Design of an EBNN-PID based adaptive charge controller for variable DC charging applications

Mochammad Machmud Rifadil, Putu Agus Mahadi Putra, Amalia Muklis
Department of Electrical Engineering, Bachelor of Applied Industrial Electrical Engineering,
Politeknik Elektronika Negeri Surabaya (PENS), Surabaya, Indonesia

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ABSTRACT

This paper presents an adaptive charging system for lithium-ion batteries using an Elman backpropagation neural network (EBNN) integrated with a PID controller and a ZETA converter. The system dynamically identifies the battery type and adjusts the charging voltage accordingly. The EBNN model was trained using 1441 samples of initial current and voltage data, achieving a mean squared error (MSE) of 7.64×10^{-14}. A ZETA converter enables both step-up and step-down voltage regulation, while the PID controller ensures stability toward the predicted setpoint. Simulations in Simulink were conducted on four lithium-ion battery types with setpoints of 4.4 V, 8.8 V, 14.4 V, and 21.6 V. The results show that the PID-regulated output voltage closely matches the target with a maximum deviation of ±0.05 V and an average voltage error of 0.1725%. The system achieves fast response times between 0.015 and 0.033 seconds. Extended testing through 24 randomized trials confirmed consistent identification and regulation across varying battery types. These findings validate the proposed EBNN-PID-based charging system as a highly accurate, flexible, and efficient solution for managing lithium-ion battery charging in real-time embedded applications.

Corresponding Author:

Mochammad Machmud Rifadil
Department of Electrical Engineering, Bachelor of Applied Industrial Electrical Engineering
Politeknik Elektronika Negeri Surabaya (PENS)
Raya ITS St.-PENS Campus Sukolilo, Surabaya 60111, Indonesia
Email: mmrifadil@gmail.com, mmrifadil@pens.ac.id

NOMENCLATURE

V_s	:	Input voltage (V)	I_{SW}	:	Current switch (A)
V_{L1}	:	Voltage across inductor 1 (V)	ΔVo	:	Output voltage ripple (V)
V_{C2}	:	Voltage across capacitor 2 (V)	L_1	:	Inductor 1 (Henry)
V_o	:	Output voltage (V)	C_1	:	Capacitor 1 (Farad)
D	:	Duty cycle (%)	C_{in}	:	Capacitor input (Farad)
f	:	Frequency (Hz)	C_c	:	Capacitor coupling (Farad)
R	:	Resistor (Ohm)			

1. INTRODUCTION

Batteries have become indispensable energy storage devices in modern electronic systems. The continuous advancement of rechargeable battery technology aligns closely with the growth of electronic and telecommunication applications, such as mobile phones, tablets, and electric vehicles [1], [2]. Among the various battery types, lithium-ion batteries are particularly favored due to their high energy density and long cycle life [3]. Despite these advancements, the effectiveness and longevity of rechargeable batteries heavily depend on the charging process. Each battery has different specifications, including voltage and capacity, thus requiring a charging system that can adapt to these variations [4]. Most commercial battery chargers are designed for specific applications with fixed voltage and current outputs, making them less suitable for charging batteries with diverse requirements [5]. Moreover, improper charging, such as overcharging or incorrect voltage levels, can degrade battery performance and shorten its lifespan.

To address these limitations, an adaptive charging system is necessary. Unlike conventional fixed-parameter chargers, adaptive systems can dynamically identify the battery type and adjust the charging parameters accordingly. Several studies have proposed adaptive control using Artificial Neural Networks (ANN), which have shown promising results [6]. However, the conventional ANN structure still encounters limitations in dynamic environments. Elman backpropagation neural network (EBNN) has been recognized for its superior ability in handling temporal data and dynamic system behavior, which is highly relevant in adaptive battery charging scenarios [7].

This research introduces an EBNN-PID-based adaptive charge controller, aiming to improve the adaptability and precision of the charging process. The PID controller is selected due to its proven robustness in maintaining system stability and regulating output voltage at the desired set point [8]. While prior studies have commonly utilized a buck converter, this study employs a ZETA converter, which offers advantages in efficiency and the ability to produce an output voltage that is either higher or lower than the input, depending on the load condition [9].

The main contributions of this paper are threefold: i) Development of an adaptive charging mechanism using the EBNN model to dynamically determine the optimal charging parameters; ii) Integration of the EBNN with a PID controller to ensure output voltage stability during the charging process; and iii) Implementation of a ZETA converter to enhance voltage regulation and improve system efficiency compared to conventional converters.

The remainder of this paper is organized as follows: i) Section 2 describes the methodology, including the system architecture, control design, and implementation of the EBNN-PID algorithm; ii) Section 3 presents the simulation setup and experimental results, also provides a detailed discussion and comparative analysis; and iii) Finally, Section 4 concludes the paper and outlines potential future work.

2. METHOD

In this system, an adaptive power charge controller is designed to supply the appropriate charging voltage based on the specific type of DC load, which consists of rechargeable lithium-ion batteries with varying voltage and capacity requirements. Each battery type typically operates with a dedicated charging adapter [10], [11]. Therefore, the proposed system utilizes a smart control scheme to provide adaptive charging.

2.1. System overview

Figure 1 presents the system block diagram, in which a 12 V DC power supply serves as the input source. The voltage is processed through a ZETA converter, and the output voltage is regulated by adjusting the duty cycle through an STM32F4 microcontroller. The microcontroller determines the appropriate output voltage based on the type of battery connected. A key condition for initiating charging is that the output voltage must fall within the battery's acceptable charging range. If not, the charging current will be zero.

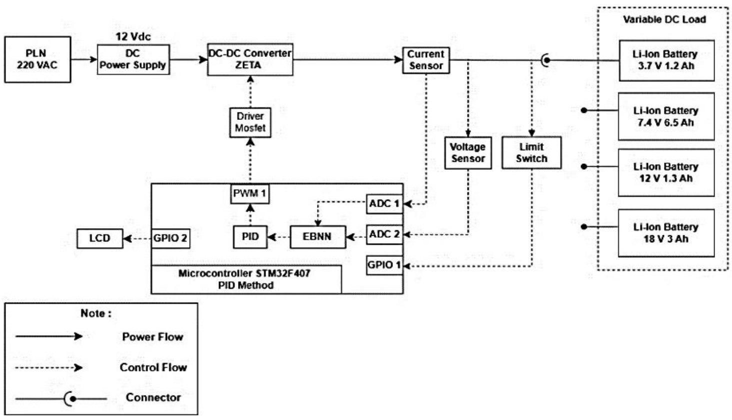


Figure 1. Block diagram adaptive power charge controller

2.2. Modeling of ZETA converter

The ZETA converter is a type of DC-DC converter capable of producing output voltages both higher and lower than the input voltage, without inverting polarity [12]-[16]. The ZETA converter operates through two modes: switch ON and switch OFF. By applying Kirchhoff's voltage law (KVL), the duty cycle and component values are derived. The converter's topology is shown in Figure 2. The (1)-(8) can be used to calculate the parameters needed to build a ZETA converter. Following the four types of DC load. Table 1 is a design parameter of the ZETA converter for the adaptive power charge controller.

$$D = \frac{Vo}{Vo+Vs} \tag{1}$$

$$\Delta IL1 = rIL \times Iin \tag{2}$$

$$\Delta IL1 = rIL \times Iin \text{ x } \frac{D}{1-D} \tag{3}$$

$$L1 = L2 = \frac{1}{2}\left(\frac{Vs \times D}{fs \times \Delta IL1}\right) \tag{4}$$

$$\Delta Vcc = rVcc \times Vo \tag{5}$$

$$Cc = \frac{D \times Io}{\Delta Vcc \times fs} \tag{6}$$

$$Cin = \frac{D \times Iout}{\Delta Vcin \times fs} \tag{7}$$

$$Cout = \frac{\Delta IL2}{8 \times \Delta Vo \times fs} \tag{8}$$

Table 1 lists the design parameters used for simulation in Simulink. Based on (1), four different voltage setpoints are used: 4.4 V, 8.8 V, 14.4 V, and 21.6 V. Corresponding duty cycles are 26.8%, 42.3%, 54.5%, and 64.3%. The open-loop simulation results in Figure 3 indicate output voltage overshoots and steady-state errors. Table 2 summarizes the voltage output data and percentage error, with an average steady-state error of 0.1943%. Therefore, a feedback control system is needed to maintain voltage stability.

Compared to the Buck converter, the ZETA converter offers better voltage adaptability for both step-up and step-down operations, which is beneficial in adaptive charging scenarios involving varying battery types. Prior research has shown that ZETA converters yield higher efficiency and better voltage regulation under load fluctuation [17], [18].

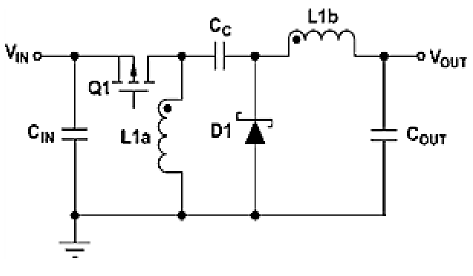


Figure 2. ZETA converter circuit topology

Table 1. ZETA converter parameters

Parameters	Symbol	Value	Unit
Input voltage	Vs	12	Volt
Output voltage	Vout	21.6	Volt
Output current	Iout	2.5	Ampere
Switching frequency	Fs	40	kHz
Inductor 1	L1	142.22	µH
Inductor 2	L2	142.22	µH
Capacitor coupling	Cc	185	µF
Capacitor input	Cin	185	µF
Capacitor output	Cout	2300	µF
Resistor	R	8.64	Ohm

Table 2. ZETA converter open-loop Simulink simulation result

Load type	Duty cycle (%)	Vout theory (Volt)	Vout steady state (Volt)	Error (%)
3.7 V Li-Ion battery	26.8	4.4	4.422	0.5
7.4 V Li-Ion battery	42.3	8.8	8.802	0.0227
12 V Li-Ion battery	54.4	14.4	14.37	0.2083
18 V Li-Ion battery	64.3	21.6	21.59	0.0462
Average error (%)				0.1943

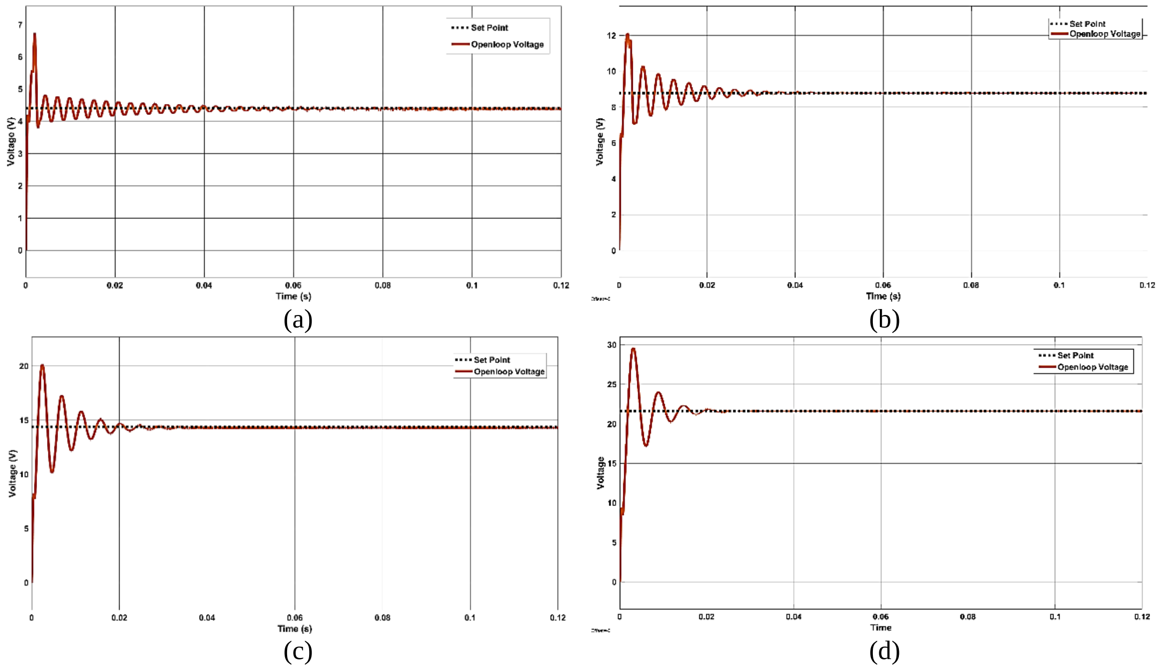


Figure 3. ZETA converter open loop wave with 4 different loads: (a) duty cycle 26.8%, (b) duty cycle 42.3%, (c) duty cycle 54.4%, and (d) duty cycle 64.3%

2.3. Design of (EBNN-PID) algorithm

2.3.1. Data collection and preprocessing

The training dataset consists of 1441 data samples collected from open-loop simulations using Simulink. Each sample includes current (Io) and voltage (Vo) measured at the start of the charging process. These are used as input features to the Elman backpropagation neural network (EBNN), while the target output is the required charging voltage setpoint. The data are divided into training (70%), validation (15%), and testing (15%) subsets.

2.3.2. EBNN architecture and training

EBNN is a recurrent neural network variant with a context layer that allows dynamic behavior learning [19], [20]. The network utilizes the Levenberg-Marquardt (Trainlm) training function due to its high efficiency in pattern recognition. Weight updates are performed using gradient descent with momentum (Learngdm). Figure 4 shows the EBNN architecture used in this study.

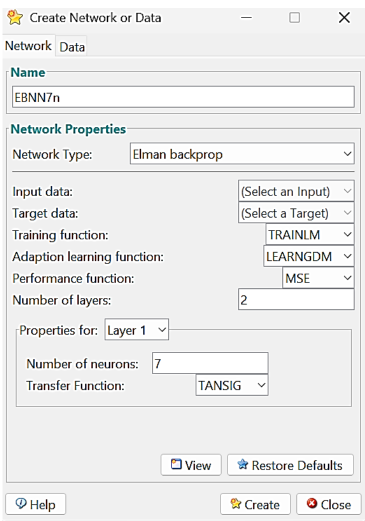
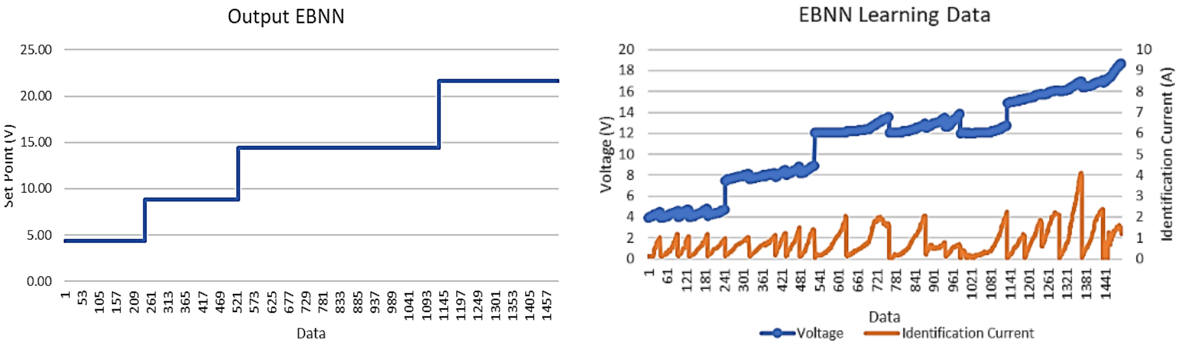


Figure 4. Design of EBNN network

Training results show that the EBNN achieves a very low mean squared error (MSE) of 7.6402e-14, indicating high accuracy in predicting the charging voltage setpoint. The trained EBNN model is implemented in the STM32F4 microcontroller to enable real-time decision-making. Figure 5(a) shows the target data (charging voltage setpoints), while Figure 5(b) illustrates the input data (current and voltage) used for learning. Figure 6 illustrates the relationship between inputs and the target output for the performance Lavernberg-Marquardt algorithm [21].



(a) (b)

Figure 5. Data graph learning of EBNN: (a) target data and (b) input data

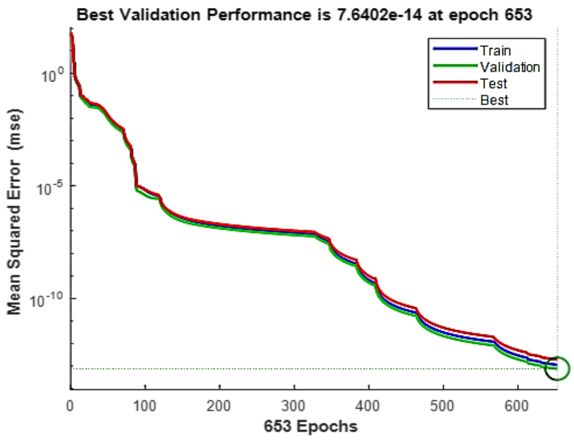


Figure 6. Performance Lavernberg-Marquardt algorithm

2.3.3. PID control design and tuning

Once the algorithm design is completed, the next step involves tuning the PID controller to regulate the output voltage of the EBNN algorithm, ensuring it consistently maintains the predefined setpoint according to the load requirements. To enable the PID controller to effectively stabilize and regulate the output voltage despite variations in input voltage and load conditions, a precise and well-structured PID control design is essential [22]-[25].

The PID controller stabilizes the output voltage at the setpoint predicted by EBNN. The Ziegler-Nichols tuning method is used to determine initial PID parameters based on the experimental response of the system. Table 3 lists the formulas for various controller types. From simulation and tuning:

$$K_p: 0.00102762 \tag{9}$$

$$K_i: 35.5525 \tag{10}$$

$$K_d: 1.425822 \times 10^{-10} \tag{11}$$

These values are implemented in the controller to minimize error and ensure voltage stability during charging.

Table 3. Ziegler-Nichols tuning PID controller parameters

Type of controller	Kp	Ti	Td
P	T/L	~	0
PI	0.9 (T/L)	L/0.3	0
PID	1.2 (T/L)	2L	0.5L

2.3.4. System implementation workflow

Figure 7 shows the system flowchart. The implementation follows this sequence:

i) Initialization: duty cycle (D), Vo, Io, Vsp;
ii) Load detection: If no load is connected, D = 0 → Vo = 0;
iii) Duty cycle tracking: If load is detected, increase D until Io ≥ 0.2 A;
iv) EBNN execution: Input Vo and Io → predict setpoint voltage Vsp; and
v) PID control: Regulate Vo to match Vsp.

Charging setpoints used: i) 4.4 V for a 3.7 V battery, ii) 8.8 V for a 7.4 V battery, iii) 14.4 V for a 12 V battery, and iv) 21.6 V for an 18 V battery. This design enables adaptive charging based on real-time battery identification using EBNN and ensures constant charging voltage through PID regulation. The integration of EBNN and PID offers a hybrid intelligent control system for flexible DC charging applications.

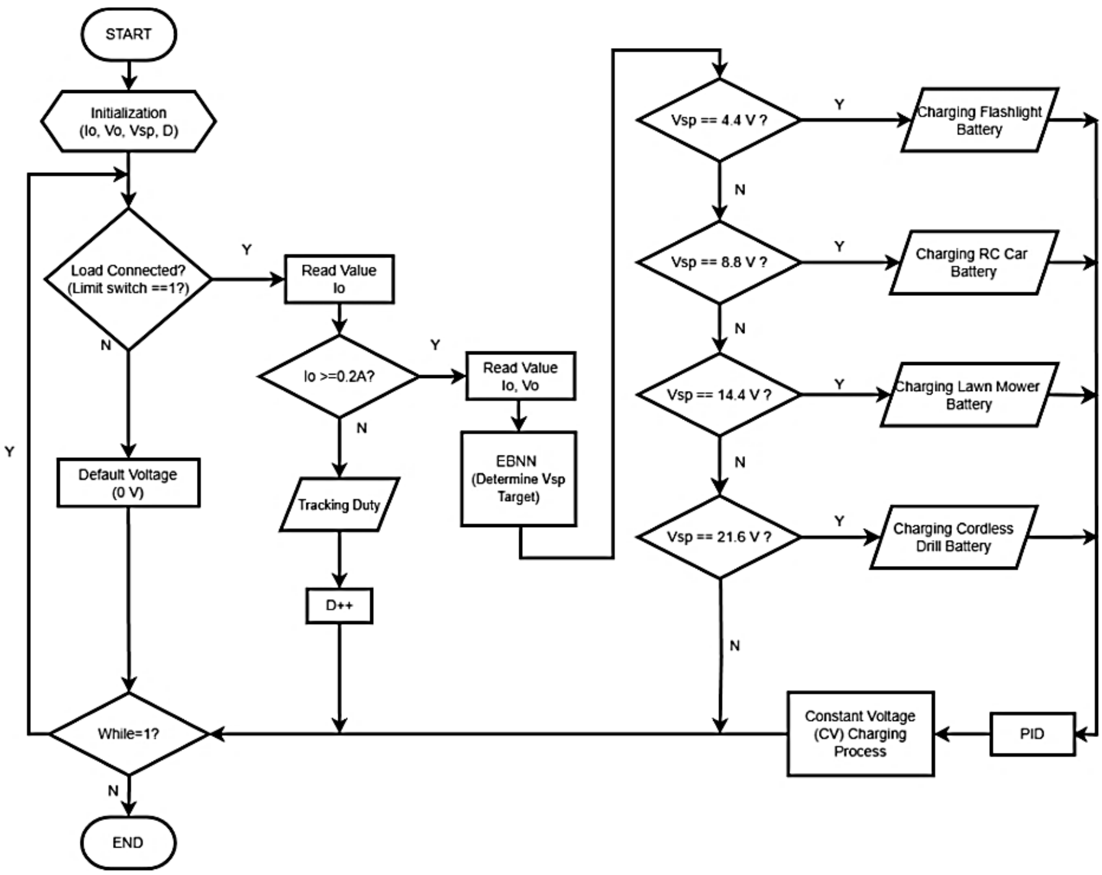


Figure 7. Flowchart system adaptive power charge controller

3. RESULTS AND DISCUSSION

The adaptive power charge controller system that has been developed was evaluated through simulation-based testing to verify its performance. This includes load identification testing to confirm that the Elman backpropagation neural network (EBNN) algorithm can accurately recognize the characteristics of the connected battery load using current and voltage parameters to determine the appropriate charging voltage setpoint.

3.1. Load identification testing

The system was tested using MATLAB Simulink with data samples representing four different types of lithium-ion batteries: i) 3.7 V battery with 4.4 V charging setpoint, ii) 7.4 V battery with 8.8 V charging setpoint, iii) 12 V battery with 14.4 V charging setpoint, and iv) 18 V battery with 21.6 V charging setpoint.

Lithium-ion batteries typically require charging currents between 0.3 C and 1 C, where C is the battery capacity [26]. The simulated current values used for load identification fall within this standard range. The EBNN was trained using 1441 data samples, and the battery identification test focuses on observing voltage and current values during the initial charging stage. Figure 8 illustrates the voltage and current responses for each battery load, while Table 4 summarizes the identification results using the EBNN algorithm.

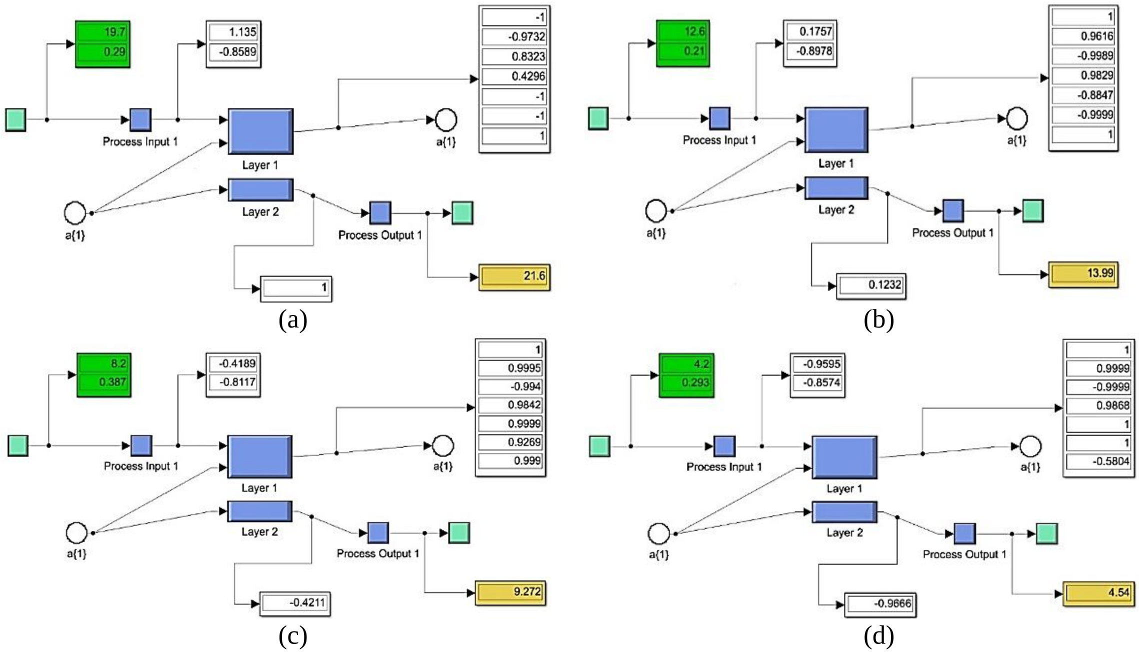


Figure 8. Load identification test result with 4 different loads: (a) lithium-ion 18 volt, (b) lithium-ion 12 volt, (c) lithium-ion 7.4 volt, and (d) lithium-ion 3.7 volt

Table 4. Load identification results using EBNN

Load type	Set point voltage (volt)	Identification voltage (volt)	Error (%)
Lithium-ion 18-volt battery	21.6	21.6	0
Lithium-ion 12-volt battery	14.4	14.00	2.7
Lithium-ion 7.4-volt battery	8.8	9.2	4.5
Lithium-ion 3.7-volt battery	4.4	4.54	3.1
	Average error (%)		2.57

3.2. System integration and adaptive charging performance

After successful identification testing, the adaptive charging system was tested in a fully integrated simulation environment. As shown in Figure 9, the setup includes a ZETA converter circuit whose output is connected to one of four lithium-ion battery loads. The EBNN algorithm determines the appropriate charging setpoint, and the PID controller ensures accurate voltage regulation. The output voltage is controlled such that it aligns with the predicted setpoint voltage determined by the EBNN. Figure 10 presents the output voltage waveforms for each battery type. From the simulation results in Figure 10, the system's performance can be analyzed as follows:

i) For the 18 V battery, the EBNN generated a setpoint of 21.6 V, and the PID controller achieved a final charging voltage of 21.53 V within 0.025 seconds;
ii) For the 12 V battery, the setpoint was 14.4 V, and the achieved voltage was 14.39 V in 0.015 seconds;

iii) For the 7.4 V battery, the setpoint was 8.8V, with a PID-regulated voltage of 8.77 V within 0.026 seconds; and
iv) For the 3.7 V battery, the setpoint was 4.38 V, and the final voltage was 4.366 V in 0.025 seconds.

These results demonstrate that the EBNN successfully identifies the appropriate charging voltage and that the PID controller effectively regulates the ZETA converter's output.

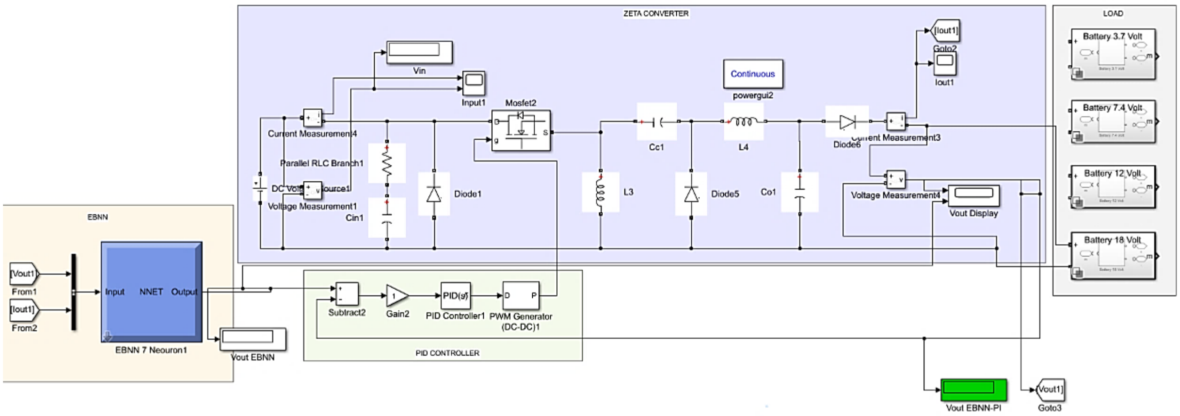


Figure 9. Adaptive power charge controller system integration circuit

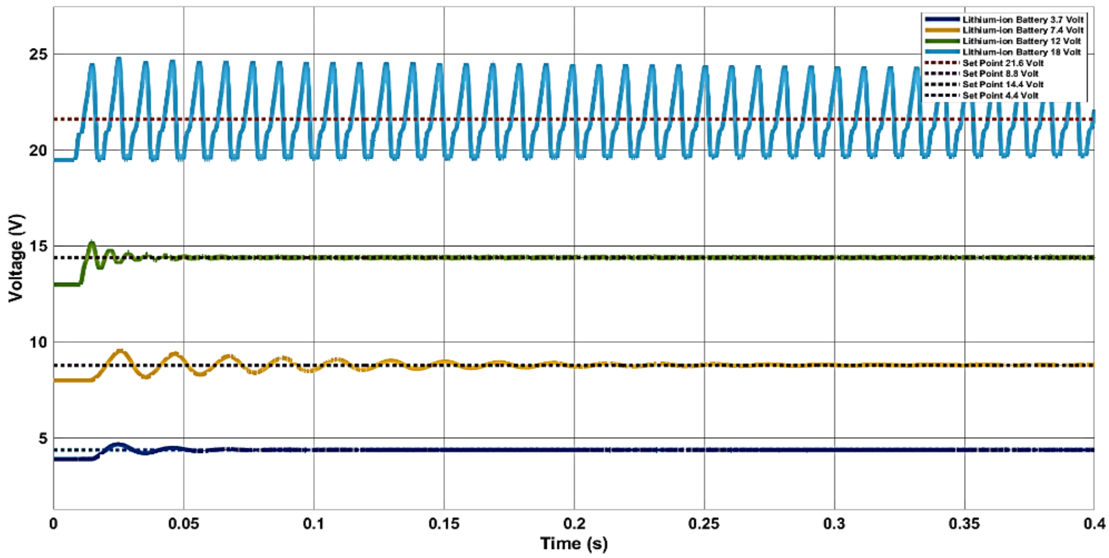


Figure 10. Adaptive output voltage waves for 4 types of batteries

3.3. Extended testing and performance evaluation

To further assess the system's reliability, 24 randomized trials were conducted using the four types of lithium-ion batteries previously tested: i) 3.7 V Lithium-ion battery (target setpoint: 4.4 V), ii) 7.4 V Lithium-ion battery (target setpoint: 8.8 V), iii) 12 V Lithium-ion battery (target setpoint: 14.4 V), and iv) 18 V Lithium-ion battery (target setpoint: 21.6 V)

Each trial involved random selection of one of these batteries to verify whether the EBNN consistently identifies the battery type and assigns the correct setpoint, while ensuring the PID controller accurately regulates the output voltage from the ZETA converter. Table 5 presents the average results of the 24 randomized tests, including output voltage, charging current, and system response time for each battery type.

The results demonstrate that the system performs consistently well. The average error between the EBNN-predicted voltage and the actual voltage achieved by PID control remains well below the 1% threshold, with an overall average error of 0.1725%. This confirms the high reliability and accuracy of the adaptive power charge controller, indicating that it can be effectively applied to a wide range of lithium-ion battery types in practical charging scenarios. In summary, the simulation results validate that the EBNN-PID method enables reliable adaptive charging for multiple lithium-ion battery types, ensuring accurate setpoint voltage tracking and efficient system response.

Table 5. Test result of the adaptive power charge controller system with EBNN-PID algorithm

Average	3.7-volt battery	7.4-volt battery	12-volt battery	18-volt battery
Voltage (Volt)	4.347	8.748	14.330	21.570
Current (Ampere)	0.216	0.403	0.301	0.215
Time (s)	0.033	0.026	0.015	0.025

4. CONCLUSION

This study presents an adaptive battery charging system that integrates an Elman backpropagation neural network (EBNN) with PID control and a ZETA converter to enable accurate load identification and dynamic voltage regulation for lithium-ion batteries. The system was tested on four battery types—3.7 V, 7.4 V, 12 V, and 18 V, with EBNN successfully predicting the charging setpoints, and PID maintaining stable voltage regulation. The simulation results show that the system achieved an average voltage error of only 0.1725%, and minimal overshoot with fast settling times (e.g., 0.350 seconds for the 3.7 V battery reaching 4.4 V).

The results confirm that the EBNN-PID approach significantly enhances adaptability, precision, and charging efficiency compared to conventional methods. The ZETA converter further ensures reliable output across various voltage levels. Overall, this combination of intelligent identification and real-time regulation provides a promising framework for future adaptive power management systems. Future work may include hardware prototyping and real-time validation to evaluate performance under dynamic operating conditions.

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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
Mochammad Machmud Rifadil	✓		✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
Putu Agus Mahadi Putra	✓	✓		✓		✓		✓		✓	✓			✓
Amalia Muklis	✓	✓	✓		✓		✓		✓	✓	✓		✓	

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article [and/or its supplementary materials].

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BIOGRAPHIES OF AUTHORS

Mochammad Machmud Rifadil is a lecturer at the Electronic Engineering Polytechnic Institute of Surabaya (EEPIS). He has a bachelor's degree in applied engineering from Industrial Electrical, originating from PENS, and a master's degree from ITS. His areas of expertise are power electronics, computer vision, artificial intelligence, control systems, and photovoltaic engineering. He also holds international Autodesk certifications, ranging from basic to advanced levels, including Autodesk Certified User in AutoCAD and Autodesk Certified User in Fusion 360. As a lecturer, he has taught subjects such as electronic circuits, electrical measurement and instrumentation, and technical drawing. Currently, he has been teaching for more than ten years. He can be contacted at email: mmrifadil@gmail.com or mmrifadil@pens.ac.id.

Putu Agus Mahadi Putra is a lecturer at the Electronic Engineering Polytechnic Institute of Surabaya (EEPIS). He completed his master's (S2) studies in Electrical Engineering - Energy Management at Udayana University in 2015. He has expertise in the field of energy management and has a competency certificate as an energy manager. He can be contacted at email: mahadi.putra@gmail.com or mahadi@pens.ac.id.

Amalia Muklis is a graduate of the Bachelor of Applied Engineering in Industrial Electrical Engineering program at the electronic engineering Polytechnic Institute of Surabaya. She specialized in power electronics, focusing on charging systems and battery management during her final research project. Her professional expertise includes technical writing, documentation, and data presentation, in addition to her strong foundation in power electronics, renewable energy, control systems, and energy management. She can be contacted at email: punyaamalia.muklis@gmail.com.