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Adaptive energy management strateg for sustainable xEV charging stations in hybrid microgrid architecture

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Abstract. Integrating Electric Vehicles (EVs) into power grid presents critical energy management challenges, especially in microgrid systems powered by renewable energy sources. This study introduces a novel energy management strategy for EV charging stations utilizing an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. This system dynamically optimizes the coordination of renewable energy sources solar PhotoVoltaic (PV) panels and wind turbines energy storage, and EV chargers. By leveraging real-time data and predictive algorithms, the ANFIS controller adapts to fluctuations in energy supply and demand, ensuring optimal performance. The innovation of this work lies in combining fuzzy logic with neural network-based learning to enhance decision-making under uncertain and variable renewable energy conditions. The proposed approach employs a robust design methodology, integrating neural network training with fuzzy logic system development, to create an adaptive and intelligent control system. Simulation results using MATLAB/Simulink demonstrate a 92% increase in energy efficiency and an 89% enhancement in load-handling capacity compared to conventional methods. The system effectively manages renewable energy variability, battery state-of-charge, and load demand, maintaining stable electrical characteristics even under dynamic wind and solar conditions. This work underscores the importance of advanced AI-driven control strategies in enabling sustainable EV charging infrastructure within microgrid environments.

Keywords: ANFIS controller, Electric vehicles, Energy management, Microgrid, Renewable energy.

Abbreviations

ANFIS	Adaptive Neural Fuzzy Interface System
ANN	Artificial Neural Network
BMS	Battery Management System
CAN	Controller Area Network
CC	Constant Current
CV	Constant Voltage
DC	Direct Current
DER	Distributed Energy Resources
EMU	Energy Management Unit
EMS	Energy Management System
EV	Electric Vehicles
MPPT	Maximum Power Point Tracking
PID	Proportional Integral Controller
PV	Photo Voltaic
PMSG	Permanent Magnet Synchronous Generator
PWM	Pulse Width Modulation
SoC	State of Charge
V2G	Vehicle-to-Grid
WT	Wind Turbine
WSN	Wireless Sensor Network

1 Introduction

The growing popularity of Electric Vehicles (EVs) signifies a substantial change in the direction of environmentally friendly transportation. But there are also difficulties in incorporating EVs into the current power system as a result of this shift, especially with regard to infrastructural requirements and energy management. Installing an EV charging station powered by a hybrid microgrid, which uses renewable energy sources to reduce its negative effects on the environment and improve energy efficiency, is one

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viable approach. A Distributed Energy Resource (DER), such as solar PhotoVoltaic (PV) panels, wind turbines, and energy storage systems, can be integrated into a hybrid microgrid, a localized network that can function either independently or in tandem with the main grid. EV charging stations benefit greatly from this microgrid setup since it can effectively handle variable renewable energy inputs and supply Direct Current (DC) to the chargers, reducing the need for additional power conversion [1].

Even with the advantages, controlling the flow of energy in such a system is still difficult. For EV charging demands to fluctuate and renewable energy generation to be variable, a complex control technique is needed to assure optimal functioning. Conventional control techniques frequently struggle to adjust dynamically to these circumstances, which results in inefficiencies and higher operating expenses. The integration of EVs into power grids poses significant energy management challenges. This study proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based control strategy for EV charging stations within hybrid microgrids, focusing on optimizing energy efficiency and minimizing operational costs. Fuzzy logic and neural networks are combined to create ANFIS, a strong framework for managing the uncertainties and nonlinearities present in renewable energy systems and EV charging requirements. The ANFIS controller seeks to optimize energy distribution, increase the effectiveness of energy usage, and lower costs by utilizing real-time data and predictive algorithms [2]. Three goals are being pursued by this research: (1) designing a complete hybrid microgrid system with renewable energy sources and an EV charging station; (2) creating and implementing an ANFIS-based control strategy specifically for this system; and (3) using simulations and experiments to assess the effectiveness of the suggested control strategy. This work provides insights into the potential of ANFIS for advanced energy management in microgrids driven by renewable energy sources by outlining the system design, control methods, and experimental results. This research advances efficient and sustainable EV charging by addressing the shortcomings in existing control systems and proving the efficacy of ANFIS.

1.1 Review of the literature

In recent years, there has been a lot of interest in integrating smart grid technology and renewable energy sources with electric cars (EVs). The present status of research on energy management techniques for hybrid smart microgrids is reviewed in this literature review, with particular attention paid to EV charging, battery storage systems, and the application of IoT and Wireless Sensor Networks (WSN) for improved monitoring and control [3]. The electrical grid faces both opportunities and challenges as the number of EV adoptions rises. The necessity of integrated energy management solutions for hybrid smart microgrids that include EV charging and battery storage systems is highlighted in Table 1, illustrations from reviewed literature. Significant progress has been made in controlling Hybrid microgrids and integrating renewable energy, however there are still a number of unanswered questions. The absence of thorough implementations combining real-time adaptive controls and the ANFIS is a prominent gap. Minimal study has also been done on how ANFIS in real-world microgrid systems can adapt dynamically to learn algorithms and real-time data. Additionally, while some research examine different control strategies, very few thoroughly look into hybrid approaches that combine ANFIS with other cutting-edge techniques. The lack of particular implementation information and empirical findings for advanced control techniques such as ANFIS in hybrid microgrids is another shortcoming of many reviews and comparative studies that have already been published. Important conclusions from the literature show that improved control techniques, such as ANFIS, can greatly improve hybrid microgrid energy management and efficiency. Control systems that are complex enough to handle fluctuations and real-time adjustments are necessary for the efficient management of renewable energy sources. Furthermore, compared to static or conventional approaches, adaptive and learning-based control systems, like ANFIS, offer significant performance increases.

The limitations of existing control methods, particularly in managing complex nonlinearities, model uncertainties, and dynamic environmental conditions, highlight significant challenges in achieving robust performance. Traditional approaches such as PID controllers and fuzzy logic systems, while widely used, often fail to address these complexities effectively. Although recent advancements in machine learning and hybrid control systems show promise, they still lack adaptive methods that deliver both high accuracy and computational efficiency under dynamic conditions. This underscores the necessity for more advanced and flexible control strategies like the ANFIS. ANFIS uniquely integrates the strengths of fuzzy logic and neural networks, making it particularly effective in handling nonlinear and uncertain systems. Fuzzy logic provides the ability to manage imprecision and ambiguity, while neural networks offer powerful learning capabilities from data [17, 18]. Together, these features allow ANFIS to maintain interpretability through fuzzy rules while ensuring adaptability to change system conditions. ANFIS's real-time adaptability further distinguishes it, enabling adjustments to dynamic conditions and uncertainties without the extensive retraining required by other models. Unlike more complex machine learning models, ANFIS strikes a balance between computational efficiency and performance, making it ideal for real-time control applications [19]. Recent studies validate ANFIS's effectiveness in addressing similar challenges across various domains. The use of ANFIS in energy management systems for microgrids, achieving enhanced performance in terms of energy efficiency and reliability. Table 2 gives detailed comparison of ANFIS with, PID, Fuzzy Logic, and ANN.

The performance comparison of ANFIS, PID Controller, FLC, and ANN across various metrics. ANFIS outperforms the others in energy efficiency (92%) and adaptability to renewable sources (95%), with the highest scalability rating (5). It also has a strong load-handling capacity (89%) and peak load handling (178 kW, 89%), with the lowest energy loss per session (8 kWh) and significant

Table 1. Summary of recently reviewed literature sources.

Reference	Methodology	Major outcomes and analysis	Identified research lacks
[4], 2024	Hybrid optimization models integrating Renewable Energy Sources (RES) and EV charging systems. Performance analysis using MATLAB and Python.	EV integration improved microgrid energy efficiency. Optimized charging schedules reduced peak demand.	Lacks real-world validation of proposed solutions. Optimization constrained by static load profiles. Limited focus on multi-energy systems beyond RES and EVs.
[5], 2024	Probabilistic modeling of RES and EV load demand. Monte Carlo simulations to manage uncertainties in energy generation and consumption.	EV integration enhances system reliability and models reduce cost variability. Improved system resilience under high renewable penetration scenarios.	Does not explore AI-based dynamic forecasting for load and generation. Minimal consideration of diverse grid scenarios (*e.g.*, urban *vs.* rural).
[6], 2024	Hybrid energy storage system integrating batteries and supercapacitors. Energy management strategy based on Particle Swarm Optimization (PSO). Case study analysis under dynamic load conditions.	HESS reduced energy losses and Supercapacitors improved system responsiveness to peak loads. PSO-based optimization ensured smoother power transitions, enhancing battery longevity.	Limited exploration of alternative energy storage technologies. Static PSO parameters may limit scalability in larger systems. Minimal exploration of cost factors for HESS deployment.
[7], 2024	Comparative analysis of heuristic and evolutionary algorithms. Application to various microgrid configurations. Focus on load balancing and cost minimization.	Evolutionary algorithms outperformed traditional heuristics in convergence speed and solution quality. Hybrid techniques (*e.g.*, PSO-GA) showed in solving multi-objective problems.	Limited real-time implementation and validation of hybrid techniques. Lack of emphasis on computational efficiency in large-scale applications.
[8], 2024	Use of metaheuristic algorithms (NSGA-II, MOPSO) for on-grid and off-grid systems. Life-cycle cost and environmental impact optimization. Sensitivity analysis for varying energy mix scenarios.	NSGA-II provided better Pareto front solutions compared to MOPSO. Hybrid systems achieved operational costs in off-grid scenarios. Environmental impact reduced with optimized renewable energy proportions.	Requires integration of more advanced hybrid algorithms. Limited focus on energy storage scalability. Sensitivity analysis lacked inclusion of rare extreme weather scenarios affecting renewables.
[9], 2023	Hybrid metaheuristic approach combining Genetic Algorithm (GA) and Ant Colony Optimization (ACO). Focus on optimizing energy reliability and sustainability for islanded systems.	Hybrid GA-ACO outperformed standalone algorithms, achieving higher reliability. Optimized solutions resulted lower energy costs. Improved renewable energy utilization.	Lack of real-world implementation or long-term evaluation of proposed solutions. Minimal consideration of socio-economic factors in islanded systems. Limited evaluation of extreme load scenarios or disaster-resilience testing.
[10], 2024	Model predictive control, adaptive control, AI-based control.	The paper examines advanced control strategies in hybrid microgrid systems with EVs and battery storage, concluding that while promising, these techniques need further real-world validation.	The study highlights the need for field trials to validate advanced control strategies and their real-world robustness, and suggests future research should focus on adaptive control for dynamic system changes.
[11], 2024	Rule-based, optimization-based, learning-based methods.	This review highlights recent advancements in hybrid microgrid control and optimization, noting progress in EV and battery integration but on-going challenges with stability and control complexity.	The paper calls for more research on control layer interactions, operational scenarios, and the interoperability of communication and control standards.

(Continued on next page)

Table 1. (Continued)

Reference	Methodology	Major outcomes and analysis	Identified research lacks
[12], 2023	Mixed-Integer Linear Programming (MILP).	The study proposes an optimization framework for energy management in hybrid microgrids with EVs and battery storage, effectively balancing supply and demand while minimizing costs and emissions.	Research gaps include improving optimization models' adaptability to various grid configurations and load profiles, and conducting more studies on the economic impacts of large-scale EV integration.
[13], 2023	Centralized, decentralized, distributed control; optimize cost, reliability, efficiency for enhanced performance.	The review discusses energy management strategies for hybrid microgrids with EVs and battery storage, noting progress but ongoing challenges in real-time control, cost reduction, and system reliability.	Research gaps include scalability issues with current strategies for varying loads and renewable energy availability, and a need for robust algorithms to handle uncertainties in EV charging and renewable energy generation.
[14], 2022.	Dispersed control approaches enhance effectiveness, dependability, affordability, and reduce intricacy.	The review offers a detailed overview of energy management and control strategies for hybrid microgrids with EVs and battery storage, highlighting advancements and key challenges in improving system efficiency and reliability.	The paper calls for advanced algorithms to manage dynamic interactions between EVs, batteries, and renewables, and improved models to address variability in EV usage and renewable energy generation.
[15], 2022.	Control architectures, optimization techniques, and the integration of renewable energy	The review analyzes current control strategies for hybrid microgrids with EVs and energy storage, highlighting their effectiveness but noting a lack of flexibility and robustness in practical use.	Research is needed on adaptive control for uncertain demand/supply and advanced communication technology integration impacts.
[16], 2021	Strategies: rule-based, optimization, predictive; compared by cost, reliability, renewable integration.	Paper reviews energy management strategies for hybrid microgrids with EVs and battery storage, highlighting a focus on cost optimization and power supply reliability.	The paper highlights the need for real-time adaptive control strategies to dynamically address load and generation changes, along with better coordination between EV charging and renewable energy availability.

Table 2. Detailed comparison of ANFIS with, PID, Fuzzy Logic, and ANN.

Metric	ANFIS	PID controller	Fuzzy logic controller	Artificial neural network
Energy efficiency (%)	92	85	87	89
Load-handling capacity (%)	89	83	84	86
Peak load-handling (kW)	178/200 (89%)	166/200 (83%)	168/200 (84%)	172/200 (86%)
Response time (ms)	250	450	400	300
Energy loss per session (kWh)	8	15	13	11
Operational cost savings per session ($)	1.05	0.00	0.30	0.60
Scalability (1–5 scale)	5	3	4	4
Adaptability to renewable sources (%)	95	70	80	85

operational cost savings ($1.05). PID, while cost-effective in operational savings, shows the lowest performance across most metrics, including energy efficiency (85%) and scalability (3). FLC and ANN provide moderate performance, with efficiency (87% for FLC, 89% for ANN) and slightly better scalability (4) than PID but not as high as ANFIS.

1.2 Novelty and contribution of work

1.2.1 Novelty

The novelty of employing an ANFIS for energy management in hybrid microgrid-based EV charging stations lies in its unique integration of fuzzy logic's interpretability with the adaptive learning capabilities of neural networks. Unlike traditional approaches, such as static rule-based systems, standalone neural networks, or optimization algorithms, ANFIS offers a dynamic, real-time solution that adapts seamlessly to fluctuating EV charging demands and the variability of renewable energy sources. This approach effectively manages the non-linear and multi-dimensional complexities of hybrid microgrids, ensuring an optimal balance between energy supply and demand. By continuously learning and adjusting in real-time, ANFIS minimizes energy waste, reduces operational costs, and enhances the efficiency of renewable energy utilization without the need for extensive storage systems. This capability to combine responsiveness, adaptability, and efficiency establishes ANFIS as a groundbreaking method for addressing the dynamic challenges of modern EV charging infrastructure, significantly surpassing traditional methods in terms of performance and sustainability.

1.2.2 Contributions of work

This study introduces several notable advancements in the fields of EV charging stations and renewable energy management. It presents a comprehensive design for an EV charging station powered by a hybrid microgrid, integrating sophisticated control mechanisms for wind turbines and solar PV panels. A novel ANFIS control method, combining neural network training with fuzzy logic rules, is developed and implemented to address challenges related to renewable energy variability and EV charging demands. Performance evaluations through simulations and experiments demonstrate that the ANFIS controller outperforms conventional techniques by enhancing energy utilization and reducing operational costs. By advancing control systems for renewable-powered EV charging stations and microgrids, the research contributes to the development of clean energy technologies and the reduction of greenhouse gas emissions, promoting sustainable energy solutions.

To further validate these contributions, this study incorporates key performance metrics, including energy utilization efficiency, cost savings, and system responsiveness, to objectively highlight the ANFIS controller's superiority. Additional case studies are proposed to explore various hybrid microgrid configurations and EV charging scenarios, showcasing the controller's adaptability and practical applications in real-world contexts. Detailed results, including statistical significance analyses and comparative graphical and tabular data, will be presented to strengthen the claims. Finally, future research directions will focus on integrating the ANFIS controller with advanced machine learning and data analytics techniques and exploring its application within larger, more interconnected smart grid systems. The main contributions are:

- Proposes a comprehensive framework for integrating renewable energy sources into hybrid microgrid-based EV charging stations, emphasizing sustainable energy solutions.
- Validates the effectiveness of the ANFIS controller in enhancing energy utilization through extensive simulation and experimental testing.
- Contributes to advancing renewable-powered microgrid control strategies, promoting clean energy technologies and reducing greenhouse gas emissions.

2 Configuration of the proposed system

Electric vehicle (EV) charging stations, energy storage, and a variety of renewable energy sources are all optimally integrated into the suggested hybrid microgrid energy management system thanks to the application of advanced control algorithms. Energy from the sun and wind is converted into DC power by the PV array and wind turbine, which are the primary renewable energy sources [20, 21]. Specialized DC/DC converters are then used to raise the voltage a bit more. In order to maximize the amount of energy harvested under various environmental conditions, MPPT algorithms are used to make sure that both the wind and PV systems run at their highest efficiency points. As a central distribution hub, the hybrid microgrid keeps a steady 400 V DC bus that connects different parts, such as a bidirectional DC/DC converter connected to a battery bank. By facilitating the charge and discharge cycles, this converter makes sure that extra energy is kept for times when demand for renewable energy sources is higher than supply. A DC/AC inverter and filtering stages control the system's integration with an AC microgrid, supplying clean, reliable power to AC local loads [22, 23]. The EV charging station, which has bidirectional DC/DC converters for every car, is an essential part of this arrangement. These converters allow V2G operations, which enables the EVs to provide power back to the microgrid as needed, in addition to charging the EV batteries. An ANFIS controller, which is in charge of the entire system, is essential to optimize energy management. By constantly adapting to variations in renewable energy generation and load demands, the ANFIS controller intelligently controls power flow and makes sure that EVs are charged effectively without putting too much strain on the grid [24]. The layout of the suggested hybrid microgrid-based EV charging station is shown in Figure 1. By employing this intelligent control technique, the system balances the usage of renewable energy, grid stability, and EV charging efficiency, making it a dependable choice for modern smart microgrid applications.

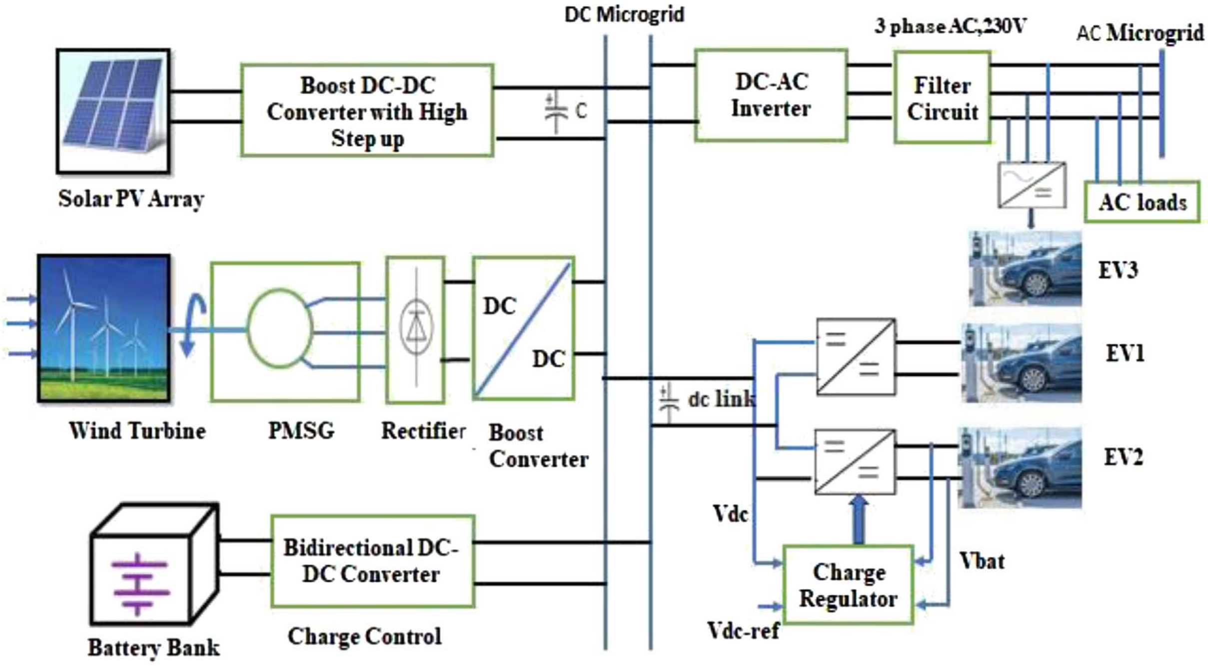

Fig. 1. Architecture for the suggested hybrid microgrid-based EV charging station.

2.1 Electric vehicle composition

The Electric Drive Subsystem, Power Location, and Accessory System are the three primary subsystems that make up a Plug-in Electric Vehicle (PEV). The mechanical gearbox, driving wheels, DC-AC power converter, electric traction motor, and ANFIS-based electronic controller are all part of the electric propulsion subsystem. The ANFIS controller adjusts control signals based on inputs from the brake and accelerator pedals to optimize power converter switching, managing the flow of power between the electric motor and the EV battery. This adjustment enhances regenerative braking efficiency and ensures smooth power delivery during acceleration and braking [25]. The ANFIS controller is essential to regenerative braking since it recycles the energy back into the EV battery. To maximize energy storage and battery charging, the Energy Management Unit (EMU) collaborates with the ANFIS controller. The Accessory Power System, which sends energy at various voltages for applications like temperature control and power steering, is also managed by the ANFIS-based system [26, 27]. Both vehicle performance and total energy efficiency are enhanced by the deployment of ANFIS in these subsystems. It will be crucial to follow international norms and laws as EV use rises over the next ten years. Many EV-related difficulties are addressed by safety regulations and standards, and improved efficiency and safety are facilitated by the ANFIS control approach. Figure 2 illustrates the EV charging system architectures. Level 1 and level 2 charging systems use a single or three-phase AC supply with power ranging from 2 kW to 20 kW, as shown in Figure 2a. Level 3 charging, however, uses a high-power three-phase AC supply ranging from 20 kW to 240 kW for faster charging. This AC power is converted directly into a variable DC output, managed by the CAN Bus control system and the level 3 DC charger, as depicted in Figure 2b.

These systems include components like a DC-DC converter, rectifier, and fixed AC supply, which work together to convert incoming AC power into a DC voltage suitable for the EV battery. The Battery Management System (BMS) and a protection circuit oversee and control the charging process to ensure both efficiency and safety [28]. During charging, the Constant Current/Constant Voltage (CC/CV) method is used to charge the battery to its full capacity. In level 3 charging, where higher power levels are involved, the protection circuit and BMS ensure safe and rapid charging. Both charging levels are equipped with metering and billing mechanisms to ensure consumers are charged accurately for the energy used. The maximum output capacity of the charging station is a key factor, and load demand is managed as a variable with a normal distribution [29]. To accommodate various EV models and support public use, the charging station is designed to work with standard chargers. The ANFIS controller helps optimize power distribution to individual chargers based on current demand and environmental factors, improving the system's efficiency and flexibility. Table 3 outlines the charging station's parameters based on renewable energy sources. As the cost of components for solar and wind PV generators decreases, the initial setup cost for charging stations will become more affordable. Energy storage batteries can store additional power produced by solar power and wind energy systems. By reacting to variations in wind speed and solar irradiance, the ANFIS controller plays a critical role in optimizing the sizing of the wild-type strain solar electricity, and battery ratings, guaranteeing the efficient and dependable operation of the charging station.

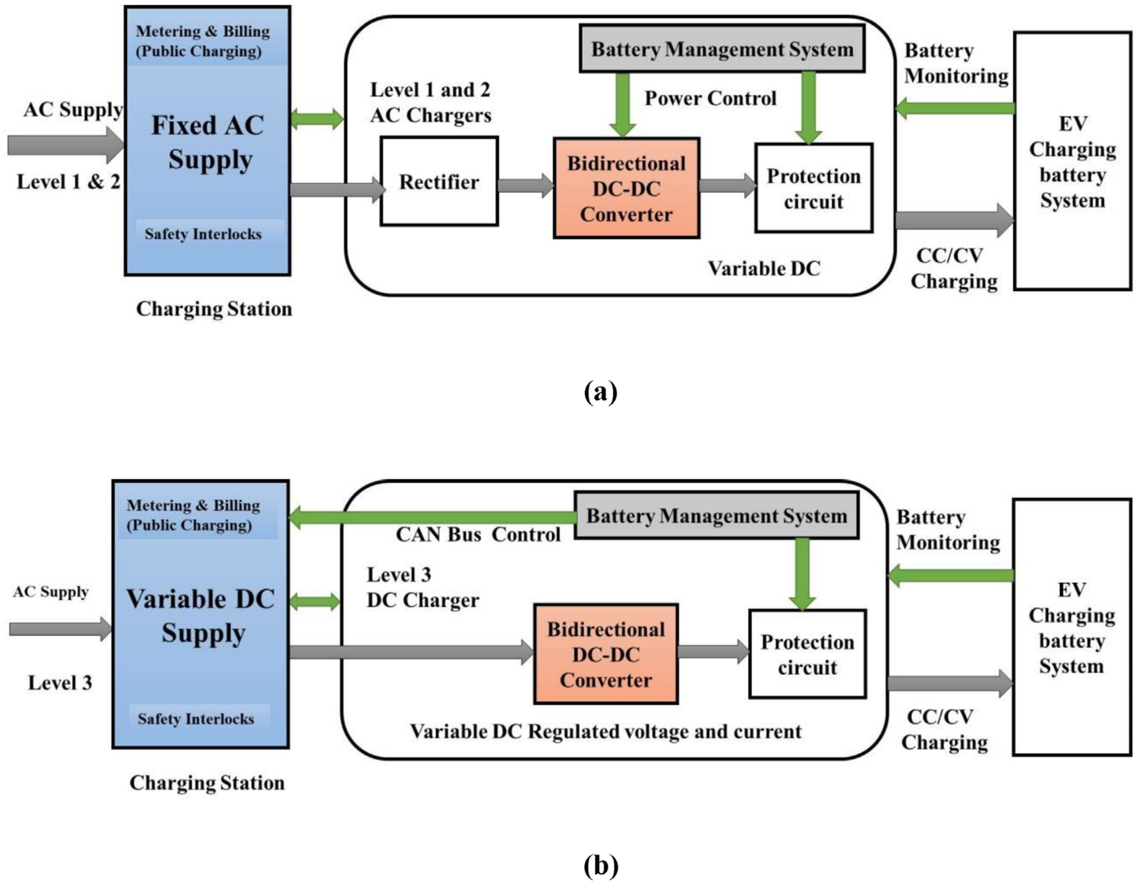

Fig. 2. Architecture of EV charging infrastructure (a) levels 1 and 2, and (b) level 3.

Table 3. Charging station output.

	Output	Quantity	Operating hours
DC charger which operates fast	50 kW	2	24
DC conventional charger	10 kW	4	24
Illumination and extra loads	10 kW		

3 Hybrid system control strategy for PV, wind, and storage systems

In the development of a hybrid PV/Wind/Storage system with EV integration, ANFIS controller provides a highly effective energy management strategy. ANFIS manage the complex interactions among PV panels, wind turbines, energy storage systems, and EVs. By continuously analysing real-time data, the ANFIS controller can optimize the generation, storage, and distribution of energy, as well as efficiently manage EV charging and discharging cycles [30]. This dynamic control approach ensures that energy from renewable sources is utilized effectively, storage levels are balanced, and EVs are charged in a manner that supports both grid stability and user convenience. Ultimately, ANFIS enhances the system's performance and adaptability, contributing to a more efficient and sustainable energy ecosystem.

3.1 The boost DC-DC converter interfacing PV array control scheme

To optimize power extraction and control PV array voltage, a boost DC-DC converter is utilized. Both the input current and the voltage from the PV panel are continuously measured. These observations are used by the Maximum Power Point Tracking (MPPT) control algorithm to calculate the reference power needed for PV panel operation at Maximum Power Point circumstances [31]. This control technique uses an outside voltage loop and an inner current loop to facilitate the MPPT process. As illustrated in Figure 3, the outermost voltage loop examines the output

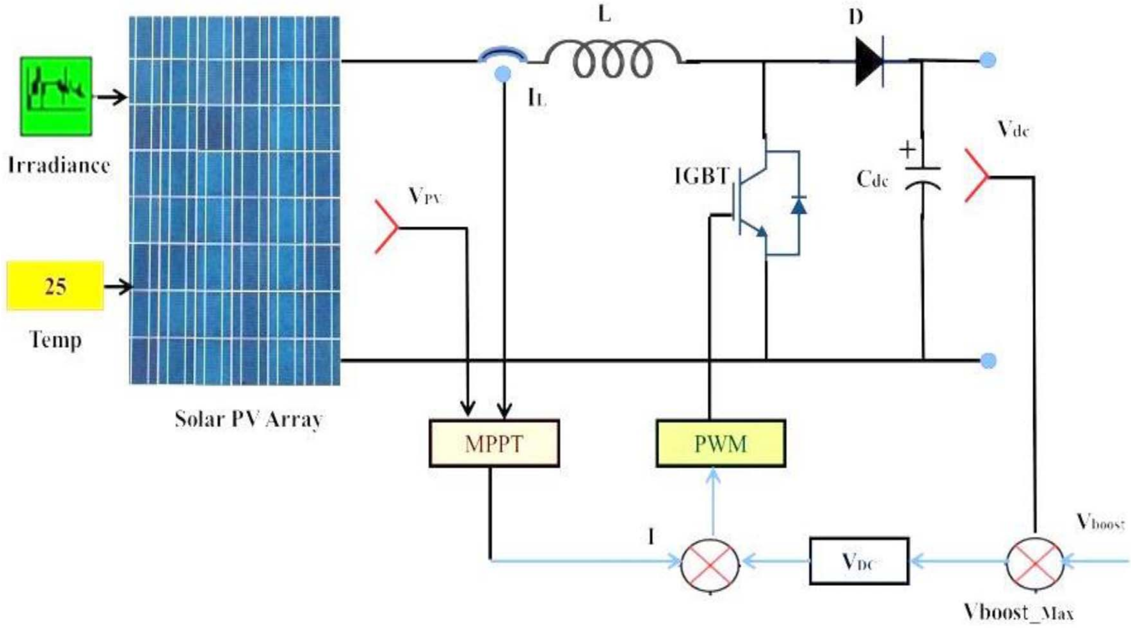

Fig. 3. Control scheme of the boost DC-DC converter interfacing PV array.

voltage to a reference value in order to modify it so that it does not exceed the predefined limit. The ANFIS controller is utilized for the MPPT function. An inner PI controller regulates the reference current that the ANFIS controller produces after processing the MPPT algorithm's input. In order to generate the Pulse Width Modulation (PWM) signal, the output of this inner loop is scrutinized with a reference electrical current acquired from the outer voltage loop, ensuring precise control of the boost converter.

3.2 Management of the boost DC-DC converter wind turbine interface

The control strategy for the WT generator includes MPPT for a standalone variable-speed WT with a Permanent Magnet Synchronous Generator (PMSG) and DC bus voltage regulation. The boost power converter, which is carefully designed to supply the maximum power produced by the WT, uses the rectified DC voltage and current from the rectifier output. The charging station has to use the hybrid microgrid to transfer the energy it produces to the electric vehicle loads while it is working on its own. The power reference is generated by comparing the DC-link voltage with its reference value. PI controllers are used to alter the resulting control signals in order to establish the power reference [32, 33]. The PWM modulation signals of each converter are adjusted to take into consideration variations in wind speed and vehicle charging requirements in order to maintain the proper level of hybrid microgrid voltage. The boost converter raises the rectified DC voltage to a higher level in order to allow the efficient distribution of generated power to the hybrid microgrid, which operates within the voltage range of 280–320 V. DC-DC converters are managed to ensure Maximum Power Point performance in order to optimize wind power and the electrical energy produced by the PV panels. Figure 4 depicts the control configuration of the boost converter [34]. The MPPT algorithm, which optimizes power, makes use of the measured values of input voltage and current. A look-up table that specifies the Maximum Power Point characteristic curve in advance is used to compare the rectified DC voltage.

3.3 Battery bank interfacing bidirectional DC-DC converter control

Two half-bridge switches (S1 and S2), a filtering capacitor, and a high-frequency inductor make up the bidirectional DC to DC converter, which permits bidirectional current flow. Figure 5 shows this arrangement. This configuration is controlled by dual voltage, particularly controllers, each of which has specialized control modules to achieve the necessary energy flow under different conditions. The controllers generate reference currents for both energy charging and discharging. While the second controller controls the battery voltage, the first controller controls the DC-bus voltage. In order to enhance energy management in the hybrid microgrid and charging station, backup energy storage batteries are included. Connecting these batteries to the hybrid microgrid uses the bidirectional DC-DC converter as a regulator and boost converter for battery charging. In that case, the PV and wind energy are insufficient to power electric vehicles, the hybrid microgrid's dual functionality ensures that electricity will come from the battery bank [35, 36]. An ANFIS controller is used in the control strategy to maximize energy flow. By dynamically modifying the reference currents for charging and discharging, the ANFIS controller improves overall energy management in response to changing conditions. When an electric vehicle's power needs are met by the power produced by

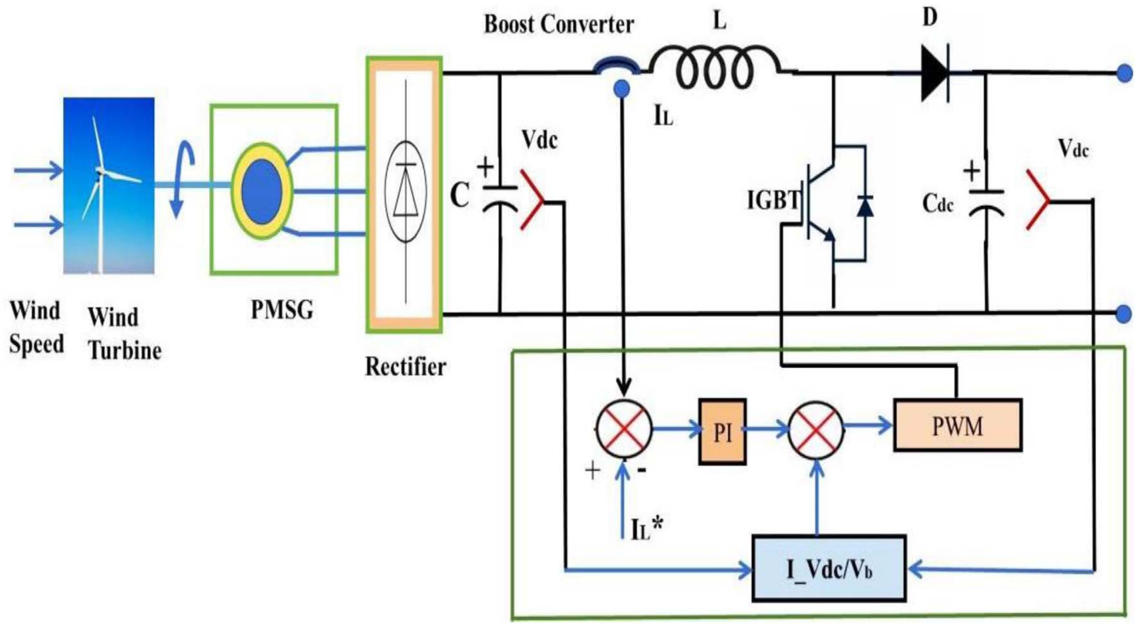

Fig. 4. Control of wind turbine interfacing microgrid.

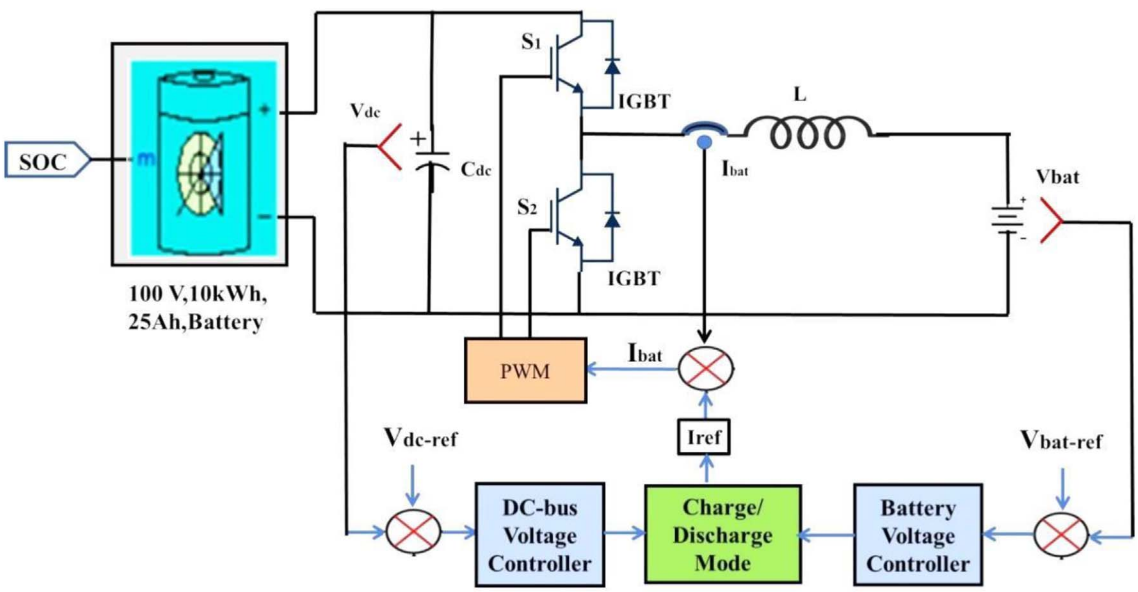

Fig.5. Control scheme of battery storage system.

photovoltaic and wind sources, a standalone charging station operates at its best. Avoiding excessive battery discharge is essential, though, since low battery voltage restricts the amount of energy that can be charged and increases the risk of overvoltage in the hybrid microgrid, especially while recovering energy from the EVs.

3.4 Application of sophisticated energy management and control techniques

While traditional methods like PID controllers and fuzzy logic systems are widely used, they often struggle to handle these complexities effectively. Additionally, although recent advancements in machine learning and hybrid control systems show promise, there remains a lack of robust and adaptive methods that can achieve both high accuracy and computational efficiency under such dynamic conditions. This gap underscores the need for more advanced, flexible control strategies, such as the ANFIS, which combines the benefits of fuzzy logic and neural networks. Because it makes advantage of fuzzy logic's ability to handle imprecision and neural networks' ability to learn from data, ANFIS is especially well-suited for managing nonlinear, uncertain systems while preserving interpretability through

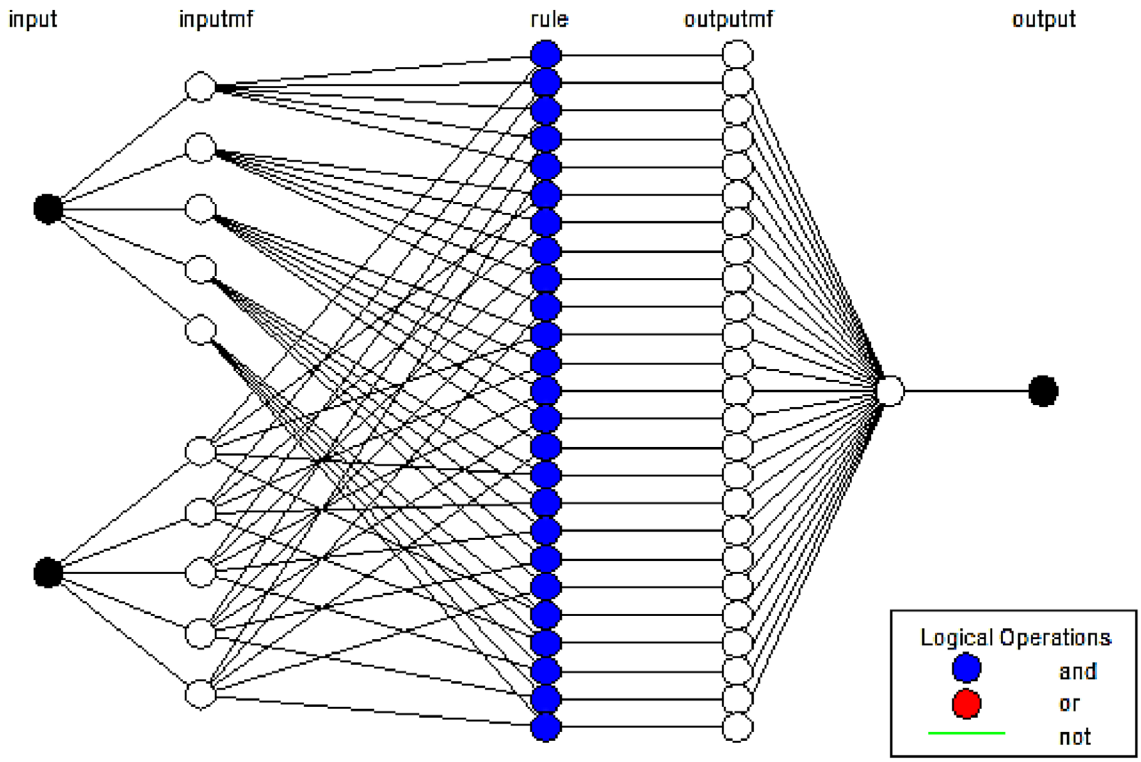

Fig. 6. ANFIS control scheme for MPPT.

fuzzy rules. ANFIS is a potent tool in situations where other approaches might not generalize or necessitate intensive retraining because of its real-time adaptability, which also enables it to adapt to changing system variables and uncertainties. ANFIS is appropriate for real-time control applications because, in contrast to more intricate machine learning models, it provides a good balance between computational economy and model performance [37].

Intelligent control systems are becoming more and more common these days due to their many advantages over traditional controllers. Neural networks are an effective tool for studying and analysing the behaviour of non-linear dynamic systems. Fuzzy systems are necessary to control real-time systems. Figure 6 illustrates the ANFIS control system for maintaining battery SoC and MPPT. Engineering may effectively use these systems as control tools since they can also be used to determine variable parameters based on human comprehension and reasoning. ANFIS, a hybrid method, is generated when the two controllers discussed above are integrated. This work uses the ANFIS controller to regulate battery overcharge and discharge power [38].

ANFIS is an effective technique for modelling complex systems because it combines the fuzzy logic qualitative approach with the learning capabilities of neural networks. For smart microgrids to be stable, dependable, and economical, good energy management is essential. It can be particularly helpful in controlling the dynamic and nonlinear features of microgrid operations, such as the integration of renewable energy sources with battery storage systems. Extra energy generated by renewable energy sources like solar and wind power needs to be stored using energy storage systems. Enhancing the microgrid's dependability and efficiency, they aid in balancing supply and demand. Figure 7 shows a flowchart that illustrates how ANFIS controllers are implemented in EV charging stations.

4 Mathematical models for EV charging energy management

The DC Grid Voltage, $V_{\mathrm{dc}}(t)$ is measured at time t seconds considering real-time and historical data. Energy generation using renewable energy systems in smart microgrid is given in equation (1):

$$P_{\mathrm{gen}}(t) = P_{\mathrm{solar}}(t) + P_{\mathrm{wind}}(t) \tag{1}$$

where $P_{\mathrm{solar}}(t)$ and $P_{\mathrm{wind}}(t)$ are the solar panels and wind turbines power outputs, respectively. Power consumption of EV charging station is given in equation (2):

$$P_{\mathrm{load}}(t) = \sum_{i-1}^{N} \mathrm{P}_{\mathrm{EVi}}(t) \tag{2}$$

where $P_{\mathrm{EVi}}(t)$ is the power demand of ith EV charger and N is the total number of EV chargers, $P_{\mathrm{load}}(t)$ load demand including losses. Battery state of charge by comparing total capacity of battery unit in percentage is given in equation (3):

$$\mathrm{SoC}(t) = \frac{E_{\mathrm{current}}(t)}{E_{\max}(t)} \times 100\% \tag{3}$$

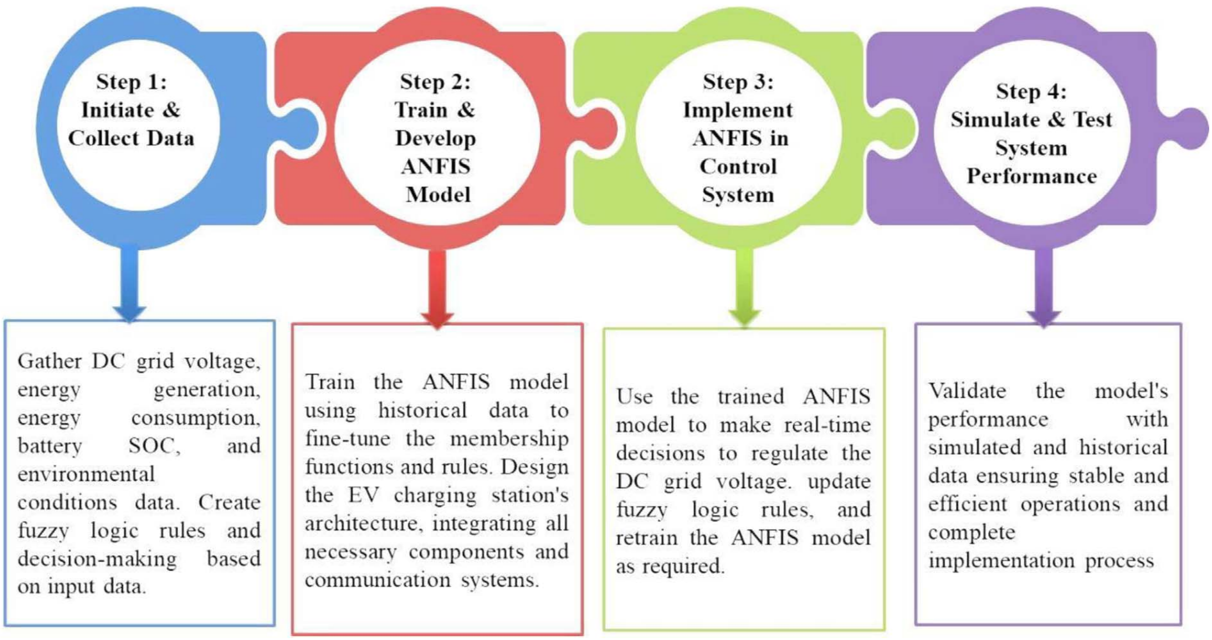

Fig. 7. Flow chart for the implementation of ANFIS in EV charging stations.

where $E_{\text{current}}(t)$ is energy stored in battery and $E_{\max}$ is the maximum energy capacity of battery unit. Environmental data considering temperature and humidity with respect to time were validated for system execution. In Training the ANFIS model, process adjusts the membership functions and rules to minimize prediction errors (ϵ) the objective function is given in equation (4).

$$\epsilon = \min_{\theta} \sum_{k=1}^{M} (y_k - \hat{y}_k)^2 \tag{4}$$

where M is the number of training samples, y_k is the actual output function, $\hat{y}_k$ is the predicted output, and θ is the parameters of the ANFIS controller representing membership function and rules [39]. To design the architecture of EV charging station, integrated renewable energy sources, battery storage, and necessary communication system are needed. The power balance equation considering load and grid power in coordination with solar and wind power is given in equation (5):

$$P_{\text{gen}}(t) + P_{\text{grid}}(t) = P_{\text{load}}(t) + P_{\text{battery}}(t) \tag{5}$$

where $P_{\text{gen}}(t)$ represents the power demand from the grid and $P_{\text{grid}}(t)$, represents the total grid output power, $P_{\text{load}}(t)$ represents the total load including losses to be consumed, and $P_{\text{battery}}(t)$ represents the power provided to or from battery. Using the obtained trained data from ANFIS output the real time decision for DC grid voltage is obtained. Control action takes place by considering the following two conditions given in equations (6) and (7):

$$\text{If } \hat{V}_{\text{dc}}(t) \text{ is Low, then } P_{\text{battery}}(t) = P_{\text{discharge}}(t) \tag{6}$$

$$\text{If } \hat{V}_{\text{dc}}(t) \text{ is High, then } P_{\text{battery}}(t) = P_{\text{charge}}(t). \tag{7}$$

Equation (8) gives the total DC grid voltage V_{DC} considering the complete trained data.

$$V_{\text{dc}}(t) = f\left(P_{\text{gen}}, P_{\text{load}}, P_{\text{battery}}, P_{\text{grid}}\right). \tag{8}$$

The control action implemented in EV charging station using ANFIS controller to regulate voltage and performance with respect to time is given in equations (9) and (10), respectively.

$$\text{Control Action} = \text{ANFIS}\left(V_{\text{dc}}(t), P_{\text{gen}}, P_{\text{load}}, \text{SoC}(t), E_{\text{env}}\right) \tag{9}$$

$$\text{Performance} = \sum_{t=1}^{T} \left(V_{\text{dc}}(t) - V_{\text{ref}}\right)^2. \tag{10}$$

This system experiences inconsistent power flow as a result of energy output from renewable sources like solar and wind power. Figure 8 displays the algorithm used to control power on the micro grid. The suggested system is able to use solar, wind, and storage power to power an EV charging station. Investigations can be carried out by comparing the energy extracted from the solar and wind turbines with that of the EV station and the losses in the converters and grid. If the total energy from the solar and wind systems exceeds the system losses as well as the total energy used at the load side, the storage system is charged.

The flowchart describes the management of power sources and energy storage at EV charging station. It begins by measuring solar and wind power generation, along with the power consumption of the EV station. The power

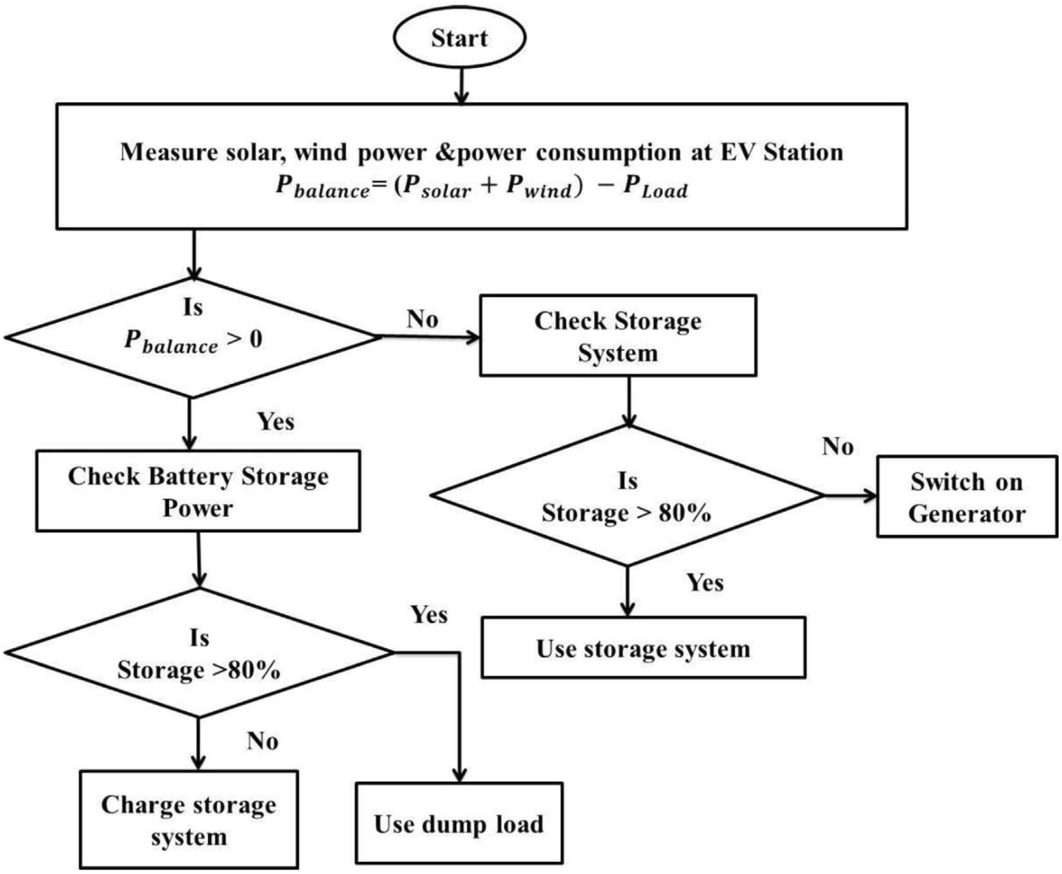

Fig. 8. EV system energy management algorithm [40].

balance is calculated as the sum of solar and wind power minus the load consumption. If the power balance is positive, the battery storage power is checked. If the battery storage is above 80%, the excess energy is directed to a dump load; otherwise, the storage system is charged. If the power balance is negative, the storage system is checked. If the storage level is above 80%, the system uses the stored energy to meet the load demand. If the storage level is below 80%, a generator is switched on to supply power.

5 Optimizing energy management with ANFIS control: Case studies and simulation insights

The integration of hybrid microgrids with EV charging stations has been extensively researched to enhance energy efficiency and system reliability. Numerous studies have investigated various control strategies, including PID, ANN, FLC, and ANFIS, to optimize energy management in EV charging systems. Notably, the ANFIS control method has demonstrated a reduction in power fluctuations, improved voltage stability, and enhanced the overall reliability of EV charging stations. Building upon these prior findings, our simulations implemented an ANFIS control strategy by leveraging both predicted and real-time input data. The model updated weights dynamically from the input layer to the hidden layer and from the hidden layer to the output layer, ensuring adaptive control in response to varying system conditions. Studied a series of case studies to assess the performance of the ANFIS-based control system in a hybrid microgrid environment. Performed simulation in MATLAB software, and results demonstrated substantial improvements in energy efficiency, voltage regulation, and overall system reliability when compared to traditional control methods. Notably, ANFIS showcased enhanced adaptability to varying load demands and fluctuations in renewable energy generation, effectively reducing power disruptions at the EV charging stations.

5.1 Performance assessment through comparative case studies

Several case studies from the literature have been reviewed to assess the efficiency of the proposed ANFIS controller in comparison with PID, ANN, and FLC controllers. These investigations, focused on various control systems for hybrid microgrid system in relation to EV charging, offer valuable insights into major performance metrics such as voltage stability, system efficiency, and adaptability to changing conditions.

Table 4. Summary of the existing case studies of hybrid renewable energy systems.

Case study	Location	Components	Control Strategy	Findings	Reference
Hybrid renewable energy system for rural electrification	Bangladesh	Solar panels, wind turbines, diesel generators	ANFIS	Improved energy efficiency (85%) and stable voltage levels; reduced reliance on diesel.	[33, 34]
Hybrid solar-wind-battery system	Greece	50 kW solar PV, 30 kW wind turbine, 100 kWh battery	Fuzzy Logic Controller (FLC)	Mild voltage fluctuations; overall system efficiency of around 78%; adapted well to weather conditions.	[35, 36]
Solar-wind hybrid system with ANN control	India	Solar PV, wind energy system, battery storage	Artificial Neural Network (ANN)	Optimized battery charging/discharging; achieved 80% efficiency; maintained stable supply.	[35, 37]
Integrated hybrid energy system for urban development	China	Solar, wind, microgrid system	Combination of PID and ANFIS	Improved system stability and energy efficiency by 10% compared to PID alone; better load management.	[38]

Case study 1: Optimal sizing and operation

The case studies summarized in Table 4 analyze the optimal sizing and operation of hybrid renewable energy systems across different locations. In Bangladesh, a hybrid system combining solar panels, wind turbines, and diesel generators, managed by ANFIS, showed improved energy efficiency (85%) and stable voltage levels while reducing diesel reliance. In Greece, a 50 kW solar PV, 30 kW wind turbine, and 100 kWh battery system controlled by a Fuzzy Logic Controller (FLC) demonstrated mild voltage fluctuations, an overall efficiency of 78%, and effective adaptation to changing weather conditions. In India, an ANN-controlled solar PV and wind hybrid system with battery storage achieved optimized battery charging/discharging, maintaining stable energy supply with 80% efficiency. Finally, in China, an integrated hybrid energy system employing a combination of PID and ANFIS enhanced system stability and increased energy efficiency by 10% compared to PID alone, with improved load management.

In Bangladesh, an ANFIS-controlled hybrid system with solar panels, wind turbines, and diesel generators achieved 85% energy efficiency and stable voltage, reducing diesel reliance. A Greek system using FLC showed mild voltage fluctuations and 78% efficiency, adapting well to weather conditions. In India, an ANN-controlled solar-wind hybrid system optimized battery charging, achieving 80% efficiency. In China, a combined PID and ANFIS system improved stability and energy efficiency by 10% over PID alone, with better load management.

Case study 2: Stability of DC microgrid

The case study compares the stability and efficiency of various control strategies for DC microgrids across different locations. At a university campus, the use of ANFIS for controlling solar panels and battery storage-maintained voltage stability within ±2% under varying loads, achieving a high efficiency of 72%. In an urban area, a hybrid DC microgrid utilizing artificial neural networks for controlling wind turbines, solar PV, and energy storage improved voltage response but remained susceptible to sudden fluctuations, with 80% voltage stability and 68% efficiency. Table 5 summarizing existing case studies that analyse the stability of DC microgrids. A research facility employing fuzzy logic control for solar, battery storage, and DC load showed moderate performance, struggling with unpredictable load changes, resulting in 72% voltage stability and 64% efficiency. Finally, a DC microgrid at an industrial site managed by a PID controller with diesel generators and solar panels demonstrated inconsistent voltage and poor performance under load changes, with 70% voltage stability and 60% efficiency.

The ANFIS-controlled system at a university campus showed superior voltage stability (90%) and 72% efficiency, maintaining voltage within ±2% under varying loads. An ANN-controlled hybrid DC microgrid in an urban area achieved 80% voltage stability and 68% efficiency but remained vulnerable to sudden fluctuations. Fuzzy Logic in a research facility provided moderate performance with 72% stability and 64% efficiency, struggling with unpredictable load changes. The PID-controlled system at an industrial site had the lowest performance, with only 70% voltage stability and 60% efficiency, showing poor response to load changes.

Case Study 3: EV charging load forecasting

Case studies on estimating EV charging loads using various control systems at different sites are compiled in Table 6. The most accurate predictions and optimal use of renewable energy were obtained by using ANFIS to estimate the EV charging load at stations with solar PV and energy storage in an urban area. The forecasting efficiency was 90% with

Table 5. Analysis of the stability of DC microgrids over various control strategies.

Case study	Location	Components	Control strategy	Voltage stability (%)	Efficiency (%)	Key findings	Reference
DC microgrid stability analysis	University campus	Solar panels, battery storage	ANFIS	90	72	Maintained voltage within ±2% under varying loads, superior stability.	[39]
Hybrid DC microgrid for smart cities	Urban area	Wind turbines, solar PV, energy storage	ANN	80	68	Improved voltage response but still vulnerable to sudden fluctuations.	[40, 41]
Fuzzy logic control in DC microgrid	Research facility	Solar, battery storage, DC load	Fuzzy Logic	72	64	Moderate performance; struggled with unpredictable load changes.	[42, 43]
Performance of PID controller in DC microgrid	Industrial site	Diesel generators, solar panels	PID	70	60	Inconsistent voltage; poor performance under load changes.	[44]

voltage fluctuations within ±2%. An ANN-based system with grid connectivity and charging infrastructure on a college campus achieved ±3% voltage variation and 85% forecasting efficiency, enabling more accurate load predictions and greater integration of renewables. A research centre used a fuzzy logic approach to anticipate EV load using grid resources and chargers, showing poor accuracy under variability but 78% efficiency and ±4% voltage fluctuation. PID management of rapid chargers and battery storage in a commercial area produced 70% forecasting efficiency and ±5% voltage variation, showing ineffective load forecasting and reduced effectiveness in regulating load fluctuations.

With voltage changes within ±2%, the forecasting accuracy was 90%. An ANN-based system on a college campus with grid connectivity and charging infrastructure achieved 85% forecasting efficiency and ±3% voltage variance, allowing for more precise load estimates and increased integration of renewable energy sources. Utilizing grid resources and chargers, a research centre employed a fuzzy logic approach to predict EV demand. The results showed 78% efficiency and ±4% voltage variation, but low accuracy under variability. A commercial area's PID management of battery storage and rapid chargers achieved 70% forecasting efficiency and ±5% voltage variance, indicating poor load forecasting and decreased efficacy in controlling load fluctuations. Specifically, a comparison of several PID, ANN, FLC, and ANFIS controller control strategies for EV charging stations in hybrid microgrid systems is conducted. A comparison of important performance measures, such as voltage stability, charging time, SoC management, power ripple, overshoot, and settling time, is shown in Table 7 references from the literature serve as the foundation for the observations and values.

The performance of PID, ANN, FLC, and ANFIS (Proposed) across various metrics. ANFIS consistently outperforms other controllers in most areas, such as voltage stability, with a voltage deviation of ±2V, lower voltage ripple (1.8%), and improved energy utilization efficiency at 95%. It also shows faster charging time (0.8 h), better SoC management with a 55% SoC drop during peak load, and quicker recovery time (1.2 s). In power quality, ANFIS has the lowest power ripple (1.5%) and overshoot (4%), along with the fastest settling time (0.7 s). This comparison highlights the superior performance of ANFIS in controlling EV charging stations in hybrid microgrid systems, offering better voltage stability, faster charging, improved SoC management, and higher energy efficiency compared to PID, ANN, and Fuzzy controllers. Figure 9 illustrates the comparison of the energy efficiency and load-handling performance of four control methods: PID, ANN, FLC, and ANFIS. The PID controller shows an energy efficiency of 89% and a load-handling capability of 83%. The ANN controller improves slightly with 90% energy efficiency and 85% load handling. FLC performs even better, with an energy efficiency of 91% and a load-handling capability of 87%. Finally, ANFIS demonstrates the highest performance, achieving 92% energy efficiency and 89% load handling, making it the most effective among the four methods in both categories.

5.2 Simulation results

Figure 10 depicts the setup of a studied hybrid microgrid that includes an EV charging station, renewable energy sources, and energy storage devices. This model is a thorough depiction of a sustainable energy system, with a battery storage system for energy management acting as support for the two main renewable energy generators a PV array and a wind turbine. An essential component of the microgrid is the photovoltaic array, which transforms solar radiation into electrical energy. A MPPT controller processes the DC voltage and current produced by the PV array. By modifying the duty cycle of the associated

Table 6. Summary of the existing case studies that analyse EV charging load forecasting.

Case study	Location	Components	Control strategy	Forecasting efficiency (%)	Voltage fluctuation	Key findings	References
EV charging load forecasting in smart grids	Urban area	EV charging stations, solar PV, energy storage	ANFIS	90	±2%	Most accurate forecasting; maximizes renewable energy utilization.	[41]
Impact of ANN on EV charging forecasting	College campus	Charging infrastructure, grid connection	ANN	85	±3%	Accurate load predictions; improved integration of renewables.	[42]
Fuzzy logic approach to EV load prediction	Research institute	EV chargers, grid resources	Fuzzy Logic	78	±4%	Limited ability to forecast loads accurately under variability.	[43]
PID control in EV charging load management	Commercial area	Fast chargers, battery storage	PID	70	±5%	Inefficient load forecasting; less effective in managing fluctuations.	[44]

Table 7. Comparative analysis of different control strategies.

Metric	Parameter	PID	ANN	FLC	ANFIS (Proposed)	References
Voltage stability	Voltage deviation (ΔV)	±5 V	±3 V	±4 V	±2 V	[45, 46]
	Voltage ripple (%)	5.5%	3.2%	4.0%	1.8%	[47, 48]
Charging efficiency	Charging time (full cycle)	1.2 h	1.0 h	1.1 h	0.8 h	[49, 50]
SoC management	SoC drop during peak load (%)	70%	60%	65%	55%	[51–53]
	SoC recovery time (s)	3.0 s	1.8 s	2.5 s	1.2 s	[54, 55]
Power quality	Power ripple (%)	5%	3.5%	4%	1.5	[56, 57]
System response	Overshoot (%)	12%	6%	8%	4%	[58, 59]
	Settling time (s)	2.5 s	1.3 s	2.0 s	0.7 s	[60]
Energy utilization	Energy utilization efficiency (%)	85%	90%	88%	95%	[61, 62]

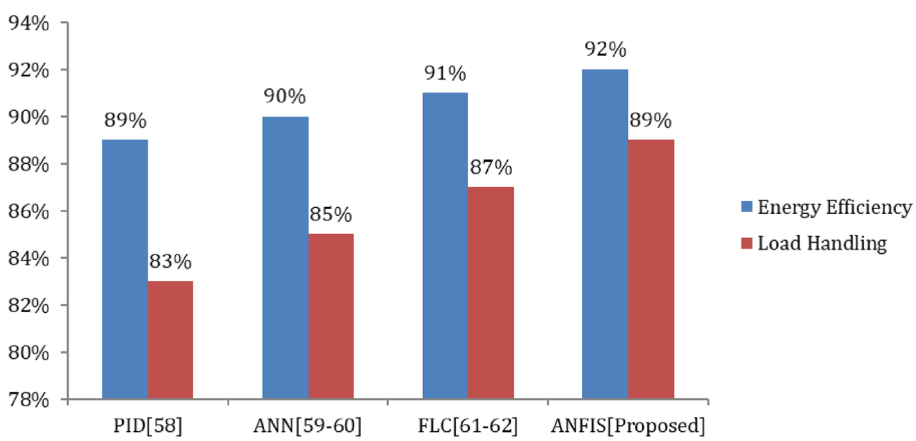

Fig. 9. Comparison of energy efficiency and load-handling performance of controllers.

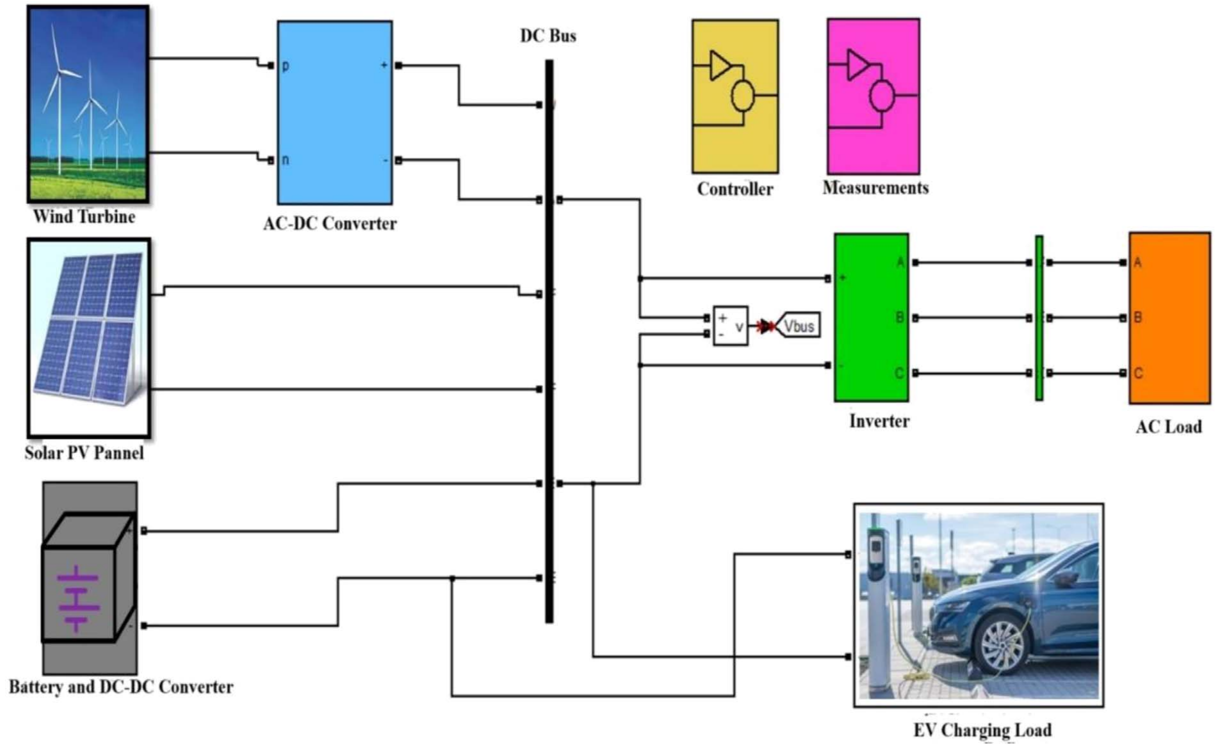

Fig. 10. Simulation model of hybrid microgrid system.

DC-DC boost converter, the MPPT controller improves the power output through the use of the incremental conductance approach in conjunction with an integrated regulator technique. This controller ensures that the PV array operates at its optimum power point despite fluctuating external conditions. The DC-DC boost converter, positioned after the MPPT controller, increases the voltage from the PV array to a level suitable for integration into the hybrid microgrid. This converter provides a stable output of 500 V DC and operates at a switching frequency of 5 kHz. Key components of the converter include an inductor, an IGBT switch, a diode, and a capacitor, which work together to transfer energy efficiently with minimal loss. In addition to the PV array, the microgrid also includes a wind turbine system with an induction generator that captures wind energy and converts it into electrical power. The wind turbine's dynamic behavior is simulated as a phasor-type system, simplifying the modeling process. The generated AC electricity is then converted to DC to match the microgrid's design. The microgrid incorporates a battery system with a bidirectional DC-DC converter to manage energy storage. This setup allows excess energy from renewable sources to be stored or used to power the microgrid when generation is low. The bidirectional converter controls the battery's charge and discharge cycles, ensuring its efficient operation and longevity. The EV charging station is another crucial component of the microgrid, receiving power directly from the DC bus. The inclusion of the EV charging load highlights the microgrid's ability to meet modern energy demands, including those of increasingly common electric vehicles.

The microgrid is additionally equipped with local loads, which signify the energy usage of commercial, industrial, or residential establishments. Depending on availability, these loads use battery-supplied electricity or power produced by renewable sources. The energy resources and storage system specifications are detailed in Table 8. The measuring and control system of the microgrid is essential for keeping an eye on several system metrics, including voltage, current, and power. It produces control signals that regulate the power electronics and other components' operations, guaranteeing the microgrid's dependable and effective operation. The fidelity with which the behaviour of the power electronic equipment, like the MPPT controller and boost converter, is captured is guaranteed by this meticulous modelling method.

The power generation in the system is simulated using both wind and solar sources, with wind power fluctuating throughout the day and solar power peaking around midday. Power consumption follows typical patterns, where EV charging increases during the evening, while AC loads remain constant throughout the day. The battery plays a crucial role in maintaining system stability, charging during periods of surplus renewable energy and discharging when there is a power deficit. Overall, the system ensures DC bus power balance, with the battery managing any excess or shortfall in the energy supply. Figure 11 illustrates performance analysis of the wind-solar-battery system over a 24-hour period. Figure 11a shows wind and solar power generation along with consumption by EV charging and AC loads. Wind power gradually raises, peaks at 16 h, and then declines. Solar power begins after 6 h, peaks at

Table 8. Details of energy resources and storage system specification [63].

PV module		Wind generating system	
Specifications	Metrics	Technical specifics	Metrics
Voltage on the open circuit	87.72 V	Wind speed	14 m/s
Current at short circuit	2.66 A	Power rating	3 kW
Highest possible voltage	70.131 V	Turbine speed rating	360 RPM
Highest possible current	2.448 A	Boost converter ratings	
Photovoltaic plant	5 KW	Technical specifics	Metrics
Lithium ion battery bank	100 kWh	Inductor (L)	150 mH
DC link capacitance	24000 μF	Capacitor (C)	470 μF

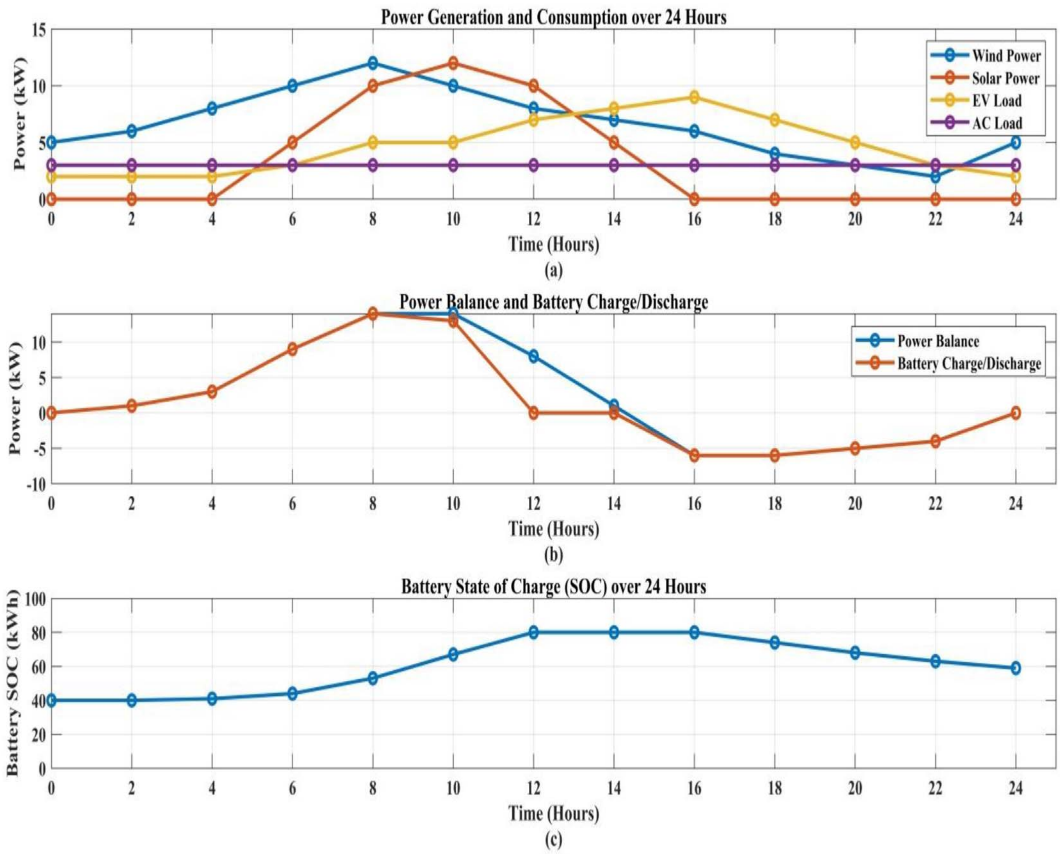

Fig. 11. Performance analysis of the wind-solar-battery system over a 24-hour period: (a) Power generation and consumption; (b) Power balance and battery charge/discharge dynamics; (c) SoC of the battery.

midday, and drops by evening. EV load remains low until increasing after 16 h, typical of evening charging. AC load remains constant throughout the day. Figure 11b shows the system's power balance, where positive values represent surplus power, and negative values show deficits. The battery charges when there is excess power and discharges to cover shortfalls, helping to maintain system balance. In Figure 11c, the SoC increases when renewable generation exceeds demand (6–14 h), indicating battery charging. As generation decreases and EV charging rises (16–24 h), the SoC drops, reflecting battery discharge to meet the system load.

To simulate the voltage and current characteristics of a DC microgrid system comprising wind turbines, solar PV arrays, and EV charging, we will first assess the stability of the 400 V DC bus voltage [64]. Dynamic variations can be introduced with this arrangement by applying disturbances to the load or generation. Next, we will evaluate the current profiles of the various components inside the system. The computation of the wind turbine current will

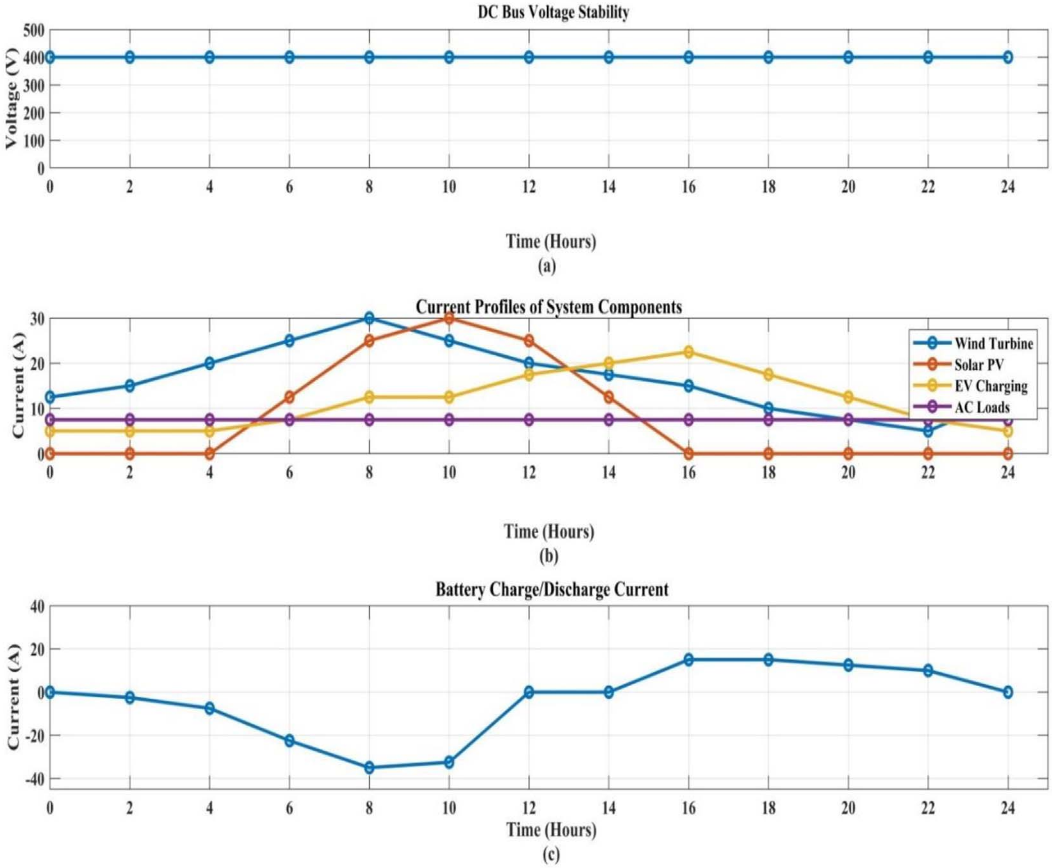

Fig. 12. The 24-hour simulation of hybrid microgrid data for every 2 h: (a) DC bus voltage stability; (b) Current contributions from the wind turbine, solar PV array, and EV charging station; (c) Battery charge and discharge currents.

include dividing the wind power generation by the DC bus voltage. Meanwhile, the solar PV current will be obtained in a similar manner from the solar power generation. Furthermore, the AC load current will show the converted current needed for AC loads, and the EV charging current will show the current consumed by the EV charging station at different times. Battery cycles will also be taken into account in the simulation; the battery will charge during times of surplus renewable generation and drain when power consumption exceeds available generation. The simulation is set to run for an entire day, collecting data points every two hours, as depicted in Figure 12. As seen in Figure 12a, which displays the DC bus voltage stability (modifiable to reflect fluctuations), three plots will comprise the output. The DC bus voltage stability is demonstrated by its capacity to maintain a constant 400 V throughout the day, demonstrating that the system can still regulate voltage successfully in the face of variations. Figure 12b displays the current contributions from the wind turbine, solar PV array, EV charging station, and AC loads in addition to the current profiles of the major system components, including the wind turbine, solar PV, EV charging, and AC loads. The solar PV current peaks during midday (4–16 h), when sunshine is abundant, then reduces to zero throughout the night, but the wind turbine current climbs progressively until 16 h and then diminishes. During 20 h, there is a modest fall in current for both EV charging and AC loads, suggesting a decrease in demand during the night, and the battery's charge and discharge currents are shown in Figure 12c, which shows the currents based on power surplus or deficit. Positive values indicate discharging and negative values indicate charging. When generation is low, often between 10 and 24 h, the battery discharges to supply electricity; during periods of low demand or excess generation, typically between 0 and 10 h, the battery charges.

Overall, the system effectively maintains DC bus voltage stability while integrating multiple renewable sources and managing load variations, with the battery playing a crucial role in balancing the system through strategic charging and discharging [65].

Using an ANFIS controller to govern power flow and voltage stability in a DC microgrid system will entail the following steps: Create the training data that the ANFIS controller needs first. The training data for the ANFIS controller is displayed in Figure 13, which also displays the relationship between the relevant control signal, voltage error, and error change. In order to do this, input-output pairs must be created, with the control signal required to modify the voltage as the output and the voltage error (the difference between the nominal and real value) and the rate of change of the voltage (the derivative of the voltage error) as the inputs. The ANFIS membership

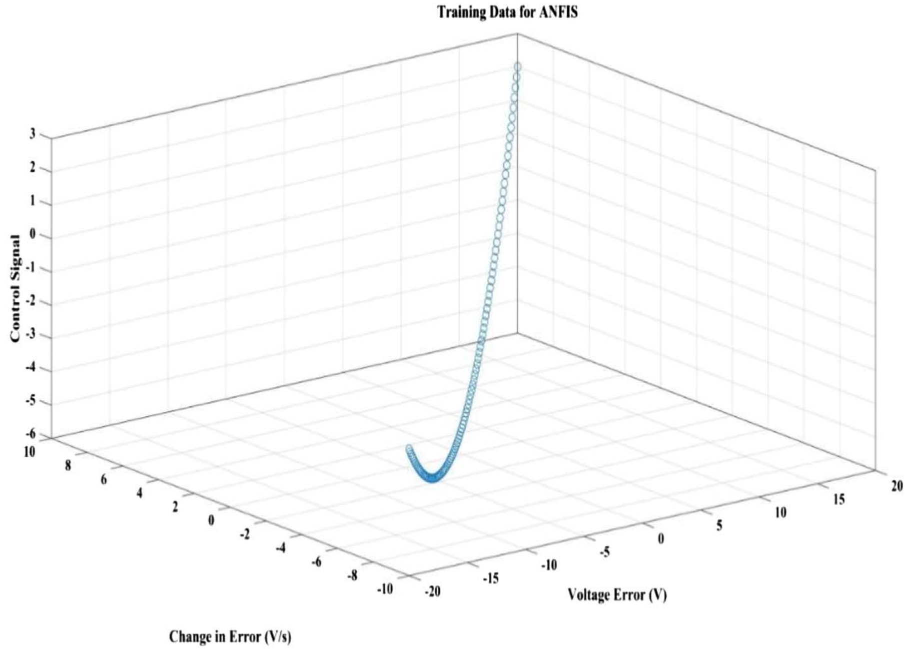

Fig. 13. Training data for the ANFIS controller, illustrating the relationship between the voltage error, change in error, and the corresponding control signal.

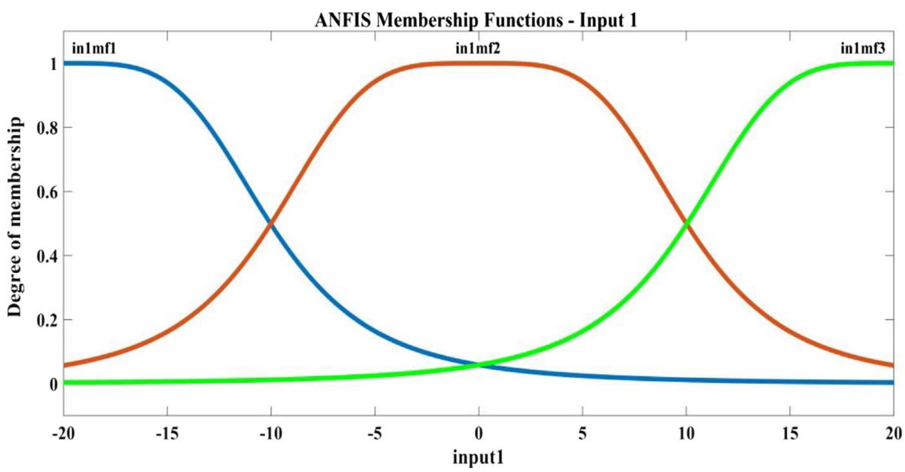

Fig. 14. ANFIS membership functions for input 1, displaying the degree of membership for the three fuzzy sets (in1mf1, in1mf2, in1mf3) across the input range.

functions for input 1 are shown in Figure 14. It also shows the degree of membership for the three fuzzy sets (in1mf1, in1mf2, and in1mf3) over the input range. Based on this input-output data, the ANFIS controller will next be trained using the MATLAB ANFIS function. The current PI controller will be replaced by the ANFIS controller when the training is over, controlling power flow between loads, storage, and renewable energy sources as well as bus voltage.

During the simulation, the ANFIS controller demonstrated its effectiveness in regulating the DC bus voltage under varying load conditions. Initially, an increase in load caused the voltage to drop to 390 V, prompting the controller to adjust it back to 400 V with a +10 V change. Once the load stabilized, the voltage held steady at 390 V, requiring no further adjustments. When the load decreased later on, the voltage rose to 405 V, and the controller effectively responded by reducing it by 5 V to maintain the target range. After another load increase caused the voltage to fall to 380 V, the controller made a +20 V adjustment to restore stability. Ultimately, the voltage remained at 380 V without any additional modifications. In Figure 15, the bus voltage is illustrated over time to evaluate how effectively the ANFIS controller maintains voltage stability

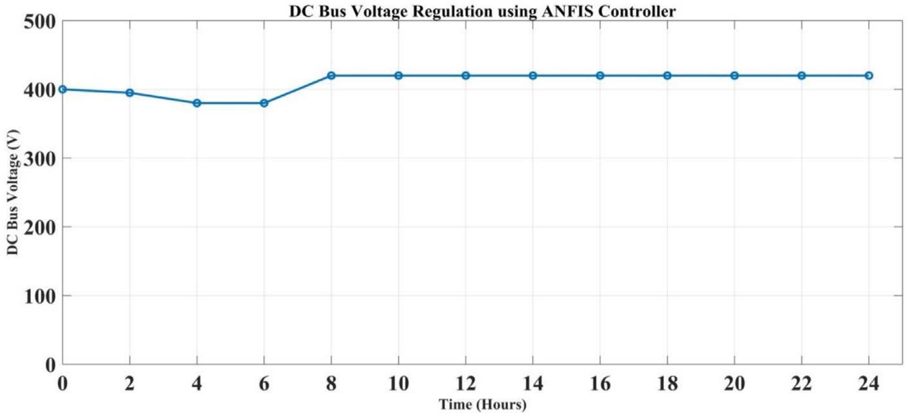

Fig. 15. Bus voltage is monitored and plotted over time.

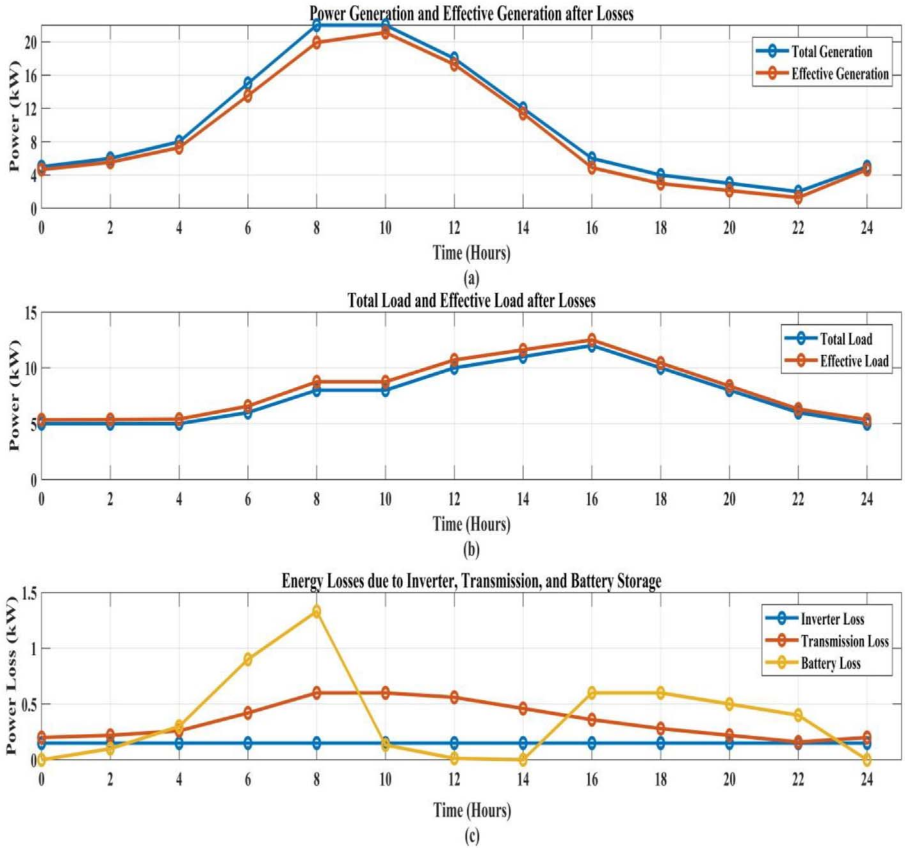

Fig. 16. Performance of microgrid over a 24-hour period: (a) Power generation and effective generation after losses; (b) Total load and effective load after losses; (c) Energy losses due to inverter, transmission, and battery storage.

across different load and generation scenarios. Within the main control loop, the trained ANFIS controller calculates the voltage error and its rate of change, generating the control signal necessary for adjusting the DC bus voltage. Optimizing convergence speed involves fine-tuning the learning rate; a smaller learning rate may lead to more stable learning, while a larger rate can accelerate convergence but risks overshooting optimal values. Additionally, updating the membership functions from triangular to trapezoidal shapes can enhance the controller's ability to manage voltage fluctuations and improve its overall effectiveness in maintaining stability within the desired voltage range of 380–420 V [66].

The efficiency of a DC microgrid system by considering various factors impacting energy losses at different stages of power flow. The inverter operates at 95% efficiency, leading to a 5% loss during the conversion from DC to AC for the AC loads. Additionally, the battery exhibits a 90%

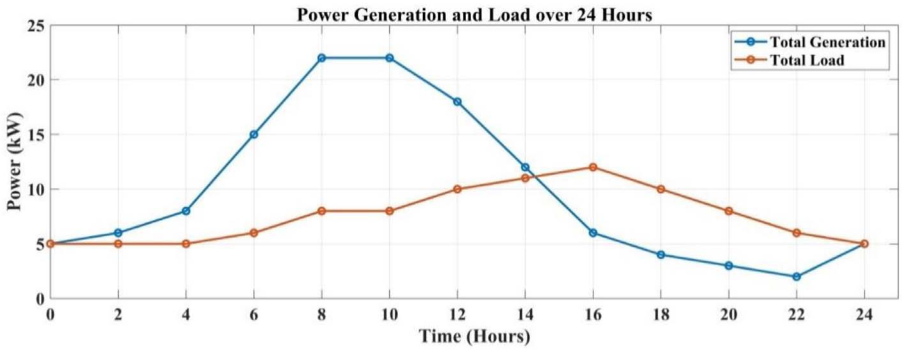

Fig. 17. Total power generation and total load.

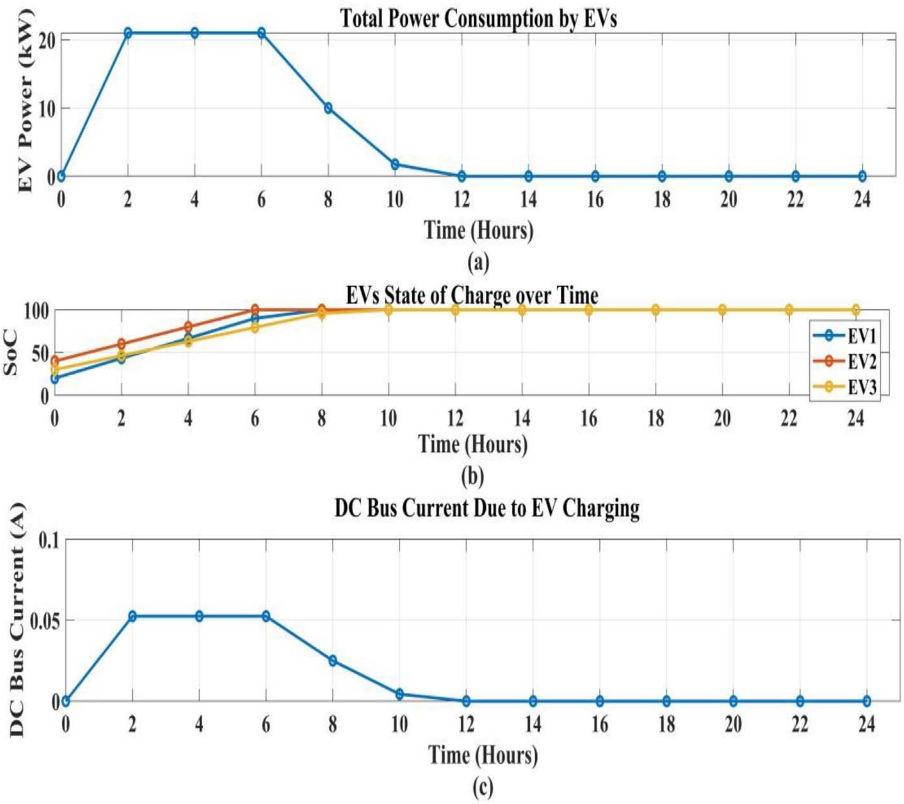

Fig. 18. EV charging station performance: (a) Total power consumption by EVs; (b) EVs' state of charge; (c) DC bus current due to EV charging.

round-trip efficiency, resulting in energy losses during both charging and discharging processes. We assume a 2% transmission loss applied to both generated power and load, further impacting overall efficiency. The simulation runs in 2-hour intervals over a 24-hour period, calculating power flow and losses attributable to the inverter, transmission, and battery storage. Effective generation, accounts for losses from the inverter, transmission, and battery, while effective total load incorporates these losses for both EV and AC loads. Power losses are quantified as 5% of the AC load power for the inverter, 2% of the total power for transmission, and 10% of the power during battery charging and discharging. This comprehensive analysis provides insights into the energy efficiency of the DC microgrid, highlighting losses at each stage as shown in Figure 16. The power generation and effective generation following losses are shown in Figure 16a. The overall power generated over a 24-hour period, as well as the effective power generated (which takes system losses into account). Peak generation occurs between 8 and 12 h, although system losses cause the effective generation to be somewhat lower. Figure 16b shows the total load and effective load after losses, which is the total load and effective load (after losses are taken into account) for a 24-hour period. The load progressively rises during the

Table 9. Comparison of the performance of the ANFIS controller with other controllers.

Metrics	ANFIS	PID	Fuzzy logic	ANN
Energy cost (per kWh)	Lowest due to dynamic optimization of energy sources.	Moderate; relies on fixed gain values.	Lower but limited by pre-set fuzzy rules.	Low, but computationally expensive to train.
Renewable energy utilization	~95% utilization through adaptive allocation.	~70-80% due to lack of adaptability.	~85% with well-defined fuzzy rules.	~90% dependent on accurate data training.
Battery health (degradation)	Minimal due to efficient charge/discharge cycles.	Higher due to fixed response parameters.	Moderate; lacks adaptive learning for cycles.	Low, if training includes battery dynamics.
Response time	0.2–0.5 s for real-time changes.	0.1–0.3 s, faster but less adaptive.	0.3–0.6 s, dependent on complexity.	0.4–0.7 s, training-dependent.
System adaptability	High; self-tunes to dynamic conditions.	Low; requires manual tuning.	Moderate; relies on fuzzy rule refinement.	High; depends on quality of training data.
scalability	Easily scalable to larger, complex systems.	Limited by complexity and tuning.	Moderate; requires more fuzzy rules.	High but resource-intensive.
Implementation cost	Moderate; requires expert design and training.	Low; simple implementation.	Moderate; depends on fuzzy rule complexity.	High; significant computational resources.
Real-time decision-making	Excellent due to hybrid fuzzy-neural learning capabilities.	Limited real-time performance in complex systems.	Performs well but slower in complex scenarios.	Real-time decision-making is challenging without pre-training.
Real-world applications	Used in hybrid microgrids for EV charging, smart grids, and renewable energy optimization.	Commonly used in industrial control systems but less in energy optimization.	Applied in smart home energy systems and microgrids with less complexity.	Found in predictive maintenance and energy forecasting systems.

day, reaching its peak in 12–14 h, and then starts to decline in the evening. The power losses throughout the day ascribed to the inverter, transmission, and battery storage systems are shown in Figure 16c. The most notable battery losses occur between 8 and 12 h, after which there is a decrease. With very minor fluctuations, inverter and transmission losses are comparatively constant.

Figure 17 illustrates the variations in total power generation and total load over a 24-hour period. The total generation curve exhibits a sharp increase starting around 6 a.m., peaking at approximately 20 kW around noon. After reaching its peak, power generation gradually declines, falling to around 5 kW by 6 p.m., with a slight increase near midnight. In contrast, the total load follows a steadier progression, starting at about 5 kW and rising gradually throughout the day to a peak of approximately 10 kW in the late afternoon before tapering off in the evening. Notably, power generation exceeds the total load between 8 a.m. and 4 p.m., while in the evening, generation falls below the load, indicating the potential need for stored energy or supplemental power sources during those hours.

To model the performance of an EV charging station integrated with a DC microgrid over a 24-hour period, we simulate the EV charging profiles, system voltage/current levels, and the microgrid's capacity to support multiple EVs. The setup includes several key components: EV charging profiles, which describe the power consumption of electric vehicles as a function of time; grid conditions, detailing the interaction between the DC microgrid and the external grid, whether in grid-connected or islanded modes; and renewable energy and storage, accounting for the power generated from sources like wind and solar, along with the contribution from battery storage and its impact on EV charging. There are three EVs with different battery capacities (60, 70, and 85 kWh and initial SoC of 20%, 40%, and 30%, respectively. The charging profiles vary throughout the day depending on factors such as the EVs' arrival times, available renewable energy, and grid conditions. Each EV is subject to a maximum charging power limit of 7 kW, and the available power is shared among all three vehicles based on the total renewable energy and grid power. Renewable power generation follows a sinusoidal pattern, peaking around noon to simulate typical solar or wind energy behavior [67, 68].

The microgrid operates in two modes: grid-connected mode, where an additional 100 kW of power is available from the external grid, and islanded mode, where only renewable energy (with fluctuations around 50 kW) is available for EV charging. The SoC of each EV is updated every two hours, with charging ceasing once the SoC reaches 100%. The total power consumption of the EVs is converted to DC bus current, with the assumption of a constant 400 V DC bus voltage [69], and the system monitors the impact of EV charging on the DC bus voltage and current levels is shown in Figure 18. It provides insights into the number of EVs the system can support the impact of charging on the microgrid, and the behavior of the system under different grid and renewable energy conditions. Figure 18a shows the power usage by the EVs peaking during the first few hours and tapering off as the batteries reach full charge. Figure 18b illustrates the increase in SoC for the three EVs as they charge, eventually reaching 100% SoC after a few hours. Figure 18c depicts the DC bus current drawn by the EVs during charging, with current dropping to zero once all EVs are fully charged.

The total energy consumption of the EV charging system over the 24-hour period amounts to 149.50 kWh. Of this, 149.50 kWh is sourced from renewable energy, with a cost of $7.48, reflecting the lower cost of renewable energy. Additionally, 29.90 kWh is drawn from the battery storage system, incurring a cost of $2.99. The total operational cost for charging the EVs, combining renewable and battery energy sources, is $10.46. This highlights the system's reliance on renewable energy, minimizing the overall cost of charging the EVs. In Table 9, the performance of the ANFIS controller with other controllers (PID, Fuzzy Logic, and ANN) based on real-world applications in hybrid renewable energy systems for EV charging are compared [70–71].

The comparison highlights that ANFIS outperforms other controllers in energy cost, renewable energy utilization, and battery health, offering high adaptability and scalability, though with moderate implementation costs. PID is faster and cheaper to implement but lacks adaptability and performs less efficiently in complex systems. Fuzzy Logic shows moderate performance, especially in smart home and microgrid applications, while ANN excels in prediction tasks but is resource-intensive and struggles with real-time decision-making.

6 Conclusion and future scope

6.1 Conclusion

The present research creates an energy management strategy for a standalone hybrid microgrid employing an ANFIS controller. An EV charging outlet is incorporated into the system, offering a complete energy generation and consumption solution. The efficiency of the ANFIS controller in controlling the relationships between load demand, battery state of charge, and renewable energy sources was confirmed using MATLAB/Simulink simulations. The ANFIS controller successfully regulated power disparities in spite of variations in wind speed and solar radiation, guaranteeing steady and dependable energy output. By storing excess energy during periods of low demand and supplying electricity during periods of peak demand, a battery energy storage system reduced dependency on fossil fuels and improved system reliability. With a load-handling capacity of 89% and an energy efficiency of 92%, the ANFIS controller fared better than PID, ANN, and FLC control techniques. These findings demonstrate how crucial adaptive control techniques are for incorporating renewable energy sources into microgrids. Significant benefits in stability, efficiency, and dependability are provided by the ANFIS-based system, especially for off-grid and rural locations with plentiful but erratic renewable resources. All things considered, ANFIS is a reliable, affordable, and energy-management tool for maximizing hybrid microgrid performance.

6.2 Future scope

Future research could focus on scaling the system to larger microgrids and exploring integration with smart grid infrastructure. This could enable more extensive energy distribution networks, enhance grid stability, and facilitate demand-side management. Additionally, evaluating the environmental benefits, such as reductions in greenhouse gas emissions, and economic impacts, including operational cost savings and long-term sustainability, would strengthen its feasibility for real-world applications. Such insights would promote adoption in diverse settings, from urban grids to remote microgrids, advancing renewable energy utilization globally.

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The authors state that they have no known competing financial interests or personal ties that could have seemed to affect the work reported in the present research.

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Author contribution statement

All the authors have equal contributions in writing and review the paper.

Saleha Tabassum: Idea generation, Draft Writing, Formal Analysis, Conceptualization

Attuluri R Vijay Babu: Writing-Original Draft, Review, Supervision,

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