characteristics were recorded. Following a resting period of 2 hours, the battery was discharged at a constant current rate of 0.2 C until the open-circuit voltage (OCV) reached 3 V. The discharge capacity (DC) was then measured, and the charging efficiency (CE) was determined based on the obtained values. This procedure was repeated until all predefined charging current patterns had been evaluated. The experimental findings presented in Table 6 include five charging performance metrics: TC, CS, DC, CE, and ATI.

Table 6 summarizes the experimental performance metrics, including total charging time (TC), charging capacity (CS), discharge holding capacity (DHC), charging efficiency (CE), and average temperature increase (ATI). For each charging technique, the battery is charged using the corresponding current profile and subsequently subjected to a controlled discharge process after a designated rest period. The discharge holding capacity and charging efficiency are then evaluated. The strong agreement between simulation and experimental findings validates the efficacy of the suggested charging procedures, and this consistent process guarantees a fair comparison.

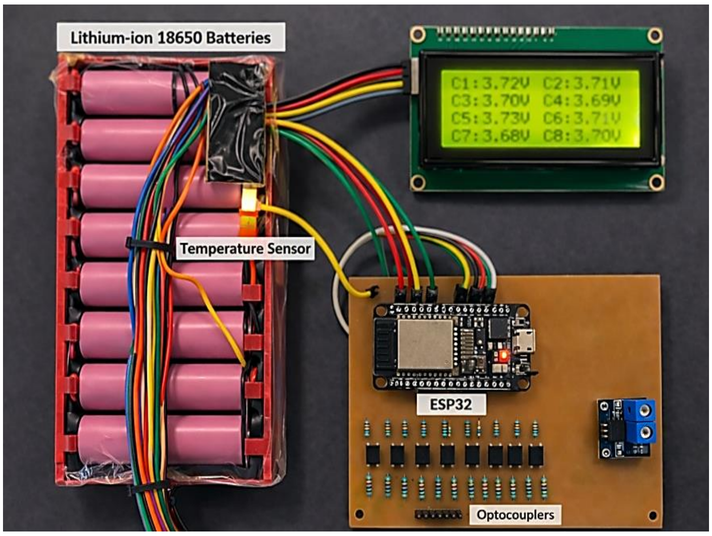

Figure 3. The setup for real-time monitoring

Table 6. Experimental results

Technique	TC (s)	CS (Ah)	DHC (Ah)	CE (%)	ATI (◦C)
WOA	10,328	3.3892	3.3563	99.0292	1.9028
MFO	10,885	3.2900	3.2500	98.7841	2.1222
MPSO	10,650	3.2986	3.1899	96.7046	2.2870
GWO	10,750	3.3924	3.3138	97.6830	2.2063
CC-CV	11,449	3.4453	3.3978	98.6270	3.9251

Among the evaluated methods, the WOA-based technique exhibits superior performance with a charging time of 10,328 s, the highest CE of 99.03%, and the lowest temperature rise of 1.90 °C. The MFO method shows slightly inferior performance, with a longer charging duration (10,885 s), higher temperature increase (2.12 °C), and reduced efficiency (98.78%). The MPSO strategy achieves faster charging (10,650 s) but suffers from lower efficiency (96.70%) and increased thermal rise (2.29 °C), indicating higher battery stress. The GWO-based approach provides balanced performance with moderate charging time (10,750 s), CE of 97.68%, and ATI of 2.21 °C, but does not outperform WOA in terms of efficiency or thermal control.

In contrast, the conventional CC–CV method records the longest charging time (11,449 s) and the highest temperature rise (3.93 °C), highlighting its limitations in thermal management. Overall, while all NIOT-based techniques outperform CC–CV, the WOA approach offers the best trade-off between charging speed, efficiency, and thermal stability, making it the most effective strategy for battery performance enhancement.

Direct measurement of energy loss during battery charging is difficult; hence, this study uses charging TI as the evaluation metric for loss of energy. As shown in Figure 4, the CC-CV method displays significantly higher cumulative TI, indicating greater energy loss during the charging process. In contrast, the proposed NIOT techniques demonstrate smoother and more controlled TI curves by effectively balancing TC and Loss of Energy. This highlights the improved thermal and energy performance achieved through the NIOT-based charging strategies.

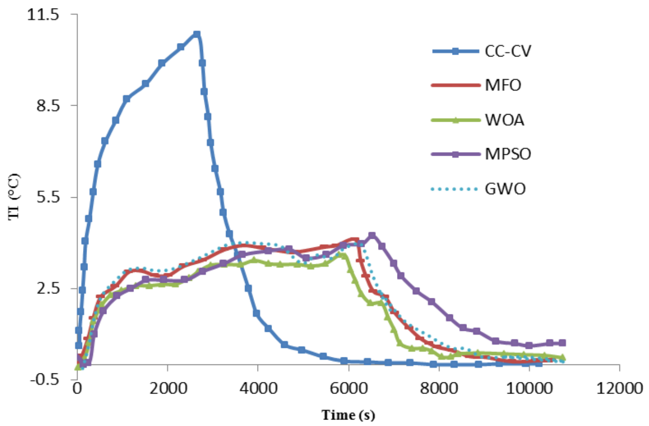

Figure 4. TI for the charging techniques

6. AN ASSESSMENT OF THE NIOTs USED

This study critically evaluates the four CPMs: TC, CS, CE, and ATI. The results provide useful guidance for selecting an appropriate charging method for lithium-ion batteries. Since each CPM is based on different performance criteria, a common normalized evaluation score was computed by assigning a value of 1 to the best-performing result and 0 to the least desirable result. The common normalized evaluation scores are presented in Table 7.

Figure 5 presents the radar chart comparison of the normalized charging performance metrics (TC, CS, CE, and ATI) for all techniques. The WOA method exhibits the largest enclosed area, indicating superior overall performance with balanced charging speed, efficiency, and thermal control. GWO and MFO show moderate performance with trade-offs among the metrics, while MPSO demonstrates weaker overall balance. The CC–CV method attains lower normalized scores, highlighting its comparatively inferior performance across the evaluated CPMs.

Table 7. Table 6's normalized values

Technique	TC (s)	CS (Ah)	CE (%)	ATI (°C)	Total rating
WOA	1.0000	0.6387	1.0000	1.0000	3.6387
MFO	0.4969	0.0000	0.9017	0.1084	1.507
MPSO	0.2873	0.0840	0.0698	0.1900	0.6311
GWO	0.3764	1.0000	0.4615	0.1500	1.9879
CC-CV	0.0000	0.8892	0.0000	0.0000	0.8892

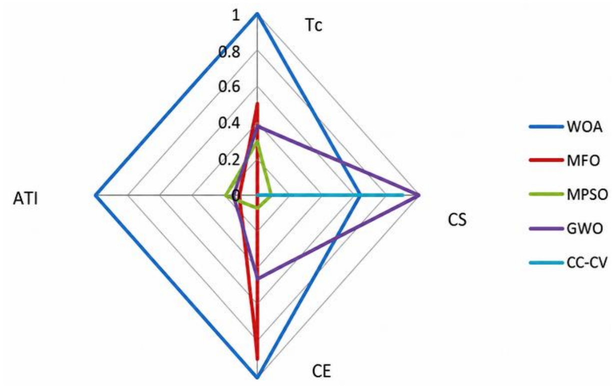

Figure 5. Radar chart for the normalized values

7. CONCLUSION

This work successfully developed and validated a thermal-aware lithium-ion battery charging strategy using a unified backpropagation neural network (BPNN) and nature-inspired optimization technique (NIOT) framework. By accurately predicting battery temperature rise and optimizing multi-stage charging current profiles, the proposed approach improves charging efficiency while maintaining thermal safety. Quantitative results confirm significant performance enhancement over the conventional CC–CV method. The whale optimization algorithm (WOA) achieved approximately a 10% reduction in charging time and nearly 50% reduction in average temperature rise, while maintaining high charge storage and efficiency. The close agreement between simulation and experimental results demonstrates the robustness and reliability of the BPNN-based thermal prediction model under practical operating conditions. Although MFO, MPSO, and GWO also improved charging performance compared to CC–CV, WOA consistently delivered the best balance between speed, thermal control, and stability.

From a power electronics and drives perspective, the optimized charging currents effectively limit thermal stress and current transients, ensuring safe DC–DC converter operation and reliable EV drive performance. Reduced temperature rise also contributes to improved battery lifespan and enhanced overall system reliability. Future research will focus on hardware-level validation, integration of the proposed charging strategy with motor drive operating cycles, and the development of hybrid machine learning–NIOT frameworks for real-time battery management in electric vehicles.

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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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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

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

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