2026 Volume: 02 Issue: 06 www.ijrpa.com ISSN 2456-9995 Research Article

International Journal Research Publication Analysis

Page: 01-20

DEVELOPMENT OF A PSO-OPTIMIZED ANFIS INTELLIGENT CONTROLLER FOR OPTIMAL CHARGING AND DISCHARGING OF ELECTRIC VEHICLE BATTERIES UNDER CC–CV STRATEGY

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Article Received: 02 June 2026

Article Revised: 22 June 2026

Published on: 11 July 2026

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DOI: https://doi-doi.org/101555/ijrpa.9621

ABSTRACT

The increasing adoption of electric vehicles (EVs) has intensified the need for intelligent battery management systems capable of reducing charging time while preserving battery lifespan. Conventional Constant Current–Constant Voltage (CC–CV) charging regulated by proportional–integral (PI) controllers exhibits limited adaptability to the nonlinear characteristics of lithium-ion batteries, resulting in prolonged charging periods, higher control errors and accelerated battery degradation. This study develops a Particle Swarm Optimization (PSO)-optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) intelligent controller for optimal charging and discharging of a 400 V, 50 Ah lithium-ion battery operating under the CC–CV framework. MATLAB/Simulink was employed to model the battery, DC–DC boost converter, DC–DC buck converter and closed-loop control system. Three controllers comprising an improved PI controller, conventional ANFIS and the proposed PSO-optimized ANFIS were implemented and comparatively evaluated using charging time, discharge duration, state of charge (SoC), state of health (SoH), current regulation, voltage stability and Integral Time Absolute Error (ITAE). Simulation results indicate that the optimized ANFIS controller achieved full charging within 2200s compared with 4200s for the conventional ANFIS and 4500s for the improved PI controller. The proposed controller also prolonged discharge duration to 98,500s while maintaining a final SoH of 97.4%, significantly outperforming the reference controllers. Furthermore, the

optimized controller exhibited faster transient response, improved voltage and current regulation and lower ITAE values, demonstrating superior robustness under varying operating conditions. The findings confirm that integrating PSO with ANFIS provides an intelligent and adaptive charging strategy capable of improving charging efficiency, minimizing degradation and extending lithium-ion battery service life. The developed controller offers a practical solution for next-generation EV battery management systems.

KEYWORDS: Electric vehicle, Lithium-ion battery, Adaptive Neuro-Fuzzy Inference System, Particle Swarm Optimization, CC–CV charging, Battery Management System.

1. INTRODUCTION

The global transition toward sustainable transportation has significantly accelerated the deployment of electric vehicles (EVs), making lithium-ion battery performance one of the most important research challenges in modern transportation systems. The efficiency, reliability and lifespan of EV batteries depend largely on the charging and discharging strategy employed by the battery management system (BMS). Among the numerous charging techniques available, the Constant Current–Constant Voltage (CC–CV) strategy remains the most widely adopted because of its implementation simplicity, operational stability and compatibility with commercial lithium-ion battery chemistries. However, despite these advantages, conventional CC–CV charging exhibits several limitations, including long charging duration, inadequate adaptation to nonlinear battery dynamics and increased battery degradation during repeated charging cycles (Kumar *et al.*, 2023). The nonlinear electrochemical behaviour of lithium-ion batteries introduces significant challenges for conventional proportional–integral (PI) controllers. Variations in state of charge (SoC), temperature, internal resistance and battery ageing continuously alter system dynamics, making fixed-parameter controllers unable to provide satisfactory performance across the entire operating range. Consequently, charging systems regulated by PI controllers often exhibit slow dynamic response, overshoot, longer settling times and reduced energy efficiency (Adejare *et al*., 2024).

Artificial intelligence has emerged as a promising solution for addressing these limitations in which among intelligent control techniques, the Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the learning capability of artificial neural networks with the reasoning mechanism of fuzzy logic, enabling adaptive modelling of nonlinear systems. Nevertheless, the performance of conventional ANFIS depends strongly on the initialization of membership functions and fuzzy rules, making the controller susceptible to local minima and slower convergence (Zhang *et al.*, 2024).

Particle Swarm Optimization (PSO) has demonstrated considerable effectiveness in solving nonlinear optimization problems due to its global search capability, rapid convergence and computational simplicity. Integrating PSO with ANFIS provides an opportunity to optimize membership functions and consequent parameters automatically, thereby improving controller robustness, reducing tracking errors and enhancing charging performance (Kumar *et al*., 2024).

This research therefore develops a PSO-optimized ANFIS controller for intelligent charging and discharging of lithium-ion EV batteries operating under the CC–CV framework. The controller is implemented within MATLAB/Simulink and compared with conventional PI and ANFIS controllers to evaluate improvements in charging speed, battery health and overall system performance.

2. LITERATURE REVIEW

2.1 Lithium-Ion Battery Charging under the CC–CV Strategy

Lithium-ion batteries remain the dominant energy storage technology for electric vehicles because of their high energy density, long cycle life, low self-discharge rate and high power capability. Their performance, however, is strongly influenced by the charging strategy employed (Zhao *et al*., 2024). Among the available charging methods, the Constant Current–Constant Voltage (CC–CV) technique has become the industrial standard owing to its simplicity, safety and compatibility with most commercial lithium-ion chemistries. During the constant-current stage, the battery is charged at a fixed current until the terminal voltage reaches the predefined upper limit, after which the charger switches to the constant-voltage stage where the voltage is maintained while the charging current gradually decreases (Hongqian *et al.,* 2021).

Although the CC–CV method provides reliable charging performance, several studies have reported that it is associated with long charging duration and accelerated battery ageing during repeated charging cycles. High charging currents increase heat generation, lithium plating and internal resistance, thereby reducing battery lifespan and overall efficiency. Consequently, improving the control algorithm employed during CC–CV charging has become an active area of research.

2.2 Intelligent Battery Management Systems

The Battery Management System (BMS) is responsible for monitoring and controlling battery operation to ensure safety, reliability and optimal energy utilization. Modern BMSs continuously estimate important battery states such as State of Charge (SoC), State of Health (SoH), voltage, current and temperature while simultaneously preventing overcharging, over-discharging and thermal runaway (Hannan *et al*., 2021).

Recent developments have shifted from conventional model-based controllers toward intelligent control strategies capable of adapting to nonlinear battery dynamics. These intelligent techniques improve charging efficiency while minimizing battery degradation under varying operating conditions. The availability of advanced simulation platforms such as MATLAB/Simulink has further facilitated the development and validation of these intelligent battery management algorithms.

2.3 DC–DC Converters in Electric Vehicle Battery Systems

Power electronic converters play an important role in regulating energy transfer between the battery and the electric vehicle powertrain. The DC–DC boost converter increases battery voltage during charging, whereas the DC–DC buck converter regulates battery energy supplied to vehicle loads during discharging (Rahim, *et al*., 2023). The performance of these converters depends significantly on the quality of the controller regulating the duty cycle of the switching devices. Conventional PI controllers are widely adopted because of their simple implementation in which they exhibit degraded performance under parameter uncertainty, load variations and nonlinear battery characteristics. Consequently, advanced intelligent controllers have attracted considerable research attention (Jian *et al.,* 2023).

2.4 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the reasoning capability of fuzzy logic with the learning ability of artificial neural networks to model highly nonlinear systems. Unlike conventional fuzzy controllers, ANFIS automatically adjusts membership functions using training data, enabling improved prediction accuracy and adaptive control (Kumar et al., 2024). Several researchers have successfully applied ANFIS to battery State of Charge estimation, battery temperature prediction and renewable energy management. These studies consistently reported improved tracking performance compared with classical controllers. However, conventional ANFIS remains sensitive to the initial selection of fuzzy membership functions and training parameters, which may result in slow convergence and entrapment in local minima.

2.5 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization algorithm inspired by the collective behaviour of birds and fish schools. The algorithm searches for optimal solutions by updating particle positions according to both individual experience and global swarm knowledge by Kennedy and Eberhart in 1995. Compared with gradient-based optimization methods, PSO offers faster convergence, fewer control parameters and greater robustness when solving nonlinear optimization problems. Because of these advantages, PSO has been successfully applied to controller tuning, parameter estimation, renewable energy optimization and intelligent battery management systems (Oladipo et al., 2023). Recent studies have demonstrated that integrating PSO with ANFIS significantly improves controller performance by optimizing membership functions and consequent parameters. This hybrid approach enhances convergence speed, reduces steady-state error and improves robustness under nonlinear operating conditions.

2.6 Related Studies

Numerous researchers have investigated intelligent charging techniques for lithium-ion batteries. Gite et al.,2013 demonstrated that ANFIS achieved higher accuracy than conventional PID control for nonlinear systems, although increased computational complexity limited its application to larger systems. Chen et al.,2020 improved the efficiency of high-voltage DC–DC buck converters for electric vehicles but noted that intelligent adaptive control remained largely unexplored. Hossain et al., 2022 investigated intelligent battery management strategies and reported improved battery regulation, however, their work employed only a single intelligent controller without optimization.

More recent studies have focused on metaheuristic optimization techniques for battery charging. Researchers have applied Genetic Algorithms, Grey Wolf Optimization, Teaching–Learning-Based Optimization and Particle Swarm Optimization to improve battery charging performance. Most of these studies considered either charging or discharging independently and rarely developed a unified intelligent controller capable of simultaneously managing both processes under the CC–CV framework.

2.7 Research Gap

Although significant progress has been made in intelligent battery charging, several limitations remain. Existing studies primarily optimize either charging or discharging separately, while relatively few consider both processes within a unified control framework (Rao et al., 2023). Furthermore, many conventional ANFIS controllers rely on manually selected membership functions, resulting in reduced adaptability under varying battery operating conditions (Singh et al., 2023). In addition, comprehensive evaluation of charging time, State of Charge, State of Health, voltage regulation, current regulation, thermal behaviour and error minimization within a single optimized controller remains limited (Zhang et al., 2024).

Therefore, this study develops a PSO-optimized ANFIS intelligent controller capable of simultaneously controlling charging and discharging of a 400 V, 50 Ah lithium-ion battery under the CC–CV charging strategy. The proposed controller is implemented in MATLAB/Simulink and evaluated against an improved PI controller and a conventional ANFIS controller using multiple battery performance indicators in which the integrated framework is intended to improve charging speed, extend battery lifespan and enhance overall battery management performance.

3. MATERIALS AND METHODS

3.1 Research Methodology

This study developed a Particle Swarm Optimization (PSO)-optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) controller for intelligent charging and discharging of a lithium-ion electric vehicle battery operating under the Constant Current–Constant Voltage (CC–CV) charging strategy. The proposed controller was implemented in MATLAB/Simulink and evaluated against an improved Proportional–Integral (PI) controller and a conventional ANFIS controller. The methodology consisted of battery modelling, converter design, controller development, optimization and comparative performance evaluation. The overall research procedure is illustrated in Figure 1.

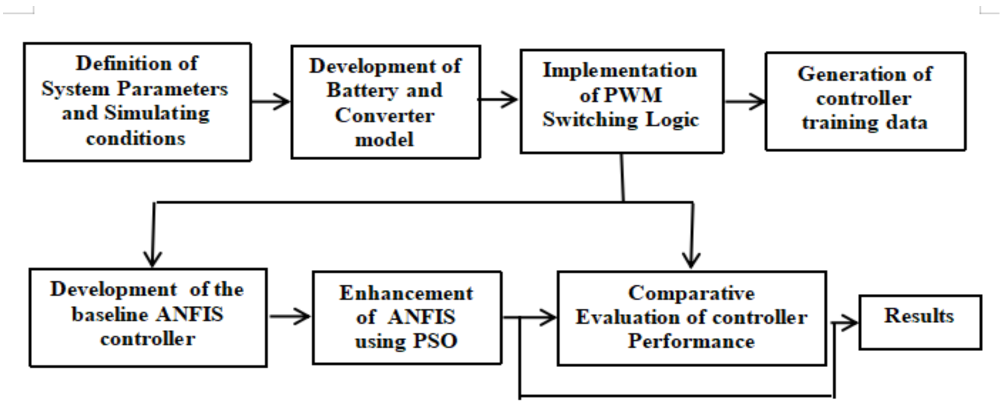

Figure 1: Research Methodology Block Diagram.

The developed system comprises four major subsystems which include Lithium-ion battery model, DC–DC boost converter for charging, DC–DC buck converter for discharging and

Intelligent PSO-optimized ANFIS controller. The battery model continuously supplies information on its voltage, charging current, State of Charge (SoC), State of Health (SoH) and temperature to the intelligent controller. The controller determines the appropriate Pulse Width Modulation (PWM) duty cycle required to regulate the boost and buck converters during charging and discharging, respectively.

3.2 System Configuration

The proposed battery charging and discharging architecture consists of a 400 V, 50 Ah lithium-ion battery connected to a DC source through a DC–DC boost converter during charging and to an inductive electric vehicle load through a DC–DC buck converter during discharging. The charging subsystem employs the boost converter to regulate battery charging according to the CC–CV strategy, while the buck converter regulates energy delivery during discharge. The intelligent controller continuously monitors battery voltage, current, SoC and temperature to generate the switching duty cycle required for stable converter operation.

For controller design, the following assumptions were adopted:

- Continuous Conduction Mode (CCM)
- Ideal semiconductor switches
- Negligible parasitic resistance
- Constant switching frequency
- Small-signal linearization for controller development

These assumptions simplify controller design while maintaining adequate modelling accuracy for system performance evaluation.

3.3 Lithium-Ion Battery Model

A lithium-ion battery rated at 400V and 50Ah was selected because of its widespread application in medium and high-performance electric vehicles. The battery model estimates the principal operating variables required for intelligent charging control, namely terminal voltage, battery current, State of Charge (SoC), State of Health (SoH) and battery temperature. The State of Charge is estimated using the Coulomb counting approach,

$$\mathrm{SoC} = \mathrm{SoC}(0) - \frac{1}{C_n}\int_0^t I(t)\,dt \quad (1)$$

Where, Cn represents the nominal battery capacity, I denotes battery current and SOC(0) is the initial state of charge.

Battery State of Health is estimated as

$$SoH = \frac{Q_{current}}{Q_{initial}} \times 100 \qquad (2)$$

Where, Qcurrent is the present battery capacity and Qinitial is the rated battery capacity.

Battery temperature is modelled using the energy balance equation.

$$C\frac{dT}{dt} = I^2 R - \frac{T - T_{ambient}}{R_{th}} \qquad (3)$$

Where, R is the internal resistance, R_{th} is the thermal resistance and C is the thermal capacitance .

These battery parameters constitute the input variables supplied to the intelligent controller throughout charging and discharging.

3.4 DC–DC Boost Converter Design

The charging subsystem employs a DC–DC boost converter to increase the input supply voltage to the battery charging voltage required under CC–CV operation. For an ideal converter operating in Continuous Conduction Mode,

$$V_0 = \frac{Vin}{1 - D} \qquad (3)$$

Where, Vo is output voltage, Vin is input voltage and D is PWM duty cycle.

The minimum inductance required for continuous conduction is

$$L = \frac{VinD\,(1 - D)}{I_0 2 f_s} \qquad (4)$$

while the output capacitor is determined from

$$C = \frac{V_{in} D (1 - D)}{8 f_s \Delta V_o L} \qquad (5)$$

The converter was modelled in MATLAB/Simulink using MOSFET switching devices controlled through PWM signals generated by the proposed intelligent controller.

3.5 DC–DC Buck Converter Design

During battery discharge, a DC–DC buck converter regulates the battery voltage supplied to the electric vehicle load. The converter output voltage is expressed as

$$V_0 = D \cdot V_{in} \qquad (6)$$

Where, D is the switching duty cycle.

The inductor value is selected using

$$L_{min} = \frac{(V_{in} - V_0) \cdot D}{I_{out} \cdot K_{ind} \cdot V_{in} \cdot f_{sw}} \quad (7)$$

Where; I_{out} is the load current, K_{ind} is the ripple ratio and f_{sw} is the switching frequency. While the capacitor value is

$$C_{min} = \frac{\Delta I_L}{2 \cdot \Delta V_0 \cdot f_{sw}} \quad (8)$$

Where, ΔI_L is the inductor ripple current & f_{sw} is the switching frequency. The buck converter supplies a regulated voltage of approximately 345V to the traction load while minimizing voltage ripple and transient oscillations.

3.6 Pulse Width Modulation (PWM)

Pulse Width Modulation converts the controller output into high-frequency switching pulses for the converter switches. The PWM duty cycle is obtained by comparing the controller output voltage with a high-frequency triangular carrier signal. The PWM gain is

$$Gpwm = \frac{d(t)}{e(t)} = \frac{1}{V_p} \quad (9)$$

Where, d is the duty cycle, V_p is the peak voltage of the ramp r(t) and e(t) is the error signal or control signal.

The generated PWM signals regulate the MOSFET switching frequency and consequently control battery charging current and output voltage.

3.7 Improved PI Controller

An improved PI controller was implemented as the benchmark controller. The controller output is

$$U(t) = K_p e(t) + K_i \int e(t) dt \quad (10)$$

Where, Kp is proportional gain, Ki is integral gain.

The controller minimizes voltage error during charging but uses fixed gains throughout battery operation, making it less suitable for nonlinear battery behaviour.

3.8 Conventional ANFIS Controller

The ANFIS model employed consists of a five-layer feedforward architecture, integrating fuzzy logic inference with adaptive learning capability. For a two-input system, the network structure is defined as follows:

i. Fuzzification: Each input variable is mapped to fuzzy sets using Gaussian membership functions, defined as Equation 11:

$$\mu_i(x) = exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right) \qquad (11)$$

Where c_i and σ denote the center and width of the membership function, respectively.

ii. Rule base: The firing strength of each rule is computed using the product (AND) operator:

$$w_i = \mu A_i(e) \cdot \mu B_i(\Delta e) \qquad (12)$$

iii. Normalization Layer: Equation 13 is the normalized weight layer

$$\overline{w_i} = \frac{w_i}{\sum_{i=1}^{N} w_i} \qquad (13)$$

Where, w_i is the normalized weight

iv. Consequent Layer: Each rule is associated with a first-order linear function as shown in equation 14:

$$f_i = w_i(P_i e + q_i \Delta e + r_i) \qquad (14)$$

Where, P_i, q_i, r_i are the consequent parameters to be learned

v. Output Layer: The overall output of the ANFIS controller is obtained as Equation 15:

$$D(t) = \sum_{i=1}^{N} \overline{w_i} f_i \qquad (15)$$

The training objective is to minimize the squared error between the predicted and target outputs as shown in Equation 16:

$$J = \sum_{k=1}^{M}\left(D_k^{target} - D_k^{ANFIS}\right)^2 \qquad (16)$$

Where, M is the number of training samples. Training data were obtained from the improved PI controller simulation and subsequently used for ANFIS learning through MATLAB's Neuro-Fuzzy Toolbox.

3.9 Enhanced ANFIS Controller

To improve controller adaptability and convergence, Particle Swarm Optimization was integrated into the ANFIS learning process. Each particle represents a possible set of ANFIS membership function parameters. Particle velocity is updated according to;

$$V_i^{k+1} = wv_i^k + c_1 r_1 (p_{best_i} - x_i) + c_2 r_2 (g_{best} - x_i) \quad (17)$$

while particle position is updated using

$$X_i^{k+1} = x_i^k + V_i^{k+1} \quad (18)$$

Where, w is inertia weight, c_1, c_2 are acceleration coefficients, p_{best} is the particle's best solution, g_{best} is the swarm's global optimum. The optimization objective is to minimize the Integral Time Absolute Error (ITAE) which simultaneously improves transient response, reduces overshoot and minimizes steady-state error.

$$\text{Min} \quad \text{ITAE} = \int_0^t t|e|\, dt \quad (19)$$

Subject to $K_i^{min} \leq K_i \leq K_i^{max}$

$K_p^{min} \leq K_p \leq K_p^{max}$

Where, e(t) is the instantaneous control error and T is the total simulation time, Kp is the proportional gain and Ki is the integral gain. The ITAE is used as both a performance metric for comparing PI, ANFIS and PSO-ANFIS controllers. Figure 2 illustrates the flowchart for the PSO based Optimization Process for ANFIS Controller.

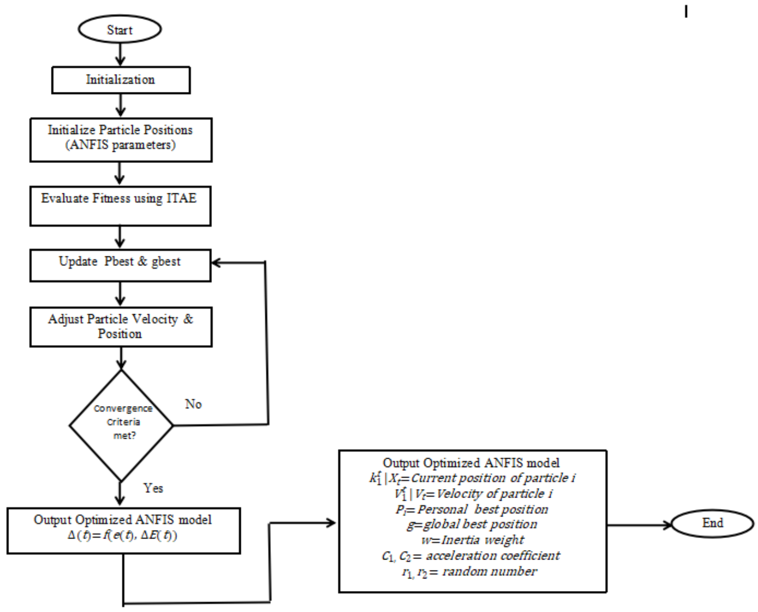

Figure 2: PSO based Optimization Process for ANFIS Controller.

3.10 MATLAB/Simulink Implementation and Perfomance Evaluation.

The entire charging and discharging system was implemented in MATLAB/Simulink R2019b. Three controller configurations were developed which are improved PI Controller, Conventional ANFIS Controller and the enhanced ANFIS Controller. Each controller was subjected to identical charging and discharging conditions to ensure fair performance comparison. Battery voltage, current, SoC, SoH, charging time, discharge duration, thermal response and ITAE were automatically recorded throughout the simulations.

The developed controllers were evaluated using the following performance indices, Charging Time, Discharging Duration, State of Charge, State of Health (%), Voltage Stability, Current Stability, Temperature Variation and Integral Time Absolute Error (ITAE) . These metrics were selected because they comprehensively assess charging efficiency, battery durability, control accuracy and overall system performance under practical electric vehicle operating conditions.

4. RESULTS AND DISCUSSION

The simulation results demonstrate that the enhanced controller consistently achieved superior performance across all evaluation criteria. By combining the adaptive learning capability of ANFIS with the global optimization capability of PSO, the controller responded more effectively to the nonlinear characteristics of the battery than either the improved PI controller or the conventional ANFIS controller.

4.1 Charging Performance Analysis (state of charge (SoC))

Accurate SoC regulation is essential for maximizing battery utilization while preventing overcharging and deep discharge. The improved PI controller regulated the charging process satisfactorily but exhibited relatively slow convergence to the reference voltage. During the constant-current stage, noticeable oscillations were observed before steady-state operation was achieved.

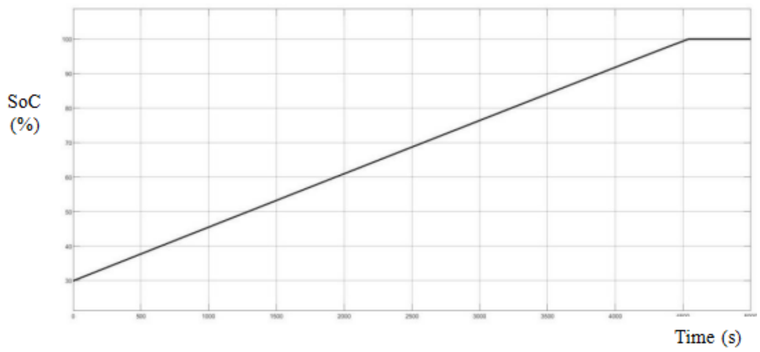

Figure 3: State of Charge (SoC) vs Time.

The conventional ANFIS controller improved the charging response by reducing overshoot and improving current tracking. However, fluctuations were still observed during the transition from constant-current to constant-voltage charging.

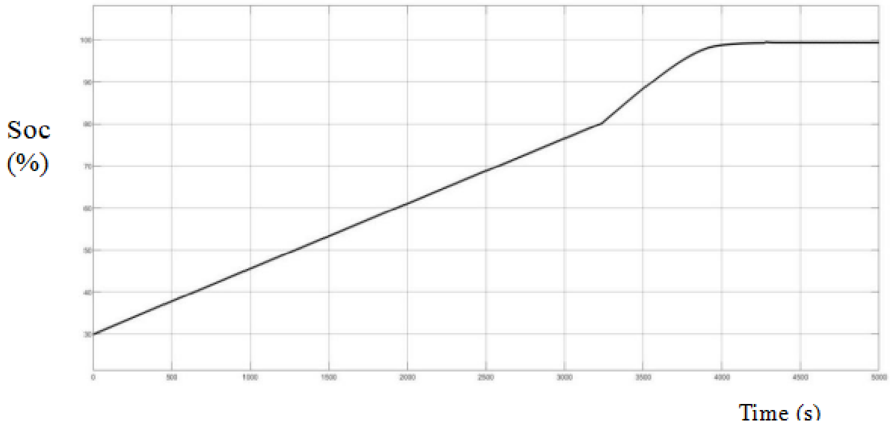

Figure 4: State of Charge (SoC) vs Time.

The enhanced ANFIS controller achieved the fastest convergence and the smoothest transition between charging stages. The controller maintained stable battery voltage throughout the charging cycle while reducing transient oscillations and minimizing charging error**.**

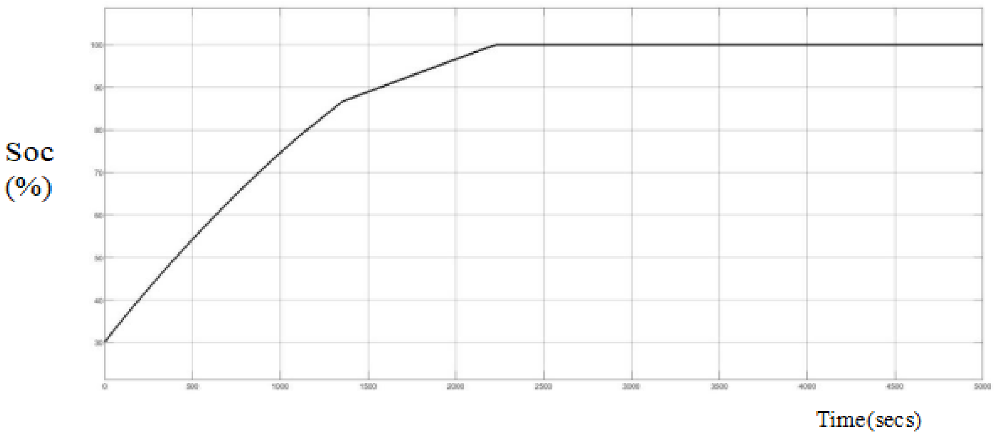

Figure 5: State of Charge (SoC) vs Time.

Figure 3, 4 and 5 presents the charging characteristics of the three controllers under identical initial conditions and the improved SoC estimation demonstrates the capability of the intelligent controller to adapt to nonlinear battery behaviour throughout the charging cycle.The charging completion times are summarized in Table 1.

Table 1. Charging Performance Comparison.

Controller(s)	Charging Time (s)	Percentage Improvement(%)
Improved PI	4500	
Conventional ANFIS	4200	6.67
Enhanced ANFIS	2200	51.11

The enhanced controller reduced charging time by approximately 51% compared with the improved PI controller, indicating that optimization of the ANFIS membership functions significantly enhanced charging efficiency.

4.2 Discharging Performance

The discharge characteristics were evaluated using the buck converter while supplying a representative electric vehicle load. The improved PI controller maintained the required output voltage but exhibited relatively larger voltage ripple and reduced discharge duration because of poorer energy utilization. Figure 6 shows the Output Current Response Under Improved PI Control.

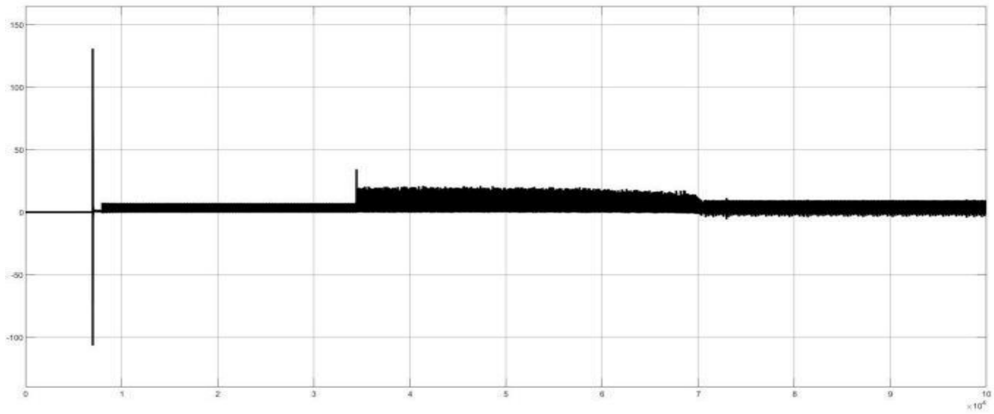

Figure 6: Output Current Response Under Improved PI Control.

The conventional ANFIS controller improved voltage regulation and extended battery operating time. Figure 7 shows the Output Current Response of the DC–DC Buck Converter During Discharging

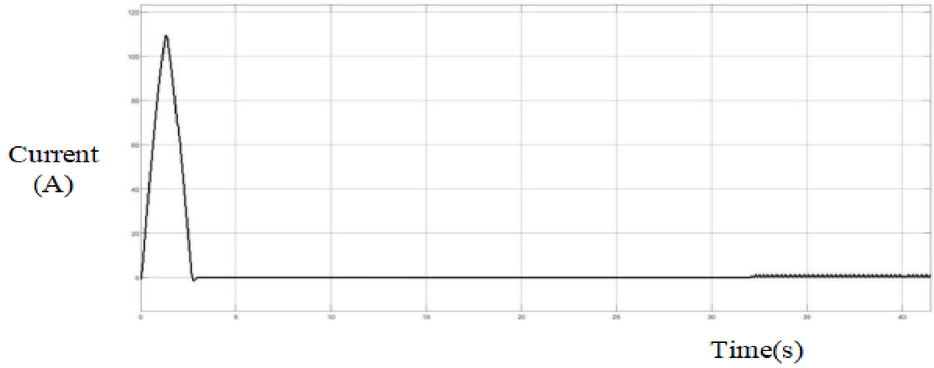

Figure 7: Output Current Response of the DC–DC Buck Converter During Discharging.

The enhanced ANFIS controller demonstrated the longest discharge duration owing to improved duty-cycle regulation and more efficient converter operation. Figure 8 illustrate the Current Response of the Enhanced ANFIS Controller During EV Battery Discharging

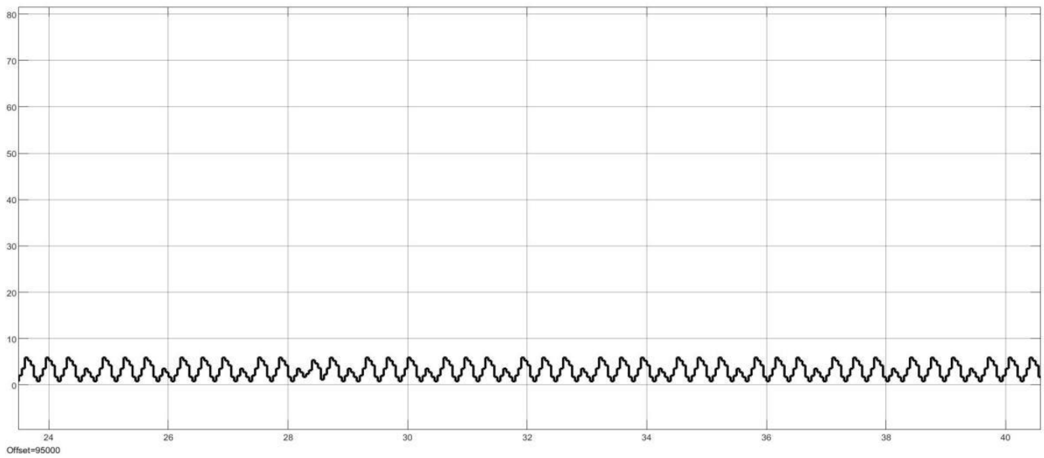

Figure 8: Current Response of the Enhanced ANFIS Controller During EV Battery Discharging.

Table 2. Discharging Performance.

Controllers	Discharge Duration (s)
Improved PI	92,000
Conventional ANFIS	95,800
Enhanced ANFIS	98,500

The extended discharge duration indicates that the enhanced controller utilized stored battery energy more efficiently than the reference controllers.

4.3 State of Health (SoH) Evaluation

Battery State of Health is an important indicator of long-term battery degradation. The improved PI controller generated relatively higher charging stress due to larger transient current oscillations, resulting in a comparatively greater reduction in SoH. Figure 8 shows the State of Health (SoH) vs Time for Improved PI Controller DC–DC Converters During Charging and Discharging

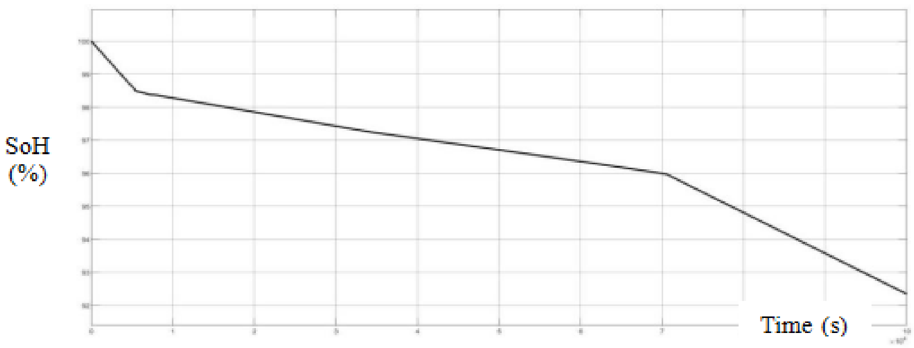

Figure 8: State of Health (SoH) vs Time for Improved PI Controller DC–DC Converters During Charging and Discharging.

The conventional ANFIS controller reduced degradation by improving current regulation. Figure 9 describes the State of Health (SoH) vs Time for ANFIS-Controlled DC–DC Converters During Charging and Discharging.

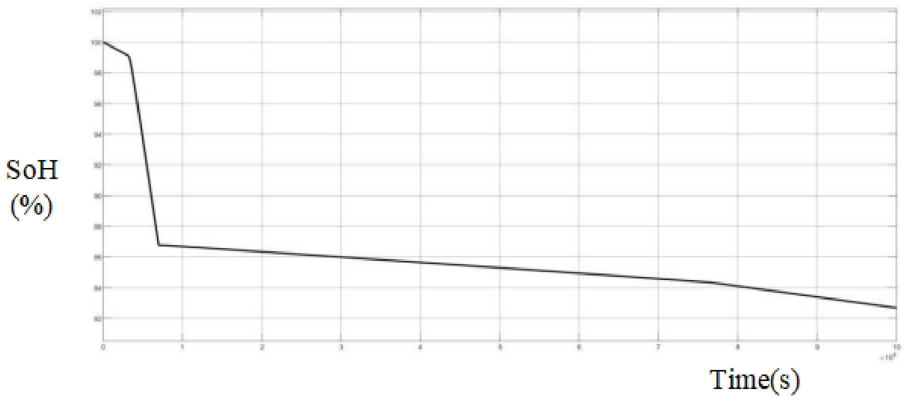

Figure 9: State of Health (SoH) vs Time for ANFIS-Controlled DC–DC Converters During Charging and Discharging.

The enhanced ANFIS controller preserved battery health most effectively through smoother current control and reduced thermal stress. Figure 10 shows the State of Health (SoH) vs Time.

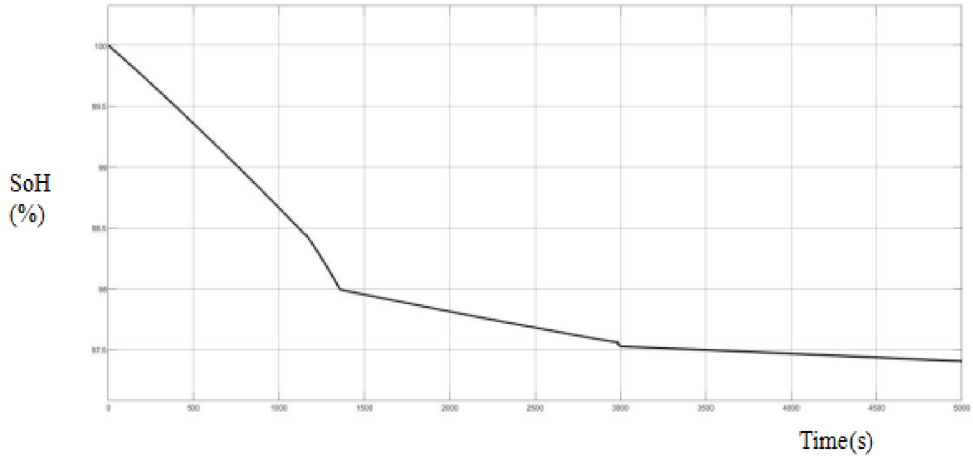

Figure 10: State of Health (SoH) vs Time.

Table 3: Battery State of Health.

Controllers	SoH (%)
Improved PI	95.8
Conventional ANFIS	96.6
Enhanced ANFIS	97.4

The higher SoH obtained with the enhanced ANFIS suggests improved battery longevity and reduced electrochemical degradation.

4.6 Voltage, Current and Thermal Performance Analysis

The voltage, current and thermal performances of the three controllers were evaluated under the CC–CV charging strategy. The improved PI controller exhibited higher voltage overshoot, larger current ripple and the highest temperature rise during transient operation. Although the conventional ANFIS controller improved voltage regulation and reduced thermal variation, it required a longer settling time.The enhanced ANFIS controller achieved minimal voltage overshoot, faster settling time and stable current regulation with significantly lower current ripple. Consequently, it recorded the lowest battery temperature rise, indicating improved charging efficiency, enhanced operational safety and reduced battery degradation. These improvements are attributed to the optimal tuning of the ANFIS parameters using the Particle Swarm Optimization algorithm which enhanced the controller's adaptability to the nonlinear dynamics of the lithium-ion battery.

4.7 DISCUSSION

The superior performance of the enhanced ANFIS controller is attributed to the integration of Particle Swarm Optimization with adaptive neuro-fuzzy learning. Unlike the improved PI controller with fixed gains and the conventional ANFIS controller with manually tuned membership functions, the enhanced ANFIS automatically optimizes its parameters, resulting in faster convergence, lower steady-state error and improved robustness. These results agree with previous studies on metaheuristic optimization and further demonstrate the effectiveness of the proposed approach in simultaneously optimizing battery charging and discharging under the CC–CV strategy, thereby improving charging efficiency, battery lifespan and energy utilization.

5. CONCLUSION

This study developed a PSO-optimized ANFIS controller for optimal charging and discharging of a 400 V, 50 Ah lithium-ion battery under the CC–CV charging strategy. MATLAB/Simulink results showed that the enhanced ANFIS outperformed the improved PI and conventional ANFIS controllers by reducing charging time, extending discharge duration, improving voltage and current regulation, minimizing ITAE and preserving battery State of Health. The integration of PSO enabled optimal tuning of ANFIS parameters, resulting in faster convergence and greater adaptability to nonlinear battery dynamics. These findings demonstrate that the enhanced ANFIS is an effective and robust solution for intelligent EV battery management with future work focusing on hardware implementation and experimental validation.

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