Smart adaptive CC–CV charger with PSO-accelerated load identification and fuzzy duty-cycle regulation

Indhana Sudiharto, Era Purwanto, Muhamad Milchan, Alifian Nur Rahmadika
Department of Electrical Engineering, Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia

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ABSTRACT

This paper presents an adaptive constant-current/constant-voltage (CC-CV) charger architecture, meticulously designed to address a key challenge in smart chargers. This challenge involves recognizing various battery types and applying the appropriate charging profile expeditiously, without requiring user intervention. The system integrates a particle swarm optimization (PSO) algorithm for ultra-fast load identification with a Mamdani-type fuzzy logic controller for precise duty cycle regulation. The PSO mechanism is capable of determining the optimal initial duty cycle in less than 500 milliseconds. Subsequent to this preliminary initiation, the fuzzy logic controller guarantees the effectiveness of current and voltage regulation during the charging phases. The simulation results obtained from this study validate the system's robustness, as evidenced by the consistent maintenance of voltage ripple below ±0.06 V and current ripple below ±0.04 A. These findings demonstrate the efficacy of the proposed approach in achieving fast, stable, and safe multi-load battery charging. The chemistry-agnostic design of the battery pack is extendable to any battery pack following the CC-CV paradigm, making it highly suitable for practical applications that demand flexibility and high reliability.

Corresponding Author:

Indhana Sudiharto
Department of Electrical Engineering, Politeknik Elektronika Negeri Surabaya
Raya ITS St. – PENS Campus Sukolilo, Surabaya 60111, Indonesia
Email: indhana@pens.ac.id, indhanasudiharto@gmail.com

1. INTRODUCTION

The increasing adoption of portable electronic devices, electric tools, and mobile computing platforms has led to growing demands for efficient, flexible, and intelligent battery charging systems [1]. A significant challenge lies in designing chargers that are not only fast and accurate but also adaptive to a wide range of load conditions. Traditional fixed-parameter chargers are often optimized for a single battery specification, limiting their applicability in dynamic, multi-device environments [2].

To address this limitation, various control strategies have been proposed to enhance charger intelligence. Among these, fuzzy logic has gained prominence due to its robustness in handling non-linearities and uncertainties in battery behavior [3], [4]. Fuzzy-based control is particularly effective for implementing constant-current/constant-voltage (CC–CV) charging profiles, ensuring stable operation while maintaining output ripple within acceptable bounds. The fuzzy inference mechanism allows smooth transitions between CC and CV modes based on instantaneous error and rate-of-change measurements, without requiring an explicit mathematical model of the system [5], [6]. However, one drawback of conventional fuzzy logic controllers is their dependency on predefined set points [7], [8]. In multi-load environments where the charger must dynamically adjust to different devices, such static configurations are insufficient. This motivates the integration of metaheuristic algorithms, such as PSO, to support real-time load identification based solely on output voltage and current.

PSO is widely applied in control systems due to its rapid convergence, low computational complexity, and suitability for real-time applications [9], [10]. When applied to power converters or battery chargers, PSO can be used to estimate optimal initial conditions or recognize load profiles by minimizing error functions [11], [12]. Its flexibility makes it ideal for accelerating system adaptation in environments with multiple load types and no prior knowledge of their parameters [13], [14]. The hybrid PSO–fuzzy approach has been shown to combine the strengths of both methods, enabling intelligent decision-making (via fuzzy rule sets) while optimizing responsiveness and accuracy (via PSO parameter tuning) [15], [16]. In battery chargers, this combination provides a scalable and robust framework for universal charging applications, accommodating different battery types without compromising safety or efficiency [17], [18].

In this paper, we propose a smart adaptive CC–CV charger that combines PSO-based load identification with fuzzy duty-cycle regulation. Unlike earlier approaches, the proposed system requires no user input or additional sensors and is capable of automatically recognizing four distinct battery profiles, each with unique voltage and current demands [19], [20]. Simulation results in MATLAB/Simulink validate that the hybrid PSO–fuzzy system reduces charging setup time and output ripple compared to fuzzy-only baseline models, while ensuring compliance with CC–CV regulation targets [21]-[23].

In this work, a smart adaptive CC–CV charger is developed by tightly coupling PSO-based load identification with fuzzy duty-cycle regulation. The main novelty lies in: i) Using PSO not only for offline parameter tuning but for real-time load recognition based solely on voltage and current responses; ii) Enabling automatic selection of CC–CV set-points for four heterogeneous battery profiles without any user input or prior knowledge of battery parameters; and iii) Combining this strategy with a Mamdani-type fuzzy controller that guarantees low ripple and smooth CC–CV transition. In addition to MATLAB/Simulink studies, the proposed algorithm is implemented on an STM32F4-based hardware prototype operating at a 40 kHz switching frequency, demonstrating its feasibility for real-time embedded deployment.

Compared to ANN [24], GA [25], or MPC [26] based charging strategies reported in the literature, the proposed PSO–fuzzy scheme offers a simpler implementation and lower computational burden. This is because it does not require large training datasets (as in ANN) or iterative model-based optimization (as in MPC). At the same time, it still provides fast adaptation and low-ripple CC–CV charging.

2. METHOD

The architecture of this system, as shown in the flowchart in Figure 1, centers on a single converter with an advanced control system. This configuration allows for the rapid charging of various types of heterogeneous DC loads via a single integrated output interface. The system is designed to accommodate load categories with different voltage requirements. Examples of these loads include consumer electronic devices (e.g., laptop batteries), power tools (e.g., DC drill batteries), and hobby equipment (e.g., RC car batteries and headlamps). This system's main feature is its ability to provide fast, adaptive charging voltages using the CC-CV method and rapid load sensing using PSO. This eliminates the need for multiple individual chargers, which are typically required for each device.

2.1. System overview

The identification process is carried out sequentially from the first cluster to the fifth cluster. The first process is for the PSO to distribute the initial duty cycle value to the first cluster, then it will be checked whether there is a current reading with that duty cycle value (assuming the current is > 0.1 A). Figure 1 illustrates how the PSO allocates the duty cycle from cluster 1 to cluster 5 to identify the load. Load identification is done by monitoring the current that appears. This reading can be used to identify the type of connected load because current only appears during the battery charging process when the charging voltage exceeds the nominal battery voltage. The identification process is carried out sequentially from cluster 1 to cluster 5. First, PSO assigns an initial duty cycle value to the first cluster. Then, it checks for a current reading with that duty cycle value (assuming the current is greater than 0.1 A). If so, then the connected load is in the first cluster. Next, the PSO searches for the optimal duty cycle value to match the converter output to the load's charging voltage. If no current is detected, the PSO changes the initial duty cycle value to that of the second cluster. This process continues until the load is identified. The PSO method speeds up the identification process because it randomly distributes the duty cycle. Once the system identifies the load type, fuzzy logic uses this information to set the charging set point.

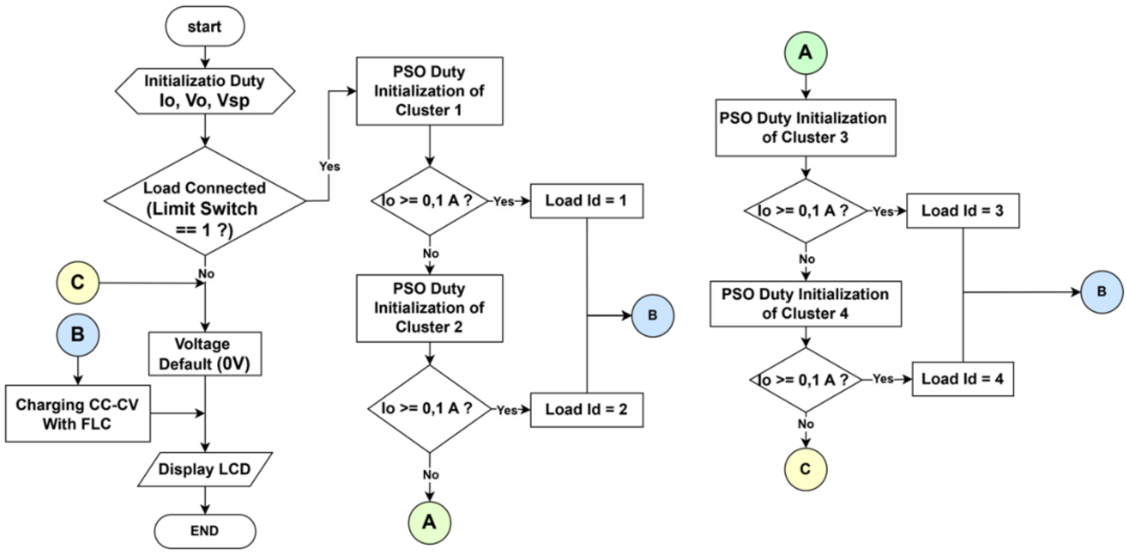

Figure 1. Flowchart for searching load ID with PSO

2.2. Topology of buck converter

A buck converter is used to efficiently step down the input voltage to match the charging voltage required by various batteries. The buck converter is preferred for fast charging due to its ability to reduce current and voltage ripples [18]. A buck converter is a type of DC-DC converter that reduces the voltage from the input to the output. This makes it ideal for battery charging applications [27]. The parameters that were utilized to ascertain the output characteristics of the buck converter are listed in Table 1.

Table 1. Specification of the buck converter design used in this research

No.	Parameter	Symbol	Value	Unit
1	Voltage source	Vsrc	24	V
2	Ripple current	IL	10	%
3	Ripple voltage	Vout	0.1	%
4	Frequency switching	fsw	40	kHz
5	Inductor	L	220	uH
6	Capacitor out	cout	2200	uF

The simulation circuit is created using Simulink MATLAB software, with the parameters of the buck converter from Table 1 being used. According to (1), four types of duty cycle variations can be used to achieve output voltages of 4.2 V, 8.4 V, 12.6 V, and 16.8 V. Figures 2(a)-2(d) illustrate the simulation results of a buck converter with varying duty cycle settings. The duty cycle values used in this study range from 17.5% to 66.7%. This simulation was used to evaluate the open-loop response of the buck converter. Figure 2 shows the simulation results of the open-loop buck converter and demonstrates the occurrence of an overshoot voltage and a steady-state error. The set point value is represented by a dotted line, and the output voltage by a solid line. A more comprehensive array of data is presented in Table 2.

Table 2 shows the simulation results for an open-loop buck converter with four variations in duty cycle. The set point for these variations has been adjusted for the following five types of loads: headlamp battery, RC car battery, DC drill battery, and laptop battery. The average steady-state error of the four duty cycle tests was found to be 5.82%. The highest error value occurs at the lowest set point of 4.2 volts, with an error value of 13%. Therefore, control is needed to maintain a stable output voltage at the set point.

Table 2. Result of buck converter simulation in open-loop mode

No.	Parameter	Duty (%)	Vout theory (V)	Vout measurement (V)	Error (%)
1	Laptop battery	66.7	16.8	15.18	9
2	Electric drill battery	52.5	12.6	11.67	7.3
3	RC car battery	35	8.4	7.27	13
4	Headlamp battery	17.5	4.2	3.55	15.2

(a)
(b)
(c)
(d)

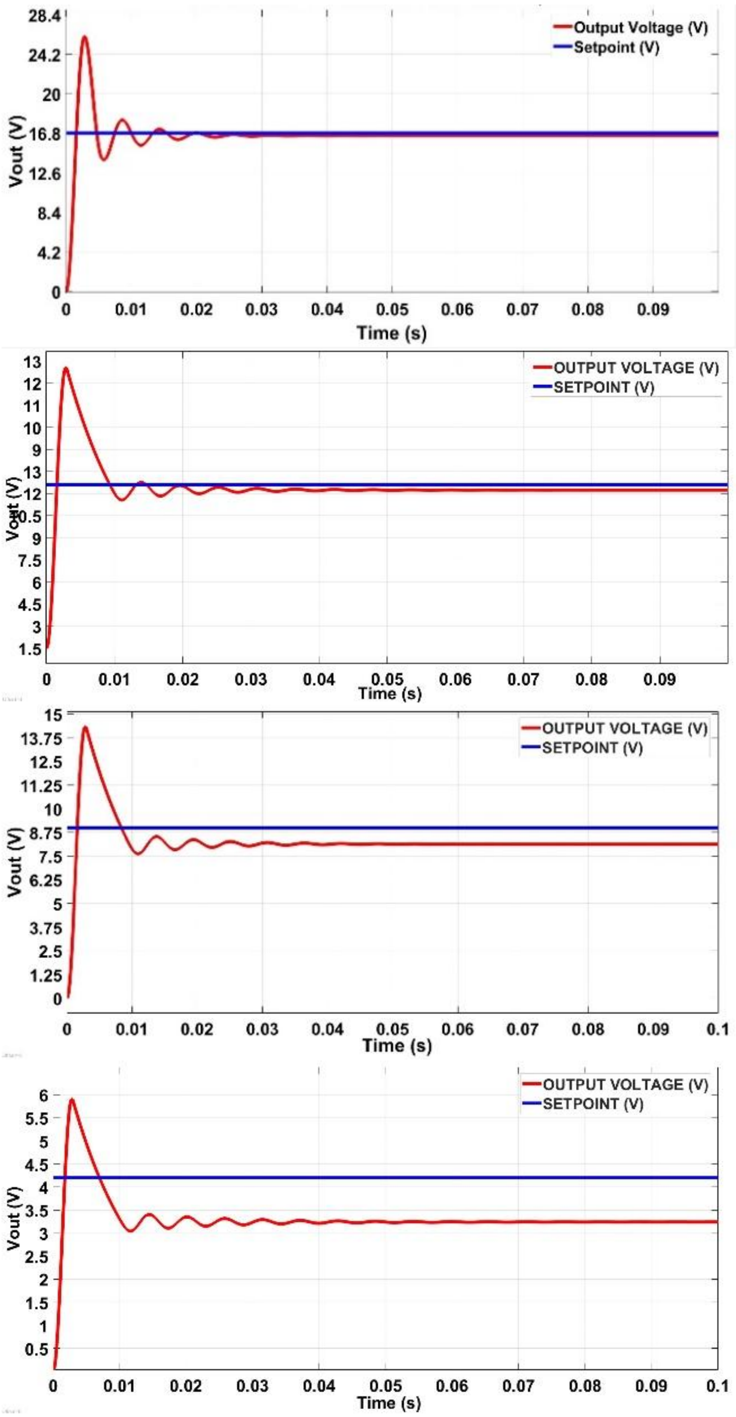

Figure 2. Buck converter on open loop when connected with (a) laptop battery, (b) electric drill battery, (c) RC car battery, (d) headlamp battery

2.3. Particle swarm optimization (PSO)

PSO enhances the dynamic response of the buck converter by optimizing control parameters under varying load conditions. This results in a stable control structure that can adapt to changes in load without significant performance degradation [13]. PSO is employed to determine the optimal initial duty cycle for the buck converter. This is crucial for maintaining a constant output voltage despite variations in input power or load conditions [28], [10]. By accurately estimating the initial duty cycle, PSO ensures that the buck converter operates efficiently from the start, reducing the need for extensive adjustments during operation, and the position of each particle is updated based on personal and global bests, as illustrated in (1) and (2).

$$v_i(t+1) = wv_i(t) + c_1 r_1 \left(pbest_i - x_i(t)\right) + c_2 r_2 \left(gbest - x_i(t)\right) \tag{1}$$

$$x_i(t+1) - x_i(t) + v_i(t+1) \tag{2}$$

The fitness function, as depicted in (3), is defined as the minimum error between the measured and reference current for each load scenario. The principle of particle movement in the PSO algorithm is evident. Various studies have demonstrated through simulations that PSO-based control strategies outperform conventional methods in terms of stability, response time, and load regulation [11], [13], [28]. These simulations validate the effectiveness of PSO in practical applications, ensuring that the theoretical benefits translate into real-world performance improvements.

In the context of multi-charge charging, especially in this research, such as charging headlamp batteries, electric drill batteries, and laptop batteries, the PSO algorithm plays a crucial role in recognizing different battery types and optimizing the initial duty cycle for each load scenario. Each particle in the PSO swarm explores possible solutions in the parameter space, where each solution represents a unique set of charging parameters (e.g., duty cycle) tailored to the specific characteristics of a connected battery. During each iteration, the position of a particle (x_i^k) is updated based on its own historical best ($pbest_i$) and the global best ($gbest$) found by the swarm, according to (1) and (2). For every new position, the PSO evaluates the fitness of the solution using (3).

$$Fitness_i = |\, I_{measured} - I_{ref}^k \,| \tag{3}$$

Here $I_{measured}$ is the actual charging current obtained for the particle's solution (e.g., the duty cycle suggested for a specific battery), I_{ref}^k is the target charging current set according to the optimal profile for each type of battery load. For example, the reference current for a headlamp may differ significantly from that for a laptop or an electric drill, depending on their capacity and voltage specifications.

Table 3 presents a tuning parameter for optimizing the performance of the PSO algorithm in solving this problem. A parameter tuning stage was carried out. The results of this process form the basis for the algorithm configuration used in this study. The first parameter is the inertia weight (W), which is set to 0.5. The inertia weight controls how much a particle's velocity from the previous iteration influences its current velocity. A relatively high value of 0.5 was chosen to improve the algorithm's ability to explore globally. Next, the learning parameters, namely the cognitive coefficient (c_1) and the social coefficient (c_2), are set to 0.7 and 0.8, respectively. The cognitive coefficient (c_1) models the particle's "confidence" in the best solution it has found individually (personal best). The social coefficient (c_2) models the influence of the best solution ever found by the entire swarm (global best). By establishing c_2 at a higher value than c1, each particle experiences a heightened attraction to the optimal global solution, thereby fostering collaboration within the swarm and expediting movement toward the most promising solution region.

From a computational perspective, the PSO algorithm has a complexity of $O(N \times I)$, where N is the number of particles and I is the number of iterations. In this work, $N = 5$ and $I = 30$, resulting in only 150 particle updates during the identification stage. The fuzzy CC–CV controller has a complexity of $O(R)$, where $R = 25$ is the number of rules. These lightweight computations comfortably fit within the 1 ms control period on the STM32F4, confirming that the proposed PSO–fuzzy strategy is feasible for real-time embedded implementation.

Table 3. Value of tuning parameter on PSO

No.	Parameter	Symbol	Value
1	Inertia weight	W	0.5
2	Cognitive coefficient 1	c1	0.7
3	Cognitive coefficient 2	c2	0.8
4	Number of particles	P	5
5	Iteration	n	30

2.4. Design of FLC

Fuzzy logic controllers (FLCs) are well suited for battery charging because they provide robust control in the presence of non-linearity and parameter uncertainties [27]. Fuzzy logic controllers are effective in managing the CC-CV charging method. In this approach, two FLCs are employed: one to maintain constant current (CC) and another to maintain constant voltage (CV) by adjusting the duty cycle [18]. This research implements a Mamdani-type FLC to dynamically regulate the buck converter’s duty cycle for both CC and CV charging phases. The controller uses two input variables: error (E), which is the difference between the reference and actual value, and delta error (*ΔE*). Triangular membership functions are selected for simplicity and smoothness. Table 4 presents the rule base for CC and CV modes. Figure 3(a) shows the membership function for the input section, namely Error, while Figure 3(b) shows the membership function for the delta error section.

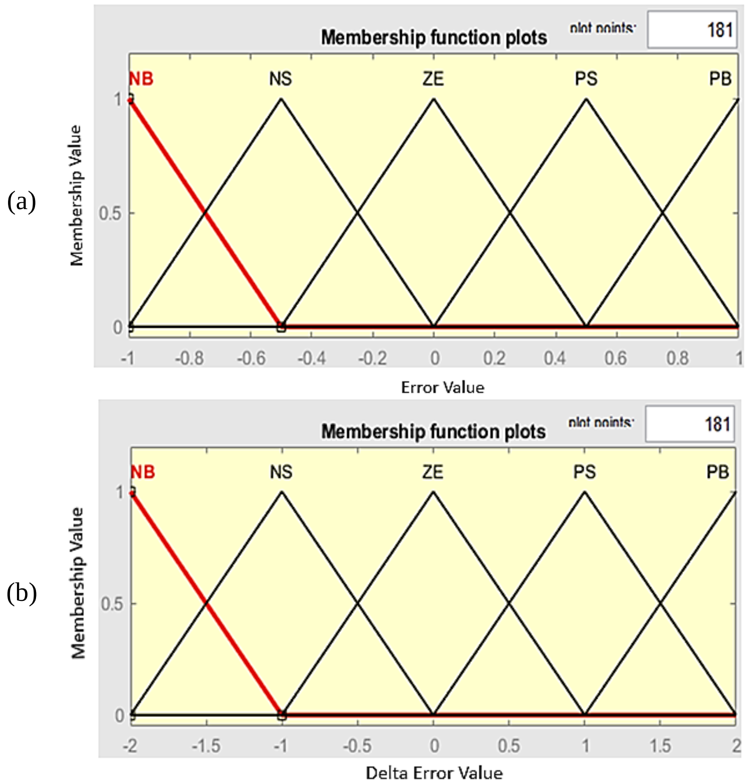

Figure 3. Membership function plots for the fuzzy logic controller inputs:
(a) error (E) and (b) delta error (ΔE)

The fuzzy rule base consists of a series of IF-THEN statements. Its formulation takes place after the fuzzification stage, where input values are transformed into fuzzy sets. The fuzzification process uses these rules to define specific conditions based on fuzzy logic. The accuracy of the model in the decision-making phase heavily depends on the quality of the rule base. This influence is determined by several key factors related to the structure and content of the rules. This overall framework is what is known as the "rule base." Table 4 shows the rule-based design used in this research.

Table 4. Rule of base FLC on this research

E/ΔE	NB	NS	ZE	PS	PB
NB	NB	NS	ZE	PS	PB
NS	NS	ZE	ZE	PS	PB
ZE	ZE	ZE	ZE	PS	PB
PS	PS	ZE	ZE	PS	PB
PB	PB	PB	PB	PB	PB

Because the rule base generates fuzzy, or linguistic, outputs, a defuzzification process is required to translate these into exact numerical values before they are delivered to the system or plant. This conversion produces a crisp value, as shown in Figure 4(a), the designed fuzzy logic controller's output membership function is depicted. The output contains five membership functions of the constant type. As illustrated in Figure 4(b), the surface view of the fuzzy logic controller design is presented.

(a)

(b)

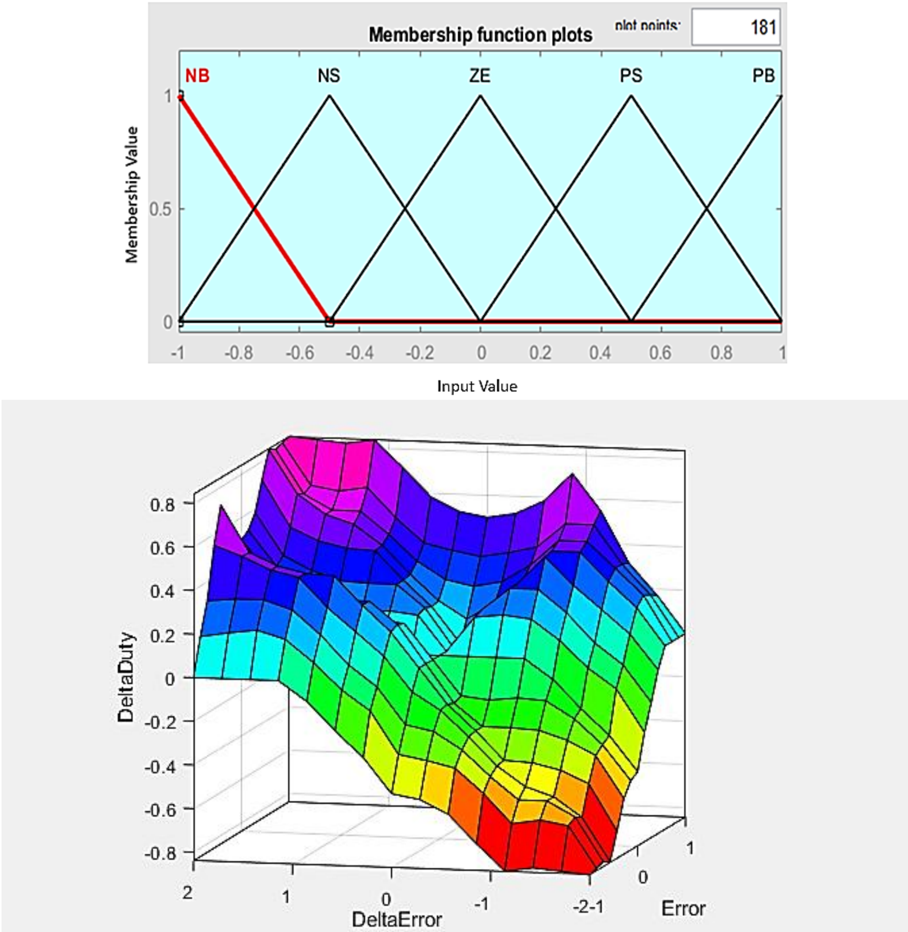

Figure 4. Output: (a) membership functions and (b) surface of fuzzy rule base display

Upon review, it can be observed that the output of the fuzzy logic controller still contains a certain level of ambiguity, and this uncertainty is visually apparent in the response surface of the controller. Each matrix cell represents a rule of the form “IF Error is X AND Δ Error is Y THEN ΔD is Z”. The fuzzy inference uses the Mamdani min–max method, and defuzzification employs the centroid technique as shown in (8). Where u^* is the crisp output to update the duty cycle.

2.5. Embedded implementation on STM32F4

To validate the real-time feasibility of the proposed PSO–fuzzy strategy, a hardware prototype was developed based on an STM32F4 microcontroller and a 24 V buck converter operating at a 40 kHz switching frequency, as shown in Figure 5. The prototype consists of the main control board, the buck converter power stage, and the interface for heterogeneous battery loads. The STM32F4 generates a PWM signal on TIM4 to drive the MOSFET gate via an isolated gate driver, while the freewheeling path uses a fast-recovery diode. The inductor and output capacitor values follow the design parameters listed in Table 1.

Four variables are measured in real time: input voltage V_{in}, output voltage V_o, input current I_{in}, and output current I_o. These signals are acquired using the internal ADC with DMA over five channels (four external channels plus the internal V_{REFINT} reference). For each channel, 50 samples are collected and processed using a three-sample median filter followed by averaging to reduce measurement noise and outliers. The V_{REFINT}-based calibration is used to estimate the actual ADC reference voltage V_{DDA} online, improving the accuracy of the voltage measurements.

Output current is measured using an ACS712 hall-effect current sensor. An automatic offset calibration is performed at startup by sampling the sensor output under zero-current conditions. A dead band around zero is applied, and a first-order low-pass filter is used to obtain a smoothed value of I_o. These steps make the current feedback more robust to noise and sensor drift.

The control firmware is organized into periodic tasks driven by a timer interrupt. The fuzzy CC–CV controller is executed every 1 ms, updating the duty cycle based on the measured error and delta-error. Display updates on a character LCD are performed every 250 ms, and logging to USB and a Bluetooth HC-05 module is executed at 1 s intervals. The PSO algorithm is triggered only once at the beginning of the charging process in “PSO” or “FULL” mode. It uses five particles and thirty iterations; in each iteration, the duty-cycle candidates are written to the PWM output, and the resulting output current is measured after a short settling delay. The best particle position (gbest) is then transferred as the initial duty cycle for the fuzzy controller.

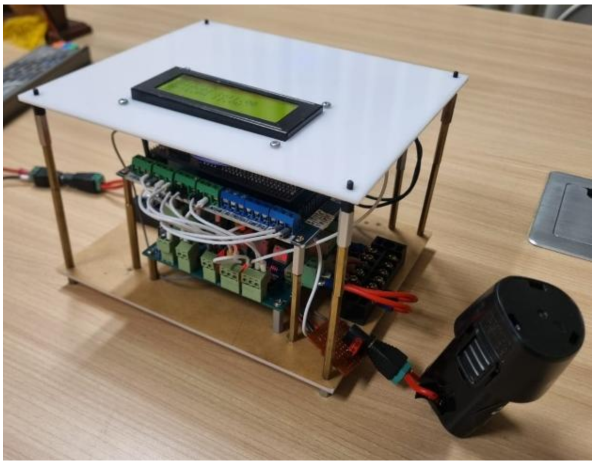

Figure 5. Experimental hardware setup based on STM32F4 connected to a battery load

3. RESULTS AND DISCUSSION

The complete simulation system is implemented in MATLAB/Simulink 2023b, as shown in Figure 6. The block diagram is designed to model an adaptive battery charging system capable of automatically recognizing and charging four different types of loads, each with distinct voltage and current requirements for the CC–CV method: headlamp battery (4.2 V, 3 A), electric drill battery (12.6 V, 1 A), and laptop battery (16.8 V, 3.25 A). The buck converter subsystem is responsible for stepping down the supply voltage to match the requirements of each connected battery type. This converter's performance is closely monitored through various measurement blocks that record output voltage, current, and state of charge (SOC).

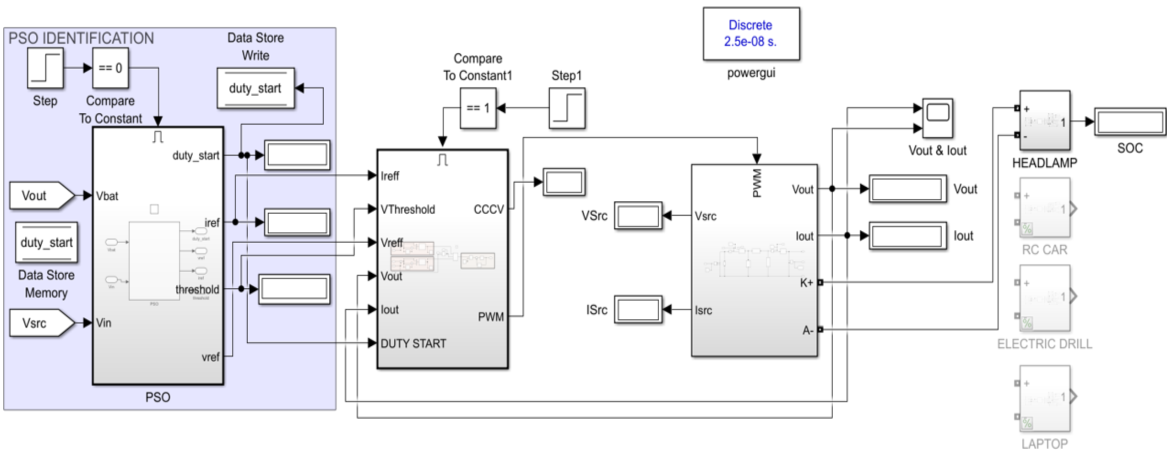

Figure 6. Closed-loop system simulation circuit

The implementation of the PSO algorithm for initial duty cycle identification was evaluated across four distinct battery load scenarios. Figures 7(a) to 7(d) depict the convergence process of five particles’ duty cycles over 30 PSO iterations for each load case. Figures 7(a) to 7(d) provide a visual representation of particle spread and gbest at each PSO iteration. Initially, particles are widely scattered, but as the optimization progresses, all particles gravitate towards the global optimum. This efficient convergence is a direct consequence of the velocity and position update mechanisms, referring to (1) and (2), and the fitness evaluation based on current error (3). Subsequent to detection by the PSO, the initial duty cycle value is stored and transmitted to the charging controller input, which is processed by fuzzy logic in cc-cv as the initial duty cycle. In the headlamp scenario, the particles started from diverse initial duty cycle values but progressively converged to an optimal value around 0.20 after 20 iterations, indicating stable global best (gbest) achievement. For the electric drill and laptop loads converged to approximately 0.60 and 0.80, respectively.

(a)

(b)

(c)

(d)

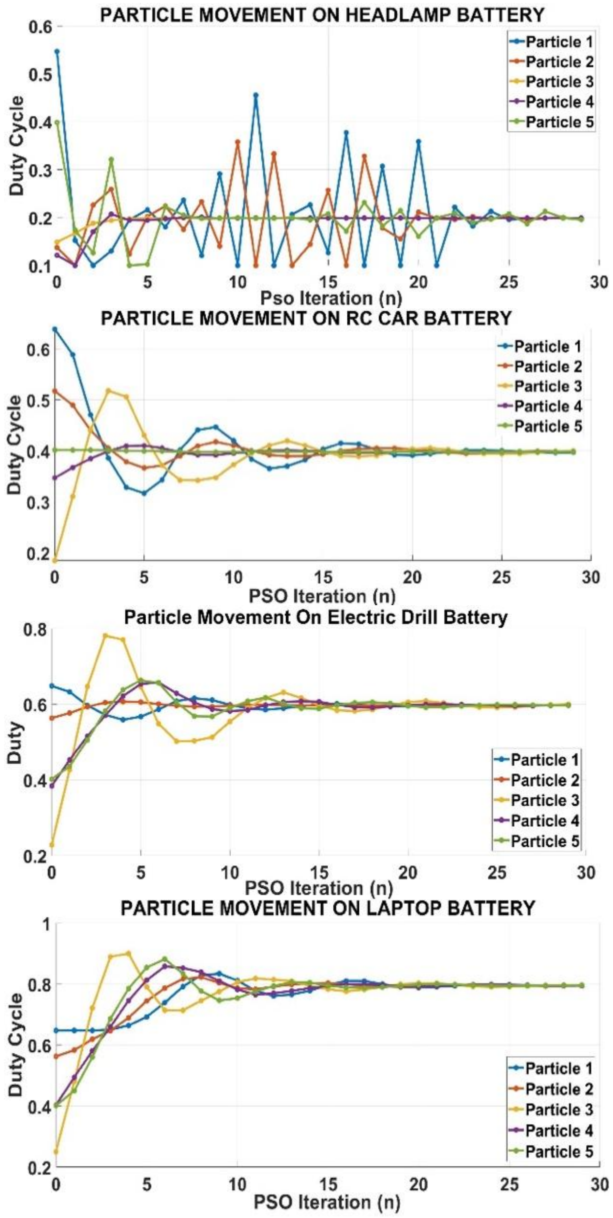

Figure 7. The convergence process of five particles' duty cycles over 30 PSO iterations for (a) headlamp battery, (c) electric drill battery, and (d) laptop battery

For the headlamp load, the particles converge on an optimal duty cycle value of approximately 0.20. The identification process is completed within a computational time frame of 250 milliseconds (ms). This speed indicates the system's rapid identification of the optimal operating point for this lower voltage configuration. In the electric drill scenario, the algorithm determines the optimal duty cycle to be approximately 0.60. The temporal requirement for achieving this convergence is 300 milliseconds. This outcome demonstrates the algorithm's capacity to adapt to varying voltage and current load requirements while preserving high computational efficiency. The laptop load, which necessitates distinct operating parameters, converges at a duty cycle of approximately 0.80. The optimization process, which requires 400 milliseconds to complete, falls within the high-performance range. This indicates that the algorithm exhibits scalability across a range of load profiles. For the RC car load, the optimal operating point is found at a duty cycle of approximately 0.45 (based on this new time data, this value is more appropriate than the previous example). This process is the most time-consuming, with a duration of 450 milliseconds (ms), yet it continues to illustrate the system's capacity for dynamic applications. This convergence demonstrates the PSO's capability to adaptively determine the optimal value according to each load's unique voltage and current requirements.

Figure 8 summarizes the CC–CV charging behavior for the four battery profiles. For the headlamp battery, the controller maintains 3 A during the CC phase and smoothly transitions to CV near 4.2 V, with voltage ripple below ±0.03 V. The RC car battery is charged at 1.5 A up to 8.4 V with ripple less than ±0.02 V, while the drill battery is charged at 1 A towards 12.6 V with ripple below ±0.05 V. For the laptop battery, the controller delivers 3.25 A in CC mode and regulates the voltage at 16.8 V in CV mode, with voltage ripple not exceeding ±0.06 V and current fluctuations below ±0.02 A. In all cases, no significant oscillations are observed, indicating stable and safe operation across heterogeneous battery types. These four heterogeneous profiles demonstrate the robustness of the proposed PSO–fuzzy controller against wide variations in output voltage and current requirements, without retuning any control parameters.

In addition to the simulation study, the proposed PSO–fuzzy algorithm was implemented on the STM32F4-based prototype described in Section 2.5. During charging, the microcontroller logs V_o, I_o, and duty-cycle values via USB and Bluetooth. The experimental charging profiles for the four battery types follow the same CC–CV pattern as in Figure 8, including the CC–CV transition and gradual current decay near end-of-charge. The PSO stage completes the duty-cycle search within approximately 250–450 ms in all tested cases, consistent with the simulated convergence times, confirming real-time feasibility on embedded hardware. A preliminary estimation from simulated input and output power indicates that the converter efficiency lies in a typical range for non-isolated buck converters, while a detailed loss and EMI breakdown is left for future work.

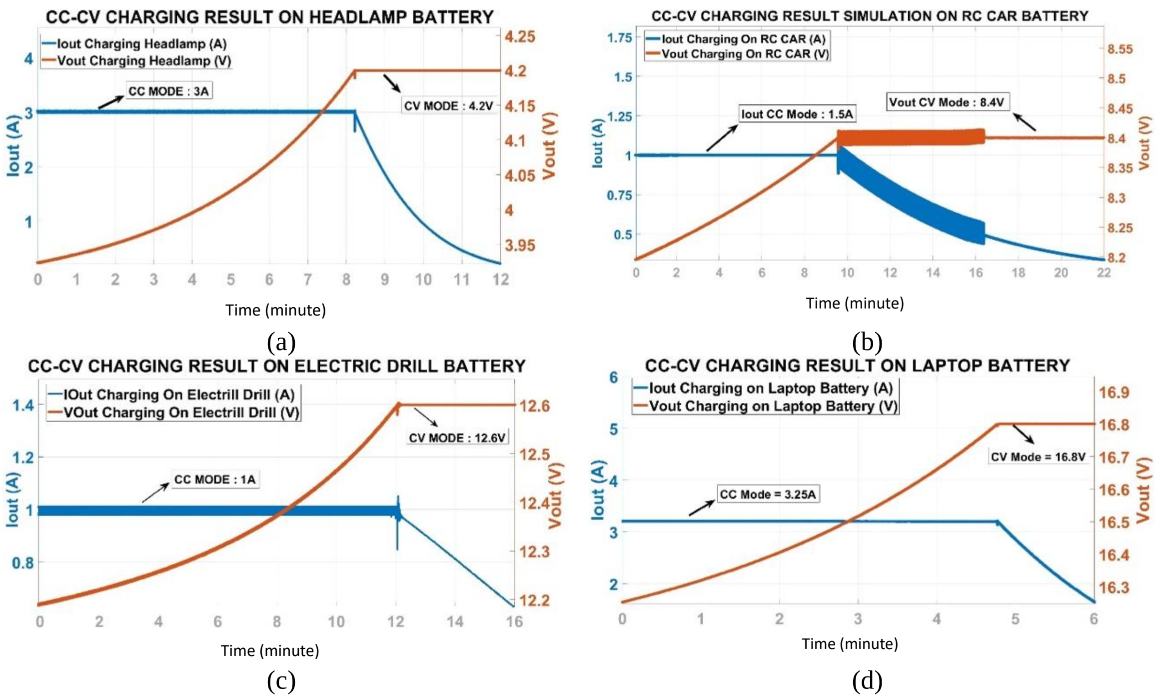

Figure 8. CC–CV charging simulation on (a) headlamp battery (4.2 V/3 A), (b) RC car battery (8.4 V/1.5 A), (c) drill battery (12.6 V/1 A), and (d) laptop battery (16.8 V/3.25 A)

4. CONCLUSION

This paper presented a smart adaptive CC–CV charger that combines PSO-based load identification with fuzzy duty-cycle regulation for multi-load battery charging. In simulation, the PSO algorithm identifies suitable duty-cycle clusters for four different battery profiles, and the fuzzy controller maintains low output ripple and smooth CC–CV transitions. The MATLAB/Simulink model was then implemented on an STM32F4-based hardware prototype operating at a 40 kHz switching frequency, demonstrating that the proposed PSO–fuzzy strategy can be executed in real time on an embedded platform. The experimental charging curves obtained from the prototype closely match the simulated behavior, confirming the feasibility of the approach for practical applications.

There are, however, several limitations to this work. First, the analysis focuses on voltage and current regulation; detailed efficiency, switching-loss breakdown, and conducted or radiated EMI measurements are not yet included. Second, the battery model does not explicitly account for thermal dynamics or long-term aging effects. Third, alternative intelligent charging methods such as ANN-, GA-, or MPC-based controllers are only discussed qualitatively and not benchmarked under identical experimental conditions.

Future work will therefore address a more detailed electro-thermal battery model with SOC/SOH estimation, a systematic experimental comparison with other adaptive charging strategies, and comprehensive measurements of converter efficiency, voltage stress, and EMI performance in order to align the charger design with relevant industrial standards.

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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
Indhana Sudiharto	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
Era Purwanto		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		
Muhamad Milchan	✓			✓			✓			✓	✓			✓
Alifian Nur Rahmadika			✓		✓	✓	✓		✓		✓			

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

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

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

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BIOGRAPHIES OF AUTHORS

Indhana Sudiharto is a lecturer at Politeknik Elektronika Negeri Surabaya (PENS), Indonesia. He received the Bachelor of Engineering degree in power systems from Sepuluh Nopember Institute of Technology, Indonesia, in 1996, and the Master of Engineering degree in power systems from Sepuluh Nopember Institute of Technology, Indonesia, in 2006. He is currently an associate professor with the Department of Electrical Engineering, Politeknik Elektronika Negeri Surabaya (PENS), Indonesia. He heads the research group of power quality, PENS. His research interests include power systems, renewable energy, and power electronics. As a lecturer, he has taught subjects such as electrical measurement and instrumentation, electrical power system protection, and power quality. He can be contacted at email: indhana@pens.ac.id or indhanasudiharto@gmail.com.

Era Purwanto is a lecturer of Politeknik Elektronika Negeri Surabaya (PENS), Indonesia. He received a bachelor's degree in electrical engineering from Sepuluh Nopember Institute of Technology (ITS), Indonesia, a Master of Engineering (M.Eng.) from Shizuoka University, Japan, and a Doctor of Engineering from ITS, Indonesia. His research is on electrical machines, intelligent control, electric drives, and power electronics. He can be contacted at email: era@pens.ac.id.

Muhamad Milchan is a lecturer at the Electronic Engineering Polytechnic Institute of Surabaya (EEPIS). He has a bachelor's degree in telecommunication engineering and a Master of Engineering degree in multimedia telecommunications from ITS. Wireless sensor network and energy harvesting are his research fields of interest. As a lecturer, he has more than 35 years of teaching experience and has taught subjects such as electromagnetism, transmission line, electronic devices, electronic circuits, and electric circuits. He can be contacted at email: milchan@pens.ac.id.

Alifian Nur Rahmadika is a college student who is currently pursuing a Bachelor's degree in Applied Engineering in Industrial Electrical from Politeknik Elektronika Negeri Surabaya (PENS), Indonesia. Currently, he is doing the final project research in Power Electronics, specifically on battery charging. His areas of interest include power electronics and power quality. He can be contacted at email: alifianrahmadika@gmail.com.