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Combination whale optimization algorithm and fuzzy logic for optimal design battery charging $LiFePO_4$

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ABSTRACT

This research proposes an optimized charging strategy for lithium iron phosphate ($LiFePO_4$) batteries by integrating the whale optimization algorithm (WOA) with a fuzzy logic controller (FLC) for adaptive constant current–constant voltage charging. The method addresses the limitations of conventional CC-CV charging, which uses fixed parameters and has limited adaptability to changing operating conditions. WOA automatically optimizes the FLC scaling factors to improve control performance and system responsiveness. The WOA-fuzzy and WOA-PI models were trained using 226 samples of initial current and voltage data. The system was evaluated in PSIM by comparing fuzzy, PI, WOA-PI, and WOA-fuzzy controllers. Open-loop simulation produced an average voltage error of 1.29%, confirming the need for closed-loop control. Under SOC conditions ranging from 30% to 97%, all controllers maintained the charging voltage near 73 V and the charging current around 10 A. The average voltage errors were 0.6635% for PI, 0.6684% for fuzzy, 0.6618% for WOA-PI, and 0.6601% for WOA-fuzzy. Hardware testing confirmed these results, with average errors of 0.14% for WOA-fuzzy and 0.31% for WOA-PI. Overall, WOA-fuzzy provides stable charging, faster convergence, and improved charging performance.

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1. INTRODUCTION

The expanding deployment of electric vehicles and sustainable-energy systems has intensified the need for battery-charging solutions offering efficiency, dependable operation, and adequate safety. Lithium iron phosphate ($LiFePO_4$) batteries have become prominent choices for such applications due to their thermal stability, favorable safety performance, and extended cycle life relative to alternative lithium-ion chemistries [1], [2]. Even so, charging conditions significantly affect battery behavior, recharge duration, energy utilization, and lifetime.

For practical charging applications, the constant current-constant voltage (CC-CV) technique continues to be employed because it provides an effective compromise between charging rate and safety [3]-[5]. Conventional CC-CV systems, however, typically rely on predetermined charging values and unchanged controller configurations. Such fixed settings cannot respond to changes in battery state of charge (SOC), load behavior, or converter operating conditions. As a result, charging performance may exhibit delayed transient response, voltage errors, oscillatory behavior, or an unsatisfactory transition from the CC phase to the CV phase.

DC-DC converters, particularly buck converters, are essential in battery chargers because they regulate the output voltage and current according to battery requirements [6]-[9]. To improve converter control performance, intelligent control methods such as fuzzy logic controllers (FLCs) have been widely investigated.

FLCs are suitable for nonlinear systems and uncertain operating conditions because they do not require an exact mathematical model of the plant [10]-[13]. Several fuzzy-based charging approaches have also been reported for lithium battery applications [11], [14]. Despite these advantages, FLC performance strongly relies on properly designing membership functions, the rule base, and scaling factors, which are commonly established using expert judgment or iterative trial-and-error methods during controller development stages.

To reduce this dependence on manual tuning, metaheuristic optimization algorithms have been introduced to determine controller parameters automatically. Inspired by humpback whales' bubble-net feeding strategy, the whale optimization algorithm (WOA) has gained considerable interest owing to its straightforward architecture and effective global exploration capability in optimization problems [15]-[18]. Previous studies have shown that WOA can improve the tuning of control strategies in power-electronic and motor-drive applications [19]-[21]. However, the use of WOA to optimize fuzzy-control parameters for $LiFePO_4$ battery charging with a buck converter under the CC-CV charging profile is still limited and requires further investigation.

Based on this gap, this research proposes a hybrid WOA-fuzzy control strategy for an optimized $LiFePO_4$ battery-charging system. In the proposed method, WOA is used to optimize the scaling factors of the fuzzy logic controller so that the buck converter can regulate charging voltage and current more accurately during CC-CV operation. The proposed control scheme is evaluated using PSIM simulations and compared with fuzzy, PI, and WOA-PI control methods under several SOC conditions ranging from 30% to 97%.

This study provides three principal contributions: first, it formulates a fuzzy controller optimized by WOA for charging $LiFePO_4$ batteries; second, it incorporates the developed controller into a buck-converter-based CC-CV charging architecture; and third, it assesses the proposed approach regarding output-voltage precision, transient behavior, and operational stability under varying SOC conditions. These findings are anticipated to facilitate the design of increasingly adaptive and dependable battery-charging systems for electric-vehicle and energy-storage applications in both academic research and practical industrial deployment contexts.

2. PROPOSED METHOD

This section describes the research design, materials and data sources, implementation procedure, control algorithms, and validation strategy used to develop the proposed LiFePO4 battery charging system. The method is arranged to support reproducibility and to directly address the need for an adaptive CC-CV charging controller identified in the Introduction section.

2.1. Research design/approach

This research employed a simulation-based experimental design. A buck converter-based charger was modeled and controlled using four control approaches, namely fuzzy, PI, WOA-PI, and WOA-fuzzy. This design was selected because it allows the proposed controller to be tested under repeatable operating conditions, different state-of-charge (SOC) levels, and identical converter parameters before practical hardware implementation.

2.2. System architecture and materials

Figure 1 illustrates the complete configuration of the developed battery-charging system. The 220 VAC input is converted into DC voltage using an SMPS and supplied to the buck converter, which is the main power stage. The output voltage and current are measured using voltage and current sensors, then fed back to the STM32F4 microcontroller. A PWM duty ratio is produced by the controller to adjust converter output according to the $LiFePO_4$ battery's CC-CV charging specifications during operation.

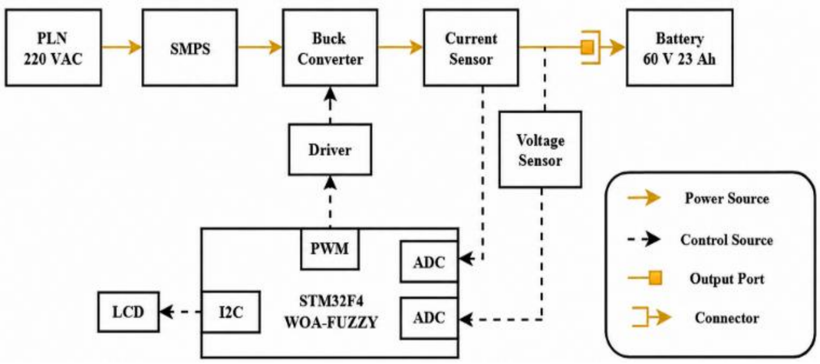


Figure 1. Block diagram controller charge

2.3. Buck converter modelling

The buck converter reduces the supplied DC voltage to the level needed for battery charging. PWM switching governs converter operation, while its duty ratio establishes the relationship among input voltage, output voltage, inductor current, and the resulting ripple across the capacitor. By applying Kirchhoff's voltage law (KVL), the converter design equations were derived, and the circuit topology used in this research is shown in Figure 2.

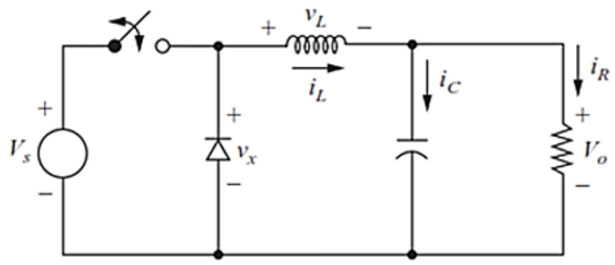


Figure 2. Buck converter circuit topology

The (1)-(5) were used to calculate the main converter parameters, including duty cycle, inductor value, capacitor value, and output characteristics. The design parameters were selected based on the required charging voltage and current, as summarized in Table 1.

$$D = \frac{V_{out}}{V_{in}} \tag{1}$$

$$\Delta i_L = 20\% \times i_{L(avg)} \tag{2}$$

$$L = \left(\frac{1}{f}\right) \times \left(\frac{V_{in} - V_{out}}{\Delta i_L}\right) \times D \tag{3}$$

$$r_{Vout} = \frac{\Delta V_{out}}{V_{out}} \tag{4}$$

$$C_{out} = \frac{\Delta i_L}{8 \times f \times \Delta V_{out}} \tag{5}$$

Where: Vs is the voltage source (V); Vo is the output voltage (V); D is the duty cycle (%); f is the frequency (Hz); R is the resistor (Ohm); ISW is the switch current (A); ΔVo is the output voltage ripple (V); L is inductor (Henry); and C is capacitor (microfarad).

Table 1. Buck converter parameters

Parameters	Symbol	Value	Unit
Voltage source	V_{in}	90	Volt
Output voltage	V_{out}	73	Volt
Output current	I_{out}	10	Ampere
Switching frequency	F_s	40	kHz
Inductor	L	172.338	µH
Capacitor	C_{out}	856	µF
Resistor	R	7.3	Ohm

2.4. $LiFePO_4$ battery model and data sources

The battery model represents a $LiFePO_4$ cell, commonly applied in electric vehicles and energy-storage systems because of its safety, thermal robustness, and extended cycle life. The simulation employed a battery model configured according to the parameters reported in Table 2: a 3.2 V nominal cell voltage, a 3.65 V maximum charging voltage, and a 9 A standard charging current, under which conventional SOC estimation relying solely on voltage measurements may provide reduced overall accuracy [22]. Simulation data are generated from the PSIM output response, including output voltage, current, SOC, steady-state value, and settling time.

Table 2. Specification of LiFePO4 battery

Characteristics	Rechargeable lithium ferro phosphate ($LiFePO_4$) prismatic battery
Model	IFP2265146-23 Ah
Dimension	146×65×22.5 mm
Nominal voltage (V)	3.2 V
Nominal capacity	23 Ah
Charging voltage (Max)	3.65 V
Standard charging current	9 A (0.5 C)
Charging termination control	Taper current: 0.05 C (≈0.9 A) at 3.65 V
Discharge cut-off voltage	2.0 V
Operating temperature (°C)	Charge: 0 °C to 60 °C Discharge: −30 °C to 70 °C Storage: −20 °C to 45 °C
Internal resistance (mΩ)	≤ 2 mΩ
Cycle life	> 1000 cycles
Weight	430 ± 5 g

2.5. WOA – FLC

The control method combines a fuzzy logic controller with the whale optimization algorithm. The FLC used can handle the nonlinearity of the converter and battery without requiring a mathematical model. However, FLC performance depends on the selection of membership functions, rule base, and scaling factors. Therefore, WOA is applied to optimize the FLC parameters and reduce the dependence on manual tuning.

2.5.1. WOA algorithm

Developed by Tomaszewska *et al.* [23], the whale optimization algorithm is a population-driven metaheuristic technique derived from the bubble-net foraging strategy of humpback whales, as depicted in Figure 3. Within this study, each whale denotes one possible combination of controller parameters. Each solution candidate is assessed according to the charger's voltage-tracking capability, aiming to reduce the deviation between the simulated converter output voltage and the specified reference level of 73 V.

The principal WOA settings considered here for this implementation comprise the population count, iteration limit, and stopping criterion. A population of 100 whales is adopted, as formulated in (7), whereas the maximum iteration count is fixed at 10 during the optimization process, as defined in (8). The convergence criterion is determined based on the minimum fitness value and the maximum iteration limit, as expressed in (9). These parameters are selected to balance convergence speed, optimization accuracy, computational effort, and controller performance.

The WOA optimization procedure comprises three mechanisms: exploration, encirclement, and spiral-based position updating. Exploration is performed when |A| > 1 by selecting a random whale position, while exploitation is performed when |A| < 1 by moving the search agent toward the best candidate solution. The coefficient vectors A and C control the balance between global search and local convergence, as expressed in (6) and (7).

$$\begin{cases} X_{t+1} = X_{rand} - A.|C.\ X_{rand} - X_t| & if\ |A| > 1 \\ X_{t+1} = X^* - A.\ |C.X^* - X_t| & if\ |A| < 1 \end{cases} \tag{6}$$

$$[\mathrm{X} = \{X_1, X_2, X_3, \dots, X_{N_p}\}] \tag{7}$$

$$a(t) = 2 - 2\frac{t}{t_{max}} \tag{8}$$

$$X_{best} = \arg \min_{X_i} J(X_i), t = T_{max} \tag{9}$$

The (6) and (7) define t as the present iteration, T_{max} as the permitted iteration limit, and r as a randomly generated value within [0, 1]. The spiral bubble-net position-update procedure is formulated in (10), with l representing a random variable selected from the interval [-1, 1]. These mechanisms allow the algorithm to search for suitable controller parameters and gradually converge toward the best solution.

$$X_{t+1} = X^* + |X^* - X_t|.e^{bl}.cos\ (2\pi l) \tag{10}$$

Where l is a random number in [−1,1].

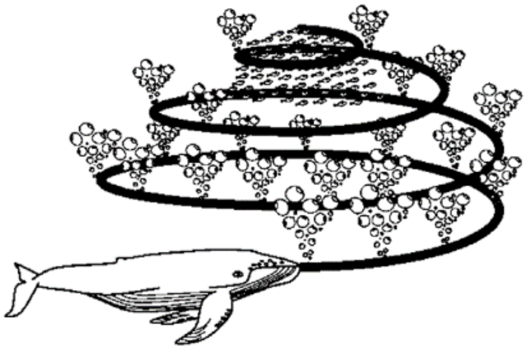


Figure 3. Spiral bubble-net behavior of humpback whales [23]

2.5.2. Meta-heuristic tuning via whale optimization algorithm (WOA)

Figure 4 shows the position update mechanism of the WOA, which toggles between two primary behaviors based on a probability factor p:

i) Shrinking encircling mechanism **($p < 0.5$)**

This phase models the prey entrapment. The position is updated based on the distance vector $D = |C \,.\, X^{*}(t) - X\,(t)|$, where X^{*} is the current best solution. The new position is given by $X\,(t+1) = X^{*}(t) - A \,.\, D$. The coefficient vectors A and C facilitate the balance between exploration and exploitation, which is $|A| \geq 1$ forces the search agent to move away from the reference whale (exploration), also $|A| < 1$ encourages convergence toward the best solution (exploitation).

ii) Spiral updating position ($p \geq 0.5$)

This phase mimics the helix-shaped movement of whales. It is mathematically modelled using a logarithmic spiral equation:

$$X(t+1) = D' \cdot e^{bl} \cdot \cos\,(2\pi l) + X^{*}(t) \tag{11}$$

In (11), the distance parameter quantifies the separation between each current candidate and the optimal solution, while b determines the spiral geometry, and l denotes a random value drawn within [-1, 1].

iii) Procedures steps

- Define the charging battery $LiFePO_4$ target, including the 73 V output voltage reference and 9 A charging current, and SOC test points: 30%, 60%, 90%, and 97%.
- Calculate the buck converter parameters using (1)-(5), then build the converter circuit in PSIM using the parameters in Table 1.
- Develop the LiFePO4 battery model using the specifications in Table 2.
- Method implement variations of the fuzzy, PI, WOA-PI, and WOA-Fuzzy controllers the same converter and battery conditions.
- Run closed-loop simulations for each SOC condition, then record output voltage, current response, tracking error, settling time, and the CC-CV transition.

iv) Validation

The method was validated using PSIM simulations using close loop tests. The research data includes output-voltage accuracy, percentage error, average error, settling time, overshoot, and stability during the CC-CV transition. The voltage error was calculated as error (%) = |Vout theory - Vout simulation| / Vout theory x 100%. The WOA-Fuzzy method was considered effective; it reduced voltage error and improved dynamic response compared with the other implement method (fuzzy, PI, and WOA-PI) [24]-[30].

2.5.3. Fuzzy design

For this research, the fuzzy logic controller receives two inputs, error (E) and change in error (ΔE), while producing the duty cycle as its single output. Within the converter, the duty-cycle command is crucial since it establishes the switching proportion and consequently influences output voltage. The membership-function definitions assigned to E, ΔE, and the duty-cycle output are presented in Figure 5.

As shown in Figure 5, the error and delta error variables are represented by seven linguistic terms: NB, NM, NS, Z, PS, PM, and PB. The duty cycle output is defined within the range of 0.72 to 0.90 and uses the same seven linguistic terms. Triangular membership functions are applied to provide smooth transitions between adjacent regions, enabling the fuzzy controller to determine the appropriate duty cycle based on the inference process.

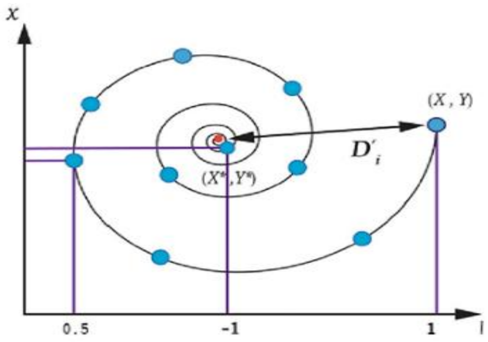
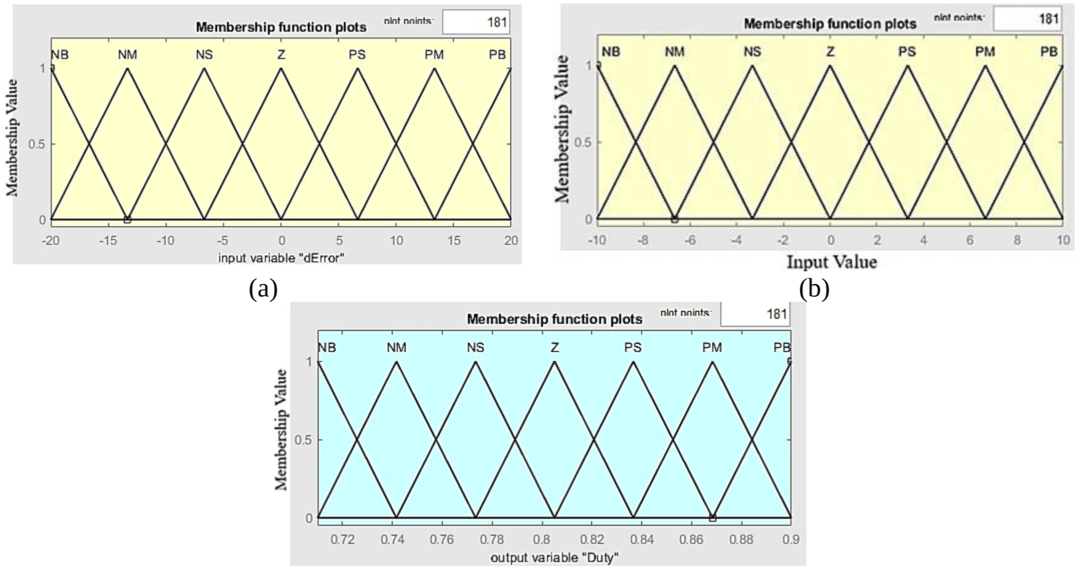


Figure 4. Position update in a spiral



(a) (b)

(c)

Figure 5. Membership function plots for the fuzzy logic controller inputs:
(a) error (E), (b) delta error (ΔE), and (c) duty

3. RESULTS AND DISCUSSION

Simulation results obtained from PSIM are used to test the performance of the WOA–fuzzy-based charging system under various operating conditions. This analyze emphasize the setpoint and accurate regulation of charging in constant current (CC) mode, constant voltage (CV) mode, and SOC test points of 30%, 60%, 90%, and 97%. The observed smooth transition between the CC and CV stages demonstrates stable system behavior with minimal overshoot. This uses PSIM with example data illustrating four methods: i) fuzzy, ii) PI, iii) WOA – PI, and WOA - fuzzy.

Figure 6 illustrates a closed-loop $LiFePO_4$ battery charging circuit employing four control strategies: fuzzy, PI, WOA-PI, and WOA-fuzzy. The converter regulates the output voltage and current delivered to the battery. It continuously monitors key parameters, including output current and voltage, and feeds these measurements back to the controllers to reliably maintain optimal $LiFePO_4$ battery charging conditions. Table 3 presents the open-loop buck converter without the four control methods, using a $LiFePO_4$ battery, which generates output voltages near the theoretical 73 V across SOC levels of 30%, 60%, 90%, and 97%, with an average error of 1.29%.

Figure 7 shows the experimental data of closed-loop battery charging with four control methods (PI, fuzzy, WOA-PI, and WOA-fuzzy). The results show that all controllers maintain the charging current setpoint of 10 A and the voltage setpoint of 73 V. The WOA-fuzzy-based method provides smaller error deviations due to its better iteration capability in terms of stability and overall control performance. Table 4 compares the closed-loop output voltage and current for all four controllers at each SOC level. WOA-Fuzzy gives the lowest average voltage error at 0.6601%. Table 5 summarizes the hardware test results obtained from the WOA-Fuzzy and WOA-PI controllers. The table lists the output voltage, output current, duty cycle, and error for each test point. Figure 8 compares the hardware output voltage and output current of the WOA-Fuzzy and WOA-PI controllers during the CC-CV charging process. Both methods follow the expected charging trend, but WOA-fuzzy gives the lower average error shown in Table 5.

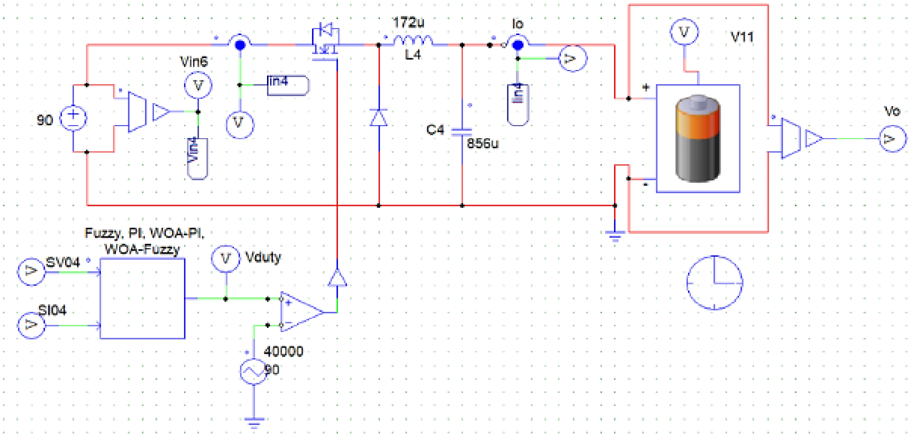


Figure 6. Closed-loop battery charging circuit with four control methods

Table 3. Buck converter open-loop simulation result

SOC (%)	Load	Vout (V)	Vout Theory (V)	Error (%)
30		71.49	73.00	2.07
60	Battery	71.88	73.00	1.53
90	LifePo4	72.35	73.00	0.89
97		73.5	73.00	0.68
		Average error (%)		1.29

Table 4. Performance comparison of control methods

SOC	Vsp	Vo PI	Io PI	Vo fuzzy	Io fuzzy	Vo WOA_PI	Io WOA_PI	Vo WOA_fuzzy	Io WOA_fuzzy
30	73	72.31	10.01	72.30	9.99	72.32	10.00	72.31	10.00
60	73	72.32	10.00	72.31	10.00	72.41	10.00	72.32	9.99
90	73	72.40	10.00	72.41	10.00	72.42	10.00	72.41	10.00
97	73	73.01	9.99	73.00	10.00	73.01	10.00	73.00	10.00
Average		72.51	-	72.51	-	72,54	-	72.51	-
Error Vsp vs Vo		0.6635%	-	0.6684%	-	0.6618%	-	0.6601%	-

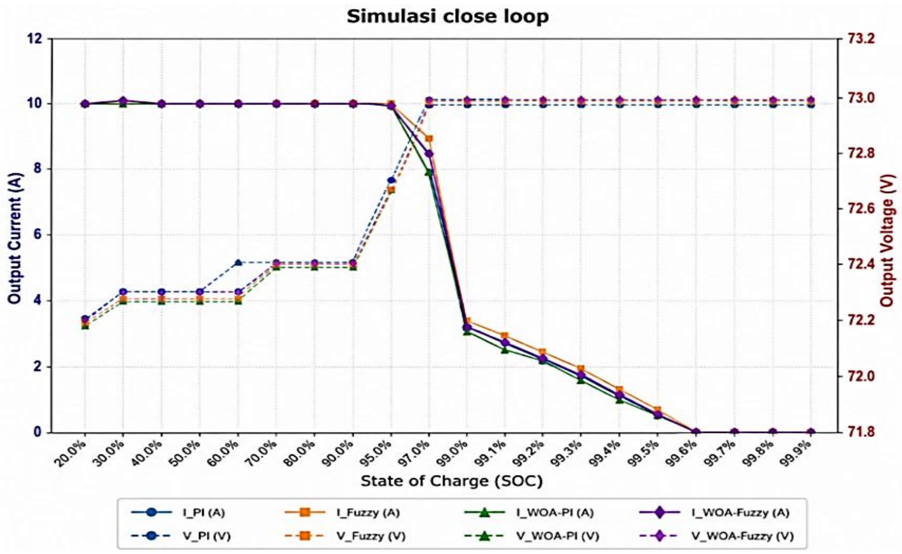


Figure 7. Battery charging in four methods

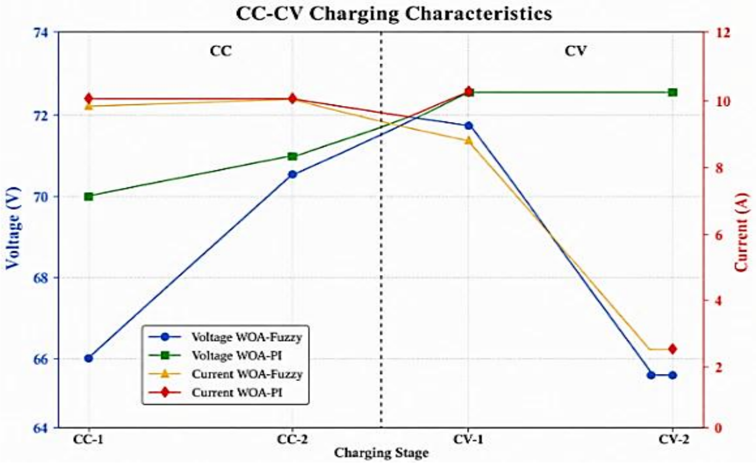


Figure 8. Output voltage and current comparison for WOA-fuzzy and WOA-PI controllers

Table 5. Hardware experiment data of WOA-fuzzy and WOA-PI controllers

Vo WOA-fuzzy	Io WOA-fuzzy	Duty WOA-fuzzy	Vo WOA-PI	Io WOA-PI	Duty WOA-PI	Error WOA-fuzzy	Error WOA-PI
65.8	9.8	79.6	70	10	80.7	0.04	0.04
70.5	10	79.8	70.9	10	80.9	0,3	0.77
72.5	9.3	83	72.5	8.8	83.2	0.18	0.27
72.5	1.7	81.6	72.5	2.7	82.6	0.04	0.14
		Average error %				0.14	0.31

4. CONCLUSION

This research develops a buck converter-based $LiFePO_4$ battery charging system using the whale optimization algorithm (WOA) and fuzzy logic controller (FLC) for adaptive CC–CV charging. Training of the WOA-fuzzy and WOA-PI controller models utilized 226 samples containing initial battery-current and battery-voltage measurement values. The open-loop simulation produced an average voltage error of 1.29%, indicating that closed-loop control is required to improve charging accuracy. The closed-loop simulation results show that all controllers can maintain the charging voltage near the 73 V setpoint and the charging current around 10 A. The average voltage errors are 0.6635% for PI, 0.6684% for fuzzy, 0.6618% for WOA-PI, and 0.6601% for WOA-fuzzy. These results indicate that WOA-fuzzy provides the lowest voltage error and better charging stability than the other methods. The hardware experimental results also support the simulation results, where WOA-fuzzy obtains an average error of 0.14%, while WOA-PI obtains 0.31%. Overall, the proposed WOA-fuzzy controller provides a stable voltage and current response during $LiFePO_4$ battery charging. Therefore, the WOA-fuzzy method is effective for improving the performance of the buck converter-based $LiFePO_4$ battery charging system. Future work can compare other control or optimization methods using the same circuit and charging configuration.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal adopts the Contributor Roles Taxonomy (CRediT) to acknowledge each author's contributions, minimize authorship conflicts, and promote 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.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this research.

DATA AVAILABILITY

The data supporting this study are presented in the article, including the PSIM simulation results and hardware test results.

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