



A Novel ANFIS with the Optimized FOPID Controller-Based Multi-Objective Metaheuristic Algorithm-Based Efficient Regenerative Control System for EV Charging

Subathradevi C*¹, Prakash S¹

¹Electrical and Electronics Engineering, Bharath Institute of Higher Education and Research, Tambaram, Chennai, Tamilnadu, India.

csubathradevi8@gmail.com

Abstract. The rapid proliferation of electric vehicles (EVs) has created an urgent need for intelligent and adaptive energy management systems, especially for optimizing regenerative braking and charging efficiency. Conventional control strategies, such as classical PID Controllers, often exhibit limitations in handling system nonlinearity, parameter variations, and multi-objective performance trade-offs, leading to energy inefficiencies and reduced battery lifespan. To overcome these challenges, this paper proposes a novel hybrid control strategy that integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Fractional-Order PID (FOPID) controller, optimized using the Self-Adaptive Honey Badger Algorithm (SA-HBA). The proposed control scheme integrates a DC-DC Buck-Boost converter to manage energy flow between the EV battery and regenerative braking system. The developed control framework dynamically adjusts key parameters in real time to Additionally, the controller demonstrates strong robustness under varying load conditions and road profiles, indicating its demonstrates strong robustness under varying load conditions and road profiles, indicating its suitability for implementation in advanced EV charging systems.

Keywords: ANFIS, FOPID, Energy Management System, HBA

1 Introduction

The Electric Vehicles (EVs) have been a game-changer in modern-day transportation, providing a clean, efficient, and sustainable type of mobility [1]. EVs are driven by electricity using either an electric motor or rechargeable batteries, creating a zero-carbon footprint and removing the dependency on fossil fuels from the transportation sector as a whole. EVs are very energy efficient and cost-effective, and serve as an excellent alternative to conventional vehicles [2]. Apart from transportation, optimizing performance and energy consumption depends on the time and the speed at which the EV is driving, as speed control is

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an essential aspect of EV drive control; EV speed impacts energy consumption [3]. EVs are also contributing to the modernization of the electric grid as they act as mobile energy storage devices, which facilitate demand response. EVs support system resiliency, frequency stability, integration of renewable resources, and provide opportunities to create a more sustainable and flexible energy system through their integration in smart grids and micro grids [4]. The performance potential of those advanced methods, like RFOSMC, FOPID, FLC, and GS-FO-PID, is good, but the implementation process is challenging. The RFOSMC framework makes use of fractional calculus and PSO-based tuning a disadvantage if the framework is expected to be implemented in real-time on low-resource systems [5]. Whereas the FOPID method incurs additional processing while tuning its multiple parameters. This leads to processing restrictions even when the device is functioning, and creates a problem of local convergence [6].

1.1 Motor controller Unit Converter Energy Management

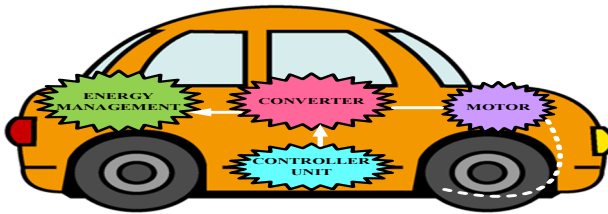


Fig. 1. Block Diagram

Fig. 1 shows the block diagram of the proposed system. The hybrid system offers benefits such as regenerative braking, steady operation, enhanced stability margins, and improved energy recovery and charging time for EV operation. More recent developments in control strategies have pointed to the efficacious impacts of Fractional-Order PID (FOPID) controllers in enhancing power system performance for a range of applications. One study optimized an FOPID controller using a Neural Network Algorithm (NNA) for the Load Frequency Control of multi-area power systems, enabling dynamic leverage of controller parameters to manage rapid load changes [9]. A second study applied an FOPID controller for a DC–DC buck–boost converter and optimized its parameters using the Snake Optimization (SO) algorithm to enhance robustness, decrease the impact of overshoot [10]. Several studies employed Average Current Control (ACC), Cuk, and SEPIC converters for power factor correction; in these cases, load voltage was regulated using PID and FOPID controllers. The TLOT and ITAE were used to tune the controller gains and also reduce harmonics from different non-linear loads, improving overall power quality [12]. The influx of electric vehicle (EV) uptake has generated a compelling opportunity for advanced energy management systems

that address the many complexities of EV operation. Established control strategies, for example, classical PID controllers, are unable to robustly represent system nonlinearities, uncertain variables and behaviours, and even competing goals, leading to inefficient regenerative braking and mediocre battery charging performance. Inefficient regenerative braking not only unnecessarily compromises energy recovery but also impacts the battery health and ultimately the robustness of the system over time. To address these shortcomings, this paper proposes a novel hybrid control design that puts together an Adaptive Neuro-Fuzzy Inference System (ANFIS) control, a Fractional-Order PID (FOPID) controller the self-adaptive optimized Honey Badger Algorithm (HBA) [11].

This intelligent and adaptive controller is capable of optimally regulating energy flow during regenerative braking and battery charging, providing improved system efficiency, improved voltage regulation, and overall improved operation under a variety of operating conditions.

2 Proposed Methodology

The proposed methodology aims to improve regenerative braking and charging performance in EVs by utilizing a hybrid model of ANFIS and an FOPID controller adapted using an SA-HBA. Fig. 2 shows the Architecture of the proposed methodology. The methodology involves system modelling and converter design, which involves EV powertrain and bi-directional DC-DC Buck-Boost converter modelling. The ANFIS controller develops adaptively, fine-tuning duty cycle regulation, while the Fractional-Order PID controller enables precision and dynamic stability. The SA-HBA optimization optimizes FOPID parameters to achieve multiple objectives, maximizing energy recovery during regenerative braking, minimizing battery charging time, and controlling boost voltage. The hybrid control framework combines ANFIS, FOPID, and SA-HBA to control energy flow, allowing smooth system operation between regenerative braking and charging. This approach contributes to the overall performance of EVs and their ability to adapt to changing conditions. A modular control scheme for power handling in an EV, likely focusing on Regenerative Braking or voltage regulation. The ANFIS-FOPID Controller, a core control intelligence system, combines an ANFIS and an FOPID algorithm for precise, flexible control.

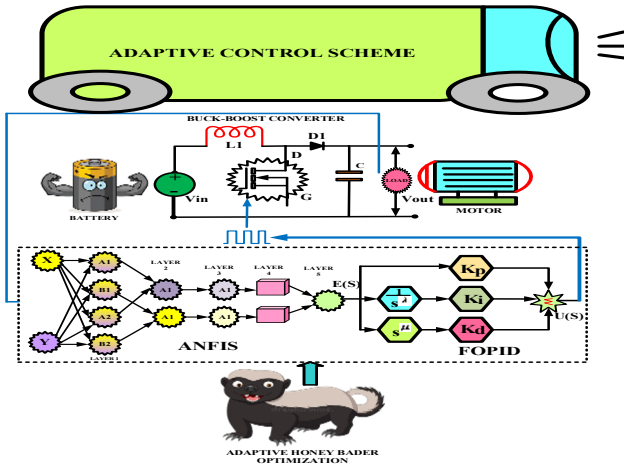


Fig. 2. Architecture of the proposed methodology

2.1 System Modelling and Converter Design

A model of the EV and bidirectional DC–DC Buck–Boost converter is developed to assess and improve the proposed regenerative energy management system.

The EV consists of three main components: a battery subsystem for energy storage, a regenerative braking subsystem for energy recovery, and a DC-DC Buck-Boost converter for bidirectional power flow. The battery model is represented by the Thevenin equivalent circuit.

$$V_{batt} = E_{oc} = I_b R_{int} \tag{1}$$

Where E_{oc} is the open circuit voltage, I_b is the battery current, R_{int} is internal resistance.

The SoC is
$$SoC(t) = SoC(0) - \frac{1}{Q_{cap}} \int_0^t I_b(\tau) dt \tag{2}$$

Where Q_{cap} is the battery capacity. Throughout, regenerative braking torque generated by the motor is converted into electrical energy.

$$P_{regen} = T_{br} \cdot \omega \tag{3}$$

Where ω is the angular velocity of the motor channel.

2.2 ANFIS-Based Controller Design

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a system used to control the duty ratio of the DC–DC Buck–Boost converter, considering non-linearities, parameter uncertainties, and dynamics variations. It incorporates the learning power of neural networks and the interpretability of fuzzy inference systems, allowing for adaptive control.

Rule 1: If x is the A_1 and y is B_1 , then,

$$f_1 = p_1x + q_1y + r_1 \quad (4)$$

Rule 2: If x is the A_2 and y is B_2 , then,

$$f_2 = p_2x + q_2y + r_2 \quad (5)$$

Where A_i and B_i are fuzzy sets, and p_i, q, r_i , are consequent parameters

The computation in ANFIS follows the Layer 1,2,3,4, and 5.

→ Layer 1: Every input is changed into a fuzzy relationship value

$$O_{1,i} = \mu A_i(x), O_{1,j} = \mu B_j(y) \quad (6)$$

Then the Gaussian relationship is used,

$$\mu(x; c, \sigma) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \quad (7)$$

Where c is the center and σ is the width.

→ Layer 2 (firing strength)

$$O_{2,i} = \omega_k = \mu A_i(x) \cdot \mu B_j(y) \quad (8)$$

→ Layer 3 (Normalization)

$$O_{3,i} = \bar{\omega}_k = \frac{\omega_k}{\sum_j \omega_k} \quad (9)$$

→ Layer 4 (consequent)

$$O_{4,i} = \bar{\omega}_k f_k = \bar{\omega}_k(p_kx + q_ky + r_k) \quad (14)$$

→ Layer 5 (Aggregation)

$$O_5 = \sum_K \bar{\omega}_k f_k \quad (10)$$

The ANFIS output is generated, which directly regulates the duty cycle D of the converter.

Input-Output Mapping for EV control

To minimize the Mean Squared Error (MSE) between the predicted duty ratio D_{ANFIS} and reference D_{ref} .

$$E = \frac{1}{N} \sum_{n=1}^N (D_{ref}(n) - D_{ANFIS}(n))^2 \quad (11)$$

ANFIS enhances energy management in workable electric-storage vehicles by providing robust compensation and seamless integration for optimal bidirectional power flow.

2.3 Honey Bader Algorithm

The Honey Badger Algorithm (HBA) is an algorithm that mimics the foraging behaviour of honey badgers, which either dig for prey or follow a guide bird, to find the optimal solution using both modes.

- Initialization: The honey badger's position is assigned an initial random value in the search space, based on the following formula

$$x_i = lb_i + r_1 \times (ub_i - lb_i). \alpha \quad (12)$$

- **Intensity of smell (I):** The intensity of smell from the prey is determined by the concentration strength (S) and the distance (d) between the badger and the prey,

$$I_i = \frac{r_2 \times S}{4\pi d_i^2} \quad (13)$$

Where, S is a random number and d is the distance.

In SA-HBA, a self-adjusting weight based on fitness ranking is applied:

$$I_i^{\text{adaptive}} = \left(1 + \delta \cdot \frac{f_{\text{best}} - f_i}{f_{\text{best}} + \epsilon}\right) \times \frac{r_2 \times S}{4\pi d_i^2} \quad (14)$$

- **Density Factor (α):** The density factor (α) decreases over time to facilitate the transition from exploration to exploitation, where C is a constant, t is the current iteration, and tmax is the maximum number of iterations.

$$\alpha = C \times \exp\left(-\frac{t}{t_{\text{max}}}\right) \quad (15)$$

In SA-HBA, an adaptive component based on population diversity is introduced.

$$\alpha_{\text{adaptive}} = C \times \exp\left(-\frac{t}{t_{\text{max}}}\right) \times \left(1 + \gamma \cdot \frac{\sigma(t)}{\sigma_{\text{max}}}\right) \quad (16)$$

- **Position Update (Digging Phase):** During the digging phase, the position of the prey is updated based on its position, intensity, and distance, using an equation:

$$x_{\text{new}} = x_{\text{prey}} + F \times \beta \times I \times x_{\text{prey}} + F \times r_3 \times \alpha \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \quad (17)$$

$$x_{\text{new}} = x_{\text{prey}} + F \times \beta \times I_i^{\text{adaptive}} \times x_{\text{prey}} + F \times r_3 \times \alpha_{\text{adaptive}} \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \quad (18)$$

- **Position Update (honey phase):** In the honey phase, the position is updated based on proximity to the prey and the time-varying density factor α , where α is a random number and d is the distance to the prey.

$$x_{\text{new}} = x_{\text{prey}} + F \times r_7 \times \alpha \times d_i \quad (19)$$

- **Escape from Local Optima (F):** The flag F alters the search direction, enabling the algorithm to escape from a local optimum, where r_6 is a random number.

$$F = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{else} \end{cases} \quad (20)$$

The composite fitness function is a mathematical formula that represents the weights for each objective, normalized to ensure equal consideration of all aspects during optimization. It is calculated using the weights E_{regen} , T , charge, and ΔV .

$$J = w_1 \frac{E_{\text{regen}}}{E_{\text{max}}} + w_2 \frac{1}{T_{\text{charge}}} + w_3 \frac{1}{1 + \Delta V_{\text{dc}}} \quad (21)$$

SA-HBA optimizes FOPID parameters for enhanced energy management in nonlinear EVs, avoids premature convergence, improves energy model recovery, charging duration, and voltage stability, and is scalable and robust.

2.4 Hybrid Control Framework Implementation

The hybrid control framework combines an ANFIS and an optimized FOPID controller for efficient energy management in EVs. This integrated control loop enhances transient performance, energy capture, and reduces switching losses, particularly during regenerative braking and charging. The ANFIS compensates system uncertainties like braking torque, road slope, and battery SoC position, using its output as a correction term for the reference control signal.

This adaptive weighting factor updates dynamically based on driving mode. The duty cycle $D(t)$ ensures bidirectional power flow regulation between the battery and the regenerative braking unit.

$$D(t) = \frac{u(t)}{V_{in}(t)} \tag{22}$$

The Hybrid Framework offers seamless regenerative braking and charging modes, reliable performance in uncertain driving conditions, improved stability margins from SA-HBA-tuned FOPID, and improved energy recovery and lower charge time. The paper aims to validate a proposed system using MATLAB/Simulink, comparing performance against a PID and a standalone FOPID controller, focusing on regenerative energy recovery efficiency.

3. Results and discussions

This section analyzes the performance of a proposed method compared to conventional and state-of-the-art techniques. The results show that the proposed approach outperformed all other approaches in key metrics such as stability, charging efficiency, charging time, robustness, energy recovery, and battery longevity. The overall findings indicate better performance across all metrics, indicating the effectiveness of the approach. An ablation study also demonstrates the individual contributions of each component to the enhanced performance of the proposed system, confirming the overall effectiveness and robust performance of the proposed solution.

3.1 Performance Evaluation

The performance evaluation demonstrates that the proposed technique is evaluated against conventional and state-of-the-art methods, focusing on key performance indicators like charging efficiency, stability, robustness, battery duration, energy recovery, and charging time. The results show that the proposed method offers the best performance across these indicators, proving to be most capable of improving system performance, efficiency, and reliability, regardless of application, battery duration, or circumstances. Fig. 3 shows the Controller performance comparison.

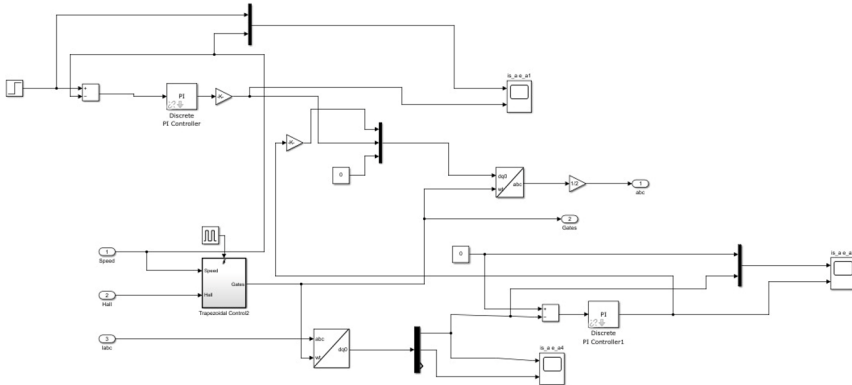


Fig. 3. Simulink Diagram

Fig.3 represents the simulation diagram of the proposed method. The article compares the transient response of three controllers: PI, PID, and FOPID. The FOPID controller is the fastest and most stable, reaching a steady state of 0.65 V after 200 seconds or less. It has minimal overshoot to stabilize the system. The PID controller has a significant amount of overshoot and initially returns higher voltage values, but ultimately returns to a steady state of 1 V. The PI controller has the slowest response, increasing slowly and not reaching the target 1 V set point even after 2000 seconds. The FOPID controller is considered the most efficient working speed and stabilizing time with high accuracy, contributing significantly to the overall proposed ANFIS-FOPID control scheme.

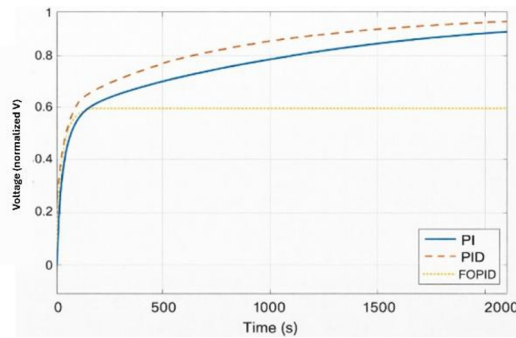


Fig. 4. Controller Performance Comparison

Fig. 4 shows that the FOPID controller is the fastest and most stable, reaching a steady state of 0.65 V in less than 200 seconds. The PID controller exhibits considerable overshoot, surpassing other controllers in voltage development before gradually settling to 1V. The PI controller has the slowest response, consistently climbing slowly and failing to reach the 1V set point in 2000 seconds. The FOPID controller is considered the fastest and most efficient at stabilizing control systems with minimal overshoot. Table 1 illustrates the evaluation of Charging Efficiency, Stability, and Robustness Across Optimization Methods.

Table 1. Comparative Performance Analysis of Optimization Techniques for Battery Charging Systems

Performance	GA	PSO	ACO	GWO	Proposed
Charging efficiency	91.56	93.05	94.24	95.65	98.68
Energy inefficiencies	0.098	0.077	0.068	0.054	0.024
Battery lifespan(cycles)	410	420	532	450	480

Energy recovery (%)	33	38	42	46	54
Charging time(min)	42	35	28	24	21
Voltage regulation	0.64	0.7	0.75	0.78	0.82
Stability	96.15	96.85	97.14	97.52	98.86
Robustness	94.25	95.68	96.14	96.58	98.86

Table 1 compares various optimization methods for battery charging performance, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolff Optimizer (GWO), and the Proposed Method. The Proposed Method outperforms the others, achieving a maximum charging efficiency of 98.68%, significantly higher than the GA and GWO. It minimizes energy loss to 0.024, improving over GA and GWO. The proposed method is a balanced approach, surpassing both GA and PSO. The method achieves a maximum energy regenerative performance of 54%, nearly double that of GA. It also provides a short charging time of 21 minutes, less than GWO and ACO. The Proposed Method outperforms all other techniques in terms of voltage stability, safety stability, and safety robustness, making it the most efficient and reliable charging scenario overall.

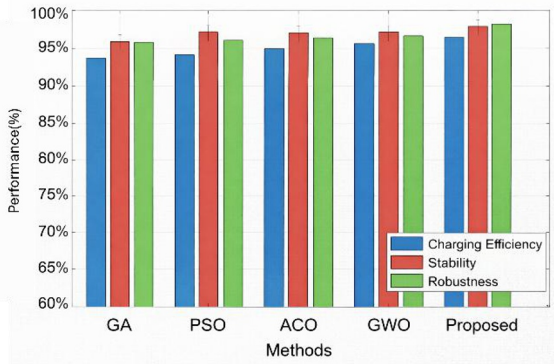


Fig. 5. Performance Comparison of Various Optimization Algorithms

Fig. 5 displays that the proposed method outperforms all other methods, like GA, PSO, ACO, and GWO, in terms of Charging Efficiency, Stability, and Robustness evaluation measures. The proposed method scores 100%, all three measures exceeding 98%. GWO, the second-best performance, has a Charging Efficiency of 96%, Stability of 97.5%, and Robustness of 97%. The Genetic Algorithm method, on the other hand, has the lowest performance, particularly in Charging Efficiency and Stability, a scores of above 90% and less than 97% respectively.

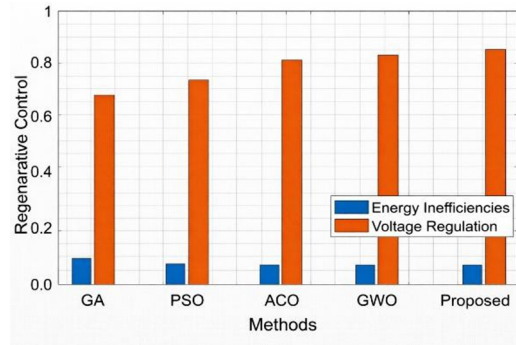


Fig. 6. Comparison of Energy Inefficiencies and Voltage Regulation for Various Methods

Fig. 6 shows that the proposed method is the most efficient, showing the lowest Energy Inefficiencies and highest Voltage Regulation values compared to the other four methods, such as GA, PSO, ACO, and GWO. The Proposed method has a low Energy Inefficiency value of nearly 0.02 and a maximum Voltage Regulation value of around 0.82. The GA method exhibits the highest Energy Inefficiencies, around 0.09, and has a comparatively lower Voltage Regulation of about 0.64. The figure shows a significant benefit of the proposed method in achieving the best performance efficiency in regenerative control.

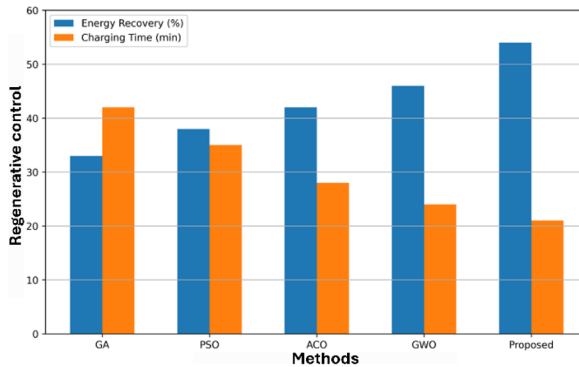


Fig. 7. Energy Recovery and Charging Time of Various Control Methods

Fig. 7 displays that the proposed method outperforms the GA method in terms of energy recovery and charging time, with a 55% recovery rate and a low charging time of 21 minutes. The GA method has the lowest recovery rate 33% and a longer charging time of 42 minutes. The PSO and ACO methods have less favorable results, longer charging times and lower energy recovery. The figure shows a progressive trend where advanced algorithms produce higher energy recovery and significantly reduce charging time.

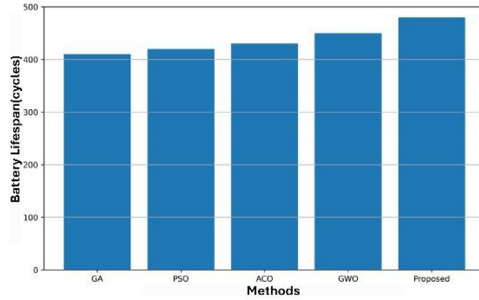


Fig. 8.Battery Lifespan Comparison of Different Methods

Fig. 8 demonstrates that the Proposed method has the most effective Battery Lifespan, exceeding 480 cycles, followed by the GWO method, 450 cycles, and the ACO method, 430 cycles. The PSO and GA methods have the lowest performance, 420 and 410 cycles, respectively. The Proposed method shows continuous improvement from the GA method, indicating that the algorithm is better at optimizing charging and discharging cycles to increase battery longevity.

Table 2. Comparative Performance of Neuro-Fuzzy-Based Models for Battery Charging Optimization

Performance	NFN	DENFIS	PALM	GENEFIS	Proposed
Charging efficiency	95.2	96.5	97.1	97.8	98.68
Energy inefficiencies	0.045	0.038	0.032	0.028	0.024
Battery lifespan	400	420	450	460	480
Energy recovery	48	50	52	53	54
Charging time	31	28	25	24	21
Voltage regulation	0.68	0.74	0.78	0.8	0.82
Stability	95.5	96.8	97.4	98	98.86
Robustness	95	96.3	97	97.8	98.86

Table 2 compares the performance of Neuro-Fuzzy Inference Network (NFN), Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS), parsimonious Adaptive Local Model Networks (PALM), Generic Evolving Neuro-Fuzzy Inference System (GENEFIS), and the proposed method in battery charging optimization. The proposed

method has the highest charging efficiency of 98.68% and the lowest energy inefficiency of 0.024, compared to NFN and GENEFIS. It has a longer battery lifespan of 480 cycles and maximizes energy recovery at 54%. The proposed method charges faster at 21 minutes than GENEFIS and NFN at 24 minutes. And has improved voltage regulation 0.82. It also shows stability of 98.86% and robustness of 98.86%, indicating improved efficiency, reliability, and long-term performance.

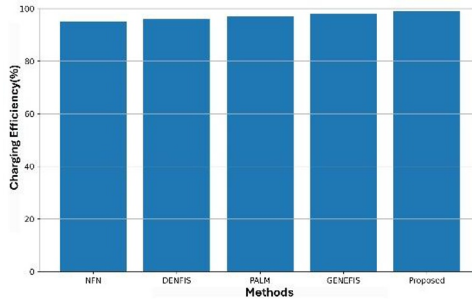


Fig. 9. Comparison of Charging Efficiency for Different Methods

Fig.9 shows that the proposed method has the highest efficiency, with a charging efficiency just below 100%. The GENEFIS method is just below this, with a charging efficiency of 98.5%. The PALM and DENFIS methods are similarly efficient, both having a charging efficiency above 97.5%. The NFN method is the least efficient, with a slightly discernible advantage. All methods are highly efficient, but the Proposed and GENEFIS offer a slight advantage.

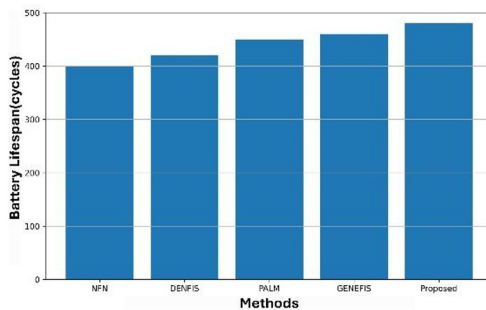


Fig. 10. Battery Lifespan Comparison of Different Methods

Fig. 10 illustrates that the proposed method has the longest battery life of 480 cycles, a significant improvement from other methods. The GENEFIS method has a longer lifespan of 460 cycles, while PALM and DENFIS have similar lifespans of 445 and 420 cycles, respectively. The NFN method has the lowest lifespan of 400 cycles. The chart shows a linear trend, indicating that as battery performance improves from the NFN method to the proposed method, the battery life also improves. Thus, the

proposed method has the highest overall battery longevity for optimizing charging.

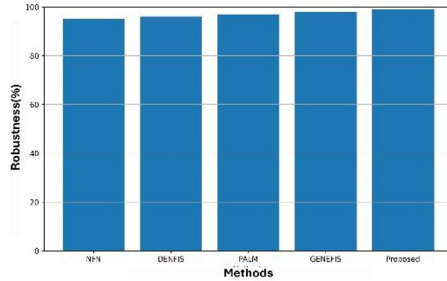


Fig. 11. Robustness Comparison of Different Methods

Fig. 11 demonstrates that the proposed method is the most robust, with a value just under 100%. The GENEFIS method is the second most robust, with a value of around 99%. The PALM and DENFIS methods are the next most robust, with values of 98.5% and 97.5% respectively. The NFN method is the least robust, with a value of 96.5%. The Proposed method is most capable of high performance in variable or difficult conditions.

3.2. Ablation Study

The ablation study examines the roles of significant components such as ANFIS, HBA, and the Buck-Boost converter in the overall efficiency of the proposed system. It shows that the actual use of these components improves energy recovery, charging time, and voltage control, while the combination of these components enhances reliability and operability. The study highlights the importance of considering these components in isolation removal. Table 3 shows the Component-wise Ablation Analysis for the Optimized Charging System.

Table 3. Ablation Study of Key System Components on Battery Charging Performance

Metrics	ANFIS	out ANFIS	HBA	out HBA	A Buck-Boost converter	out a Buck-Boost converter
Charging efficiency	98.68	98.41	98.68	98.35	98.68	98.25
Energy inefficiencies	0.024	0.025	0.024	0.026	0.024	0.027

Battery lifespan	480	470	480	468	480	465
Energy recovery	54	53	54	52	54	51
Charging time	21	24	21	23	21	22
Voltage regulation	0.82	0.81	0.82	0.79	0.82	0.79
Stability	98.86	98.81	98.86	98.78	98.86	98.75
Robustness	98.86	98.84	98.86	98.84	98.86	98.82

Table 3 demonstrates the impact of adding ANFIS, HBA, and a Buck-Boost converter to battery charging performance. ANFIS improves charging efficiency to 98.68%, energy inefficiencies falling to 0.024. Battery cycles increase to 480 cycles, and energy recovery increases to 54%. The charging time is reduced to 21 minutes compared to 24 minutes with ANFIS. HBA also increases efficiency to 98.68%, inefficiencies decreasing to 0.024. Battery cycle extension increases from 468 cycles to 480, and energy recovery increases to 54%. The Buck-Boost converter maintains 98.68% efficiency, the lowest energy inefficiency, and 54% energy recovery. The time is reduced to 21 minutes from 22 minutes. Overall, each addition enhances charging performance, stability, robustness, and overall battery performance.

4. Discussion

The study reveals that the proposed intelligent control method, likely ANFIS-FOPID SA-HBA, outperformed standard control methods, metaheuristic optimization methods, and Neuro-Fuzzy methods in battery charging and energy recovery for electric vehicles. The algorithm achieved the highest charging efficiency (98.68%), maximum energy recovery (54%), and expected charging time active stability (98.86%), robustness (98.86%), and the best-performing battery lifespan. The main components, including ANFIS for adaptive control, HBA for tuning and optimum parameters, and Buck-Boost Converter for efficient power conversion, contributed to the system's efficiency, reliability, and the best battery life.

5. Conclusion

A new hybrid control method for managing regenerative energy in electric vehicles is presented, combining an ANFIS with an FOPID controller. The Self-SA-HBA optimizes the integrated controls, resulting in intelligent and robust control of

bidirectional power flow across a DC-DC Buck-Boost converter. The SA-HBA helps maintain a balance between exploitation and exploration, preventing premature convergence and ensuring convergence towards globally-optimal control parameters. This framework is a promising candidate for applications in EVs, contributing to sustainable electric mobility.

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