

Real-time power quality enhancement in smart grids through IoT and adaptive neuro-fuzzy systems

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Abstract. To tackle the challenge of improving Power Quality (PQ) in modern power grids, we introduce an innovative Internet of Things (IoT)-based Smart Grid (SG) energy surveillance system. Our research is driven by the necessity to enhance power quality and optimize energy management in increasingly complex grids that incorporate renewable energy sources like Solar PV and Wind Generating Systems. Traditional methods for managing power quality often fall short, resulting in inefficiencies and potential disruptions. Our solution features an advanced IoT-based system that utilizes the Adaptive Neuro-Fuzzy Inference System (ANFIS), combining Artificial Neural Networks (ANN) and Fuzzy Logic Systems to enhance power distribution and control. This system uses a Wireless Sensor Network for real-time data collection and analysis, allowing for precise monitoring of electricity usage and improved energy management and cost reduction. Our findings indicate that this innovative approach not only boosts power quality but also significantly enhances the efficiency of renewable energy sources, showing a 20.50% performance increase during the startup phase of Solar PV-Wind Generating Systems. This highlights the system's potential to advance power quality management and provide substantial benefits in energy regulation and cost efficiency.

Keywords: Adaptive neuro-fuzzy inference system, Internet of things, Solar PV module, Smart grid, Wind generating system, Wireless sensor networks.

Nomenclature

AC	Alternating Current
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
DC	Direct Current
DES	Distributed Energy Storage
FLC	Fuzzy Logic Controller
HRES	Hybrid Renewable Energy Systems
ICT	Information and Communication Technology
IoT	Internet of Things
LCD	Liquid Crystal Display
MG	Microgrid
MPPT	Maximum Power Point Tracking
PV	Photo-Voltaic
SG	Smart Grid
WGS	Wind Generation System
WSN	Wireless Sensor Networks

Parameters

P_{PV}	Power output from the photovoltaic system
P_{WGS}	Power output from the wind generation system
E_{DES}	Energy stored in the distributed energy storage
V_{AC}	Voltage of the alternating current
V_{DC}	Voltage of the direct current
I_{AC}	Current of the alternating current
I_{DC}	Current of the direct current

Variables

t	Time
θ	Angle of the solar panel
η	Efficiency of the energy conversion system
Δt	Time interval for data collection
$Temp_{pv}$	Temperature of the photovoltaic panel
$Wind_{speed}$	Wind speed affecting the wind generation system

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Sets

T	Set of time intervals
S	Set of sensors in the wireless sensor network
E	Set of energy sources (e.g., PV, WGS)
D	Set of data points collected
M	Set of microgrid components

1 Introduction

The Internet of Things (IoT) is a foundational framework in communication systems, enabling data sharing among interconnected devices like sensors, software, and gadgets. A key function of IoT is data pre-processing, which involves analyzing and optimizing data for subsequent use or storage [1, 2]. Moreover, IoT prioritizes data security to safeguard sensitive information during transmission and storage. In today's interconnected world, the internet links myriad devices, facilitating seamless communication and collaboration across various applications. Recent progress has led to the widespread use of sensors in home automation, enhancing convenience and efficiency by enabling intelligent control of household appliances. These sensors act as the "sensory organs" of smart home systems, detecting environmental changes and triggering appropriate responses [3, 4]. Motion sensors that activate lights and temperature sensors regulating heating and cooling systems are integral components of modern home automation setups [5]. The integration of sensors, software, and interconnected gadgets within the IoT framework has vast potential to transform daily life, spanning from home automation to industrial applications and beyond.

As technology progresses, the IoT ecosystem is expected to advance further, ushering in an era characterized by unparalleled connectivity and intelligence [6, 7]. However, the economic feasibility of IoT can encounter challenges, particularly regarding the deployment of numerous sensors. As the number of devices in an IoT network increases, so do the costs and power requirements associated with each sensor-equipped device [8]. This scalability issue can present significant obstacles, especially in large-scale IoT implementations where deploying sensors across numerous endpoints can become costly and resource-intensive [9]. Moreover, the operation of various IoT devices contributes to power and energy consumption, further adding to the overall energy demands of the network [10, 11]. Concerns regarding sustainability, environmental impact, and increased operational costs arise due to the proliferation of IoT deployments. Nevertheless, IoT serves as a transformative technology within the electrical grid ecosystem, offering innovative solutions.

1.1 Motivation of work

The motivation behind our research stems from the pressing need to enhance power quality and manage energy more efficiently in modern grids. As power systems become increasingly complex with the integration of renewable energy sources like Solar PV and Wind Generating

Systems, traditional methods of power quality management often fall short, leading to inefficiencies and potential disruptions. To address these challenges, we propose an innovative IoT-based Smart Grid energy surveillance system that utilizes the Adaptive Neuro-Fuzzy Inference System (ANFIS). This approach combines the strengths of Artificial Neural Networks (ANNs) and Fuzzy Logic Systems to optimize power distribution and control. By incorporating a Wireless Sensor Network for real-time data collection and analysis, our system enables precise monitoring of electricity usage, facilitating improved energy management and cost reduction.

IoT technology enables the evolution of the electrical grid into a smarter, more efficient infrastructure capable of real-time monitoring, analysis, and optimization [12]. This transformation is driven by integrating complementary technologies such as big data analytics, cloud computing, and IoT devices. Big data analytics processes vast amounts of data generated by IoT devices across the electrical grid, providing insights into grid performance, energy consumption patterns, and areas for optimization [13, 14]. Cloud computing facilitates the storage, processing, and management of IoT-generated data. Utilities and grid operators can access scalable computing resources and analytical tools through cloud infrastructure, allowing them to derive actionable intelligence from IoT data cost-effectively [15].

The integration of Wireless Sensor Networks (WSNs) into electric grids offers significant benefits for enhancing monitoring and optimizing power distribution. However, several key challenges must be addressed to realize this potential fully. These challenges include scaling WSNs to handle various grid sizes and complexities, optimizing energy efficiency and reliability, and addressing cybersecurity vulnerabilities. Additionally, the economic feasibility of implementing WSNs needs thorough evaluation. Ensuring interoperability with existing infrastructure and developing advanced techniques, such as neurofuzzy algorithms and machine learning, are crucial. Effective integration of renewable energy sources and establishing standardized communication protocols are also essential for seamless operation. Addressing these research gaps is vital for advancing smart grid technologies and improving overall energy management.

In summary, the intersection of big data, cloud computing, and IoT presents significant potential for the evolution of smart electrical grids. Despite the economic challenges associated with IoT deployments, the anticipated benefits in terms of grid efficiency, reliability, and sustainability make it an attractive area for investment and innovation within the energy sector [16, 17]. As technology progresses and economies of scale are achieved, the economic feasibility of IoT in smart grids is expected to improve, leading to increased adoption and integration of IoT solutions across the industry [18]. Smart grids aim to optimize and automate many aspects of the electricity grid, reducing the need for manual intervention in areas like meter reading and outage management. However, they also empower consumers with features like dynamic pricing and demand response programs, increasing their role in managing their energy consumption [19, 20]. Smart grids gain numerous

advantages from intelligent features, cost-effective solutions, and enhanced reliability enabled by IoT and the convergence of Information Communication Technology (ICT). IoT technologies empower smart grids to automate tasks, optimize energy distribution, and enhance overall system efficiency. At the core of IoT is bidirectional communication between interconnected devices, crucial for enabling smart grid functionalities [21, 22]. This real-time exchange of information enables dynamic adjustments and responses to changing conditions.

1.2 Literature review

This section provides an overview of the literature review concerning IoT-enabled smart grids and traces the evolution of the smart grid concept from earlier endeavors aimed at monitoring and managing electrical systems through various electronic controllers, metering techniques, and observation methods. Table 1 outlines a summary of the recently reviewed literature sources, presenting key findings, conclusions, and gaps identified. The research highlights several key advancements in smart grid and energy management systems. The implementation of WSN and IoT technology has enhanced real-time monitoring and efficient power distribution. The study introduces a smart grid framework for smart homes, integrates IoT with energy management strategies for smart cities, and employs deep reinforcement learning and edge computing for advanced energy systems [23, 24]. It also explores control strategies for Distributed Energy Storage in microgrids, optimized renewable energy management, and real-time control of photovoltaic systems using Maximum PowerPoint Tracking and fuzzy logic. Additionally, the research demonstrates the integration of intelligent techniques to improve power generation and quality, with IoT modules and Smart Meters supporting efficient energy management and detailed consumption tracking.

1.3 Research gaps

Despite the promising integration of WSN into electric grids for enhanced monitoring and efficient power sharing, several critical research gaps remain. Key areas requiring exploration include the scalability of smart grids, optimization of energy efficiency and reliability, and addressing cybersecurity concerns. Future research should focus on adapting Neuro-Fuzzy algorithms for real-time efficiency, ensuring interoperability with existing grid infrastructures, and integrating renewable energy sources while tackling intermittency and grid stability issues. Additionally, advanced data analytics, machine learning techniques, and fuzzy logic algorithms need development for real-time energy management and renewable integration. The impact of integrating diverse renewable sources and the dynamics introduced by Distributed Energy Systems must be investigated. There is also a need to develop standardized communication protocols for IoT devices and PV systems and to assess advanced real-time monitoring technologies. Research should explore the application of modern systems like microgrids and nano-grids, and the comparative performance of ANFIS for Maximum Power Point Tracking [25].

Addressing the scalability of intelligent techniques in large-scale power systems and enhancing Demand Response strategies are also crucial for optimizing grid stability and efficiency.

An illustration of IoT-enabled communication technology in smart grids is the use of real-time Zigbee mesh networks with IoT capabilities, particularly in smart city contexts. Zigbee, known for its low-power wireless communication, is widely used because of its energy efficiency and reliability. Deploying Zigbee-based mesh networks in smart grid infrastructure ensures robust connectivity and communication among various devices, including smart meters and distribution automation equipment. In practice, this IoT-enabled infrastructure facilitates the seamless transmission of load consumption data from individual devices to utility providers via communication modules and power sensors. This periodic data exchange empowers utilities to analyze consumption patterns, detect anomalies, and optimize grid operations accordingly [26, 27]. Utilizing IoT-enabled communication technologies like WSN and Zigbee mesh networks, smart grids can significantly enhance their reliability, scalability, and efficiency [28]. The capacity to gather and analyze real-time data from a wide array of distributed devices enables utility companies to make well-informed decisions, bolster grid resilience, and provide cost-effective services to consumers [29, 30]. The amalgamation of IoT and ICT technologies within smart grid infrastructure offers vast potential to revolutionize the energy sector, setting the stage for the development of more sustainable, resilient, and efficient electrical grids [31, 32]. As IoT innovations continue to propel forward, smart grids are poised to become increasingly intelligent, autonomous, and capable of adjusting to the ever-changing demands of contemporary energy systems [33, 34]. This evolution represents a critical step towards optimizing energy consumption, reducing waste, and ensuring a greener future [35].

This research introduces a novel approach to smart grid systems by addressing critical gaps in power quality management through a comprehensive integration of advanced technologies and methodologies. Unlike previous studies that may focus on isolated elements such as energy management or renewable energy sources integration, our work simultaneously considers energy management, effective monitoring systems, IoT modules, GSM communication, and optimal placement of WSN. The core innovation lies in the implementation of an ANFIS controller, which enhances the control and optimization of power output from Solar PV-Wind Generating Systems, ensuring consistent power generation regardless of atmospheric conditions. This is complemented by the innovative use of IoT and WSN for real-time monitoring, providing detailed insights into power quality and system performance. Additionally, the integration of MATLAB/Simulink and Proteus software for monitoring key parameters such as voltage, current, and power metrics along with the generation of electricity billing alerts via GSM, adds a significant layer of functionality. This holistic approach not only improves system efficiency and reliability but also benefits both customers and energy providers by offering enhanced monitoring capabilities and timely billing information,

Table 1. Overview of recent reviewed literature sources.

Paper, Year	Methodology	Key findings and conclusion	Research gaps identified
[5], 2020	WSN	Implemented cutting edge WSN communication system in the electric grid infrastructure to enable smart monitoring. This integration aimed to enhance the grid's ability to efficiently share power among its components.	Despite the potential of integrating WSN communication systems in electric grids for enhanced smart monitoring and efficient power sharing, critical research gaps like scalability, grid sizes, optimizing energy efficiency and reliability, cyber security concerns, and assessing economic feasibility.
[6], 2021	ANFIS, IoT	The proposed approach leverages IoT technology and Neuro-Fuzzy concepts for power monitoring, using Simulink software for implementation. It captures key parameters such as power, current, and voltage of the load.	Several future research areas need explorations such as grid sizes and complexities, optimizing Neuro-Fuzzy algorithms for real-time efficiency, ensuring interoperability with existing grid infrastructures and protocols.
[7], 2017	IoT	They developed a specialized smart grid framework for smart homes, utilizing Internet of Things (IoT) capabilities. Their focus was on exploring IoT's dual potential in supporting smart home and grid technologies.	Research new methods for optimizing the integration of renewable energy sources into smart grids, addressing challenges such as intermittency, grid stability, and regulatory compliance.
[8], 2019	IoT	They proposed an approach for IoT-assisted energy management, emphasizing its extensive applications within smart cities and the rising energy demands from these IoT applications.	Research advanced real-time data analytics and machine learning techniques tailored to the specific needs of IoT energy management.
[9], 2019	IoT	They utilized deep reinforcement learning within edge computing to develop an IoT-based energy management system. Beginning with an exploration of IoT energy management in smart cities, they leveraged edge computing to integrate an IoT-based software model and architecture.	Research methods to effectively incorporate renewable energy into the edge computing infrastructure, ensuring reliable and efficient energy management.
[10], 2016	DES	Presented a control strategy that incorporates Distributed Energy Storage (DES) systems into MGs. Managing MGs with numerous small-scale DES systems necessitated the development of scalable control strategies capable of handling disturbances in both communication and power networks.	The integration of DES into power networks introduces longer time-scale dynamics associated with the charge levels of storage systems, which complicates the control challenges of the network due to increased complexity.
[11], 2020.	IoT	Proposed an energy management strategy that uses an IoT-assisted system to optimize renewable energy generation. Their approach monitors and controls various aspects of solar and wind power generation using IoT technology.	Investigate methods to effectively integrate and manage diverse renewable energy sources within a single IoT-assisted system, ensuring optimal performance and stability.

(Continued on next page)

Table 1. (Continued)

Paper, Year	Methodology	Key findings and conclusion	Research gaps identified
[12], 2019	EMS	Conducted an inquiry into the complexities and constraints of energy management in the distribution system. They explored limitations such as technological constraints, regulatory barriers, and economic considerations in implementing effective energy management strategies.	Explore real-time monitoring technologies and control algorithms that can enhance the responsiveness and reliability of energy management systems.
[13], 2021	IoT	Investigated the utilization, prototype development, and architectural framework of IoT-assisted SG. Explored IoT-enabled devices, communication protocols, data analytics methodologies, and control strategies within Smart Grid infrastructures.	Investigate and develop standardized communication protocols and interoperable frameworks to ensure seamless integration and communication across diverse IoT devices and platforms in Smart Grid infrastructures.
[14], 2018.	ACL, WSN	Developed a real-time flow control mechanism for a Photovoltaic (PV) system using Maximum Power Point Tracking (MPPT) technology, by integrating advanced control algorithms, sensors, and communication interfaces for monitoring and adjusting the PV system's performance in real time.	Develop standardized communication protocols and interfaces that enable seamless integration and interoperability between PV systems and external monitoring/control devices.
[15], 2018	FLC	Implemented fuzzy logic control to optimize power generation in a PV system under varying environmental conditions, including temperature and irradiation levels.	Develop advanced fuzzy logic algorithms that can adaptively adjust to varying environmental parameters such as temperature, irradiation levels, and weather conditions to maximize power output.
[16], 2024	FLC, ANN, FACTS devices	Integrating renewable energy sources into traditional models, addressing constraints, exploring deregulated load frequency control and developing tailored strategies for micro grids.	Future research focus on modern systems like micro grids, nano-grids, and IoT enabled smart grids require real-time implementation via software like opal-RT or RTDS.
[17], 2024	GWO-ANN, IoT	Solar power maximums are tracked using a Grey Wolf Optimized Artificial Neural Network (GWO-ANN). Sensors are used to monitor temperature, intensity, converter voltage and current, with data stored on an IoT webpage for analysis.	A future research gap could focus on advancing machine learning techniques for optimizing renewable energy converters in micro grid and smart grid settings by exploring complex neural network architectures/hybrid models.
[18], 2024	PI, ANFIS	Integrates a PI controller and an ANFIS-based MPPT algorithm to dynamically adjust the duty cycle, improving power output. This results in an 18.09% increase in power generation.	The comparative performance benefits and practical implementation challenges of ANFIS- based MPPT over conventional methods need to be quantified and should be validated.
[19], 2022	PI, ANFIS, VSC.	A permanent magnet synchronous generator is used to maximize wind power, while back-to-back voltage source converters with an intelligent ANFIS controller optimize overall power generation.	Research gap focus on the impact of higher power outputs on grid dynamics, including voltage regulation, power quality, incorporating real-time data monitoring techniques with the integration of RESs.

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Table 1. (Continued)

Paper, Year	Methodology	Key findings and conclusion	Research gaps identified
[20], 2022	PI, ANFIS	This work demonstrates the effectiveness of using intelligent techniques to tune conventional PI controllers for simultaneously addressing multiple power quality issues.	The scalability of intelligent techniques for tuning PI controllers in large-scale power systems and their practical implementation in real-world scenarios need further investigation.
[21], 2023	IoT	The proposed study utilizes IoT technology for power monitoring in substations and smart grids to enhance load management, energy consumption tracking, load pattern analysis, real-time monitoring, and active decision-making.	Addressing the integration challenges of RESs into smart grids is a critical research gap. Studies should focus on mitigating grid instability, and improving power quality.
[22], 2023	IoT, WSN, Arduino	This research article implements an IoT-enabled micro grid system utilizing Wireless Sensor Networks to measure temperature, voltage, and current by enabling remote monitoring and control of grid components, facilitated by an Arduino controller.	Further research is needed to integrate RESs into IoT-enabled micro grid systems, optimizing their integration to enhance grid stability, maximize energy efficiency.
[23], 2023	GRFO-ITSA	Improves active power management in grid-connected PV-PEV systems.	Integration of multiple renewable sources beyond PV (e.g., wind, hydro) needs further exploration.
[24], 2023	MPPT	The effectiveness of the multi-port converter in MPPT operation, improvements in performance metrics and system efficiency.	Potential limitations in the current design need improvements and approaches that could be explored be used for RES integration.
[25], 2022	IoT, Smart Meter	The research integrates an IoT module and Smart Meters for efficient energy management and data analysis. It collects and transmits data to a Cloud Analytics layer, providing daily/hourly energy consumption using IoT protocols.	To devise and assess various Demand Response and Demand Side Management strategies in the future including Arduino-based intelligent system to autonomously control HVAC units efficiently, while also integrating RESs.

thereby advancing the overall management of smart grid systems.

1.4 Contribution of work

The contributions outlined in the paper are:

- The paper proposes a hybrid renewable energy system that combines solar and wind power generation to meet load demand. The generated power is then transmitted through continuously monitored transmission lines.
- The system leverages WSN deployed across its infrastructure to collect data from various units.
- An ANFIS is employed to regulate power flow within the smart grid, ensuring optimal and stable operation.
- The paper investigates the application of an IoT-based Neuro-Fuzzy concept for real-time power monitoring. The concept is implemented and evaluated using MATLAB/Simulink and Proteus software.

The upcoming section delineates the proposed methodology, covering the modeling and design aspects of solar/wind

energy systems, the integration of an adaptive network-based fuzzy inference system, and the implementation of the IoT-assisted monitoring system. Following that, [Section 3](#) describes the assessment of the proposed model's performance using MATLAB/Simulink, a powerful software tool commonly employed in diverse industries for technical computing and model-based design tasks. Additionally, Proteus Software, a comprehensive suite extensively utilized in electronic design automation, is utilized for generating schematics, simulating circuits, and designing printed circuit boards. In this section, it is utilized to simulate grid power and to observe active, reactive, and apparent powers, as well as voltage and currents. Lastly, [Section 4](#) provides a summary of conclusions drawn from the study and outlines potential avenues for future research endeavors.

2 Proposed system design

The proposed system is designed to include both control and monitoring functionalities. At its core, the control

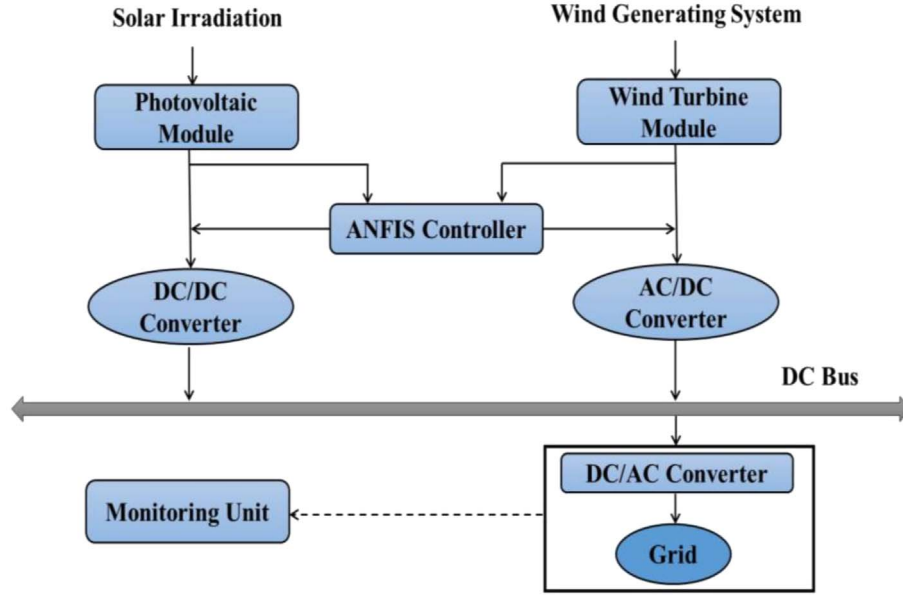


Fig. 1. Proposed schematic model of solar PV-WGS using ANFIS controller with monitoring unit.

aspect is managed by an ANFIS, which regulates the electricity generated by both solar and wind power plants [36, 37]. This system ensures an efficient distribution of power to consumers and facilitates communication within the smart grid's distributed generation framework. On the monitoring side, WSNs are deployed across the entire system to track performance and operational metrics [38]. The schematic model of the proposed system is shown in Figure 1. This setup establishes the basis for a dynamic simulation model designed specifically for a Solar PV-Wind Generator System (Solar PV-WGS) [10, 39]. The architecture incorporates a solar PV module, a wind turbine, and an induction generator. Power electronic components link the AC and DC sections of the system, requiring various controllers to manage their operation effectively [40]. Opting for a DC bus design is favored due to its straightforward control and uncomplicated nature. In the proposed system, the Solar PV-WGS units are interconnected to a shared DC bus via an AC/DC converter and a DC/DC converter, respectively.

2.1 Solar PV module/modeling

To investigate nonlinear behaviour, a conventional solar PV model is developed and simulated as part of this analysis [41]. This model generates both photovoltaic voltage and current outputs, with inputs obtained from cell temperature and solar irradiance levels. By conducting this simulation, a thorough assessment of how the solar PV module reacts to different temperature and solar irradiance conditions can be achieved; capturing its nonlinear performance attributes [42]. A schematic representation of this PV model is illustrated in Fig. 2. The photovoltaic current (I_{PV}) can be determined through the use of the PV cell circuit given by equation (1).

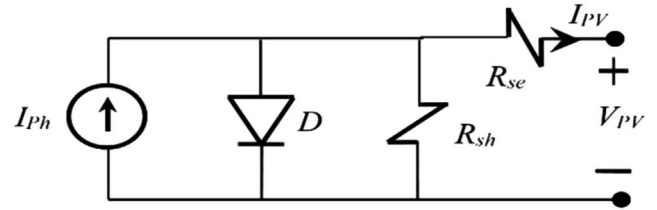


Fig. 2. Equivalent circuit of single diode solar PV cell.

$$I_{PV} = I_{ph} - I_o \left(e^{\left(\frac{E_C V_D}{K f T_A} \right)} - 1 \right) - \frac{V_D}{R_p} \quad (1)$$

where, I_{ph} – photocurrent (A), I_o – diode saturation current, E_C – electric charge, K , f – ideal factors of cell, T_A – absolute temperature, V_D – diode rectifier voltage, and R_p – parallel resistance. Equation (2) expresses the relationship governing this photocurrent. Figure 3 illustrates the correlation between voltage and current, as well as the voltage and power of PV modules, respectively.

$$I_{ph} = (\tau_{SC}(T_A - T_{ref}) + I_{SC})G_S \quad (2)$$

where, T_{ref} – reference temperature ($^{\circ}\text{C}$), I_{SC} – short circuit current (A), τ_{SC} – temperature coefficient and G_S – reference solar irradiance.

2.2 WGS design/modeling

The operational behavior of a WGS is determined by the attributes of the wind turbine and the specific types of wind generators employed within the system [43]. The wind turbine functions by producing mechanical torque through the rotation of the rotor shaft, a process that is intricately

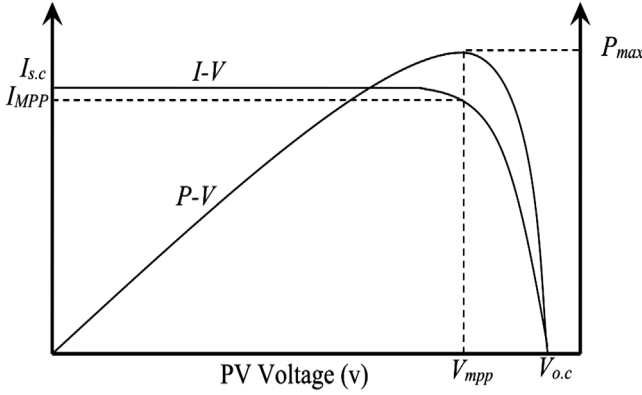


Fig. 3. Illustrates current-voltage and power-voltage characteristics of solar PV cell.

affected by variables such as wind velocity and the characteristics of the generator utilized [44]. The wind power is mathematically calculated by the following equation (3).

$$P_W = C_P(v, \phi) \frac{\rho A}{2} V_w^3 \quad (3)$$

where, P_W – power output, C_P – aerodynamic performance coefficient, v – tip speed ratio, ϕ – pitch angle, and ρ – air-density factor, A – swept area of turbine, and V_w – wind velocity. Equation (4) provides a general expression for C_P based on the characteristics of the turbine.

$$C_{P(\lambda, \beta)} = C_1 \left(\frac{C_2}{\lambda_i} - C_3 \beta - C_4 \right) e^{\frac{-C_5}{\lambda_i}} + C_6 \lambda. \quad (4)$$

The parameters related to wind turbine blade design and rotor structure can be denoted by C_1 to C_6 , where, $C_1 = 0.517$, $C_2 = 116$, $C_3 = 0.41$, $C_4 = 5.10$, $C_5 = 21.1$, and $C_6 = 0.0068$.

$$\lambda = \frac{\omega R}{V_\omega} \quad (5)$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.081\beta} - \frac{0.0352}{\beta^3 + 1} \quad (6)$$

where, R represents the radius in meters (m), V_ω signifies the wind speed in meters per second (m/s), and ω denotes the turbine's angular speed in radians per second (rad/s). The base wind speed, typically measured in meters per second (m/s), serves as the average predicted wind speed.

The wind turbine operates by driving the rotor shaft, which in turn generates mechanical torque. This torque production is contingent upon the characteristics of the generator as well as the prevailing wind speed values.

2.3 Adaptive neuro-fuzzy inference system

The ANFIS represents a hybrid approach that integrates the strengths of both ANN and fuzzy logic systems. This fusion allows ANFIS to capitalize on the advantages offered by both methodologies, thereby enhancing its performance

and adaptability [45, 46]. ANFIS serves as a versatile tool for constructing a set of fuzzy if-then rules equipped with appropriate membership functions tailored to generate the desired input-output pairs. This process is facilitated through a fuzzy technique rooted in the Takagi-Sugeno method, which enables ANFIS to effectively model complex systems and relationships. In Figure 4, a typical model of the ANFIS infrastructure is depicted, showcasing its layered structure and functionality [47]. Each layer within the ANFIS architecture plays a crucial role in the processing of inputs and the generation of corresponding outputs. The input layer receives the input data, which is then passed through subsequent layers for processing [48, 49].

The ANFIS architecture comprises five main functional nodes, and static nodes are depicted as circular nodes, while dynamic nodes are represented as squared nodes [50, 51]. The subsequent layers, known as the fuzzy set membership function layer and the rule layer, handle the fuzzification of predictor variables and the generation of fuzzy logic statements respectively. Finally, the output layer aggregates the results obtained from the previous layers to produce the final output of the ANFIS model [52]. The process of constructing an ANFIS system typically commences with the user selecting initial predictor variables and fuzzy set membership function based on available prior knowledge. To enhance performance and prevent convergence to local minima, the fuzzy rule sets are fine-tuned using various training algorithms, like Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, and Differential Evolution [53]. These algorithms offer distinct strategies: Genetic Algorithms evolve rule configurations using mutation and crossover, Particle Swarm Optimization mimics social behaviors to guide rule sets, Simulated Annealing transitions from exploration to exploitation, and Differential Evolution combines differences between candidate solutions for effective exploration [54, 55].

The choice of algorithm depends on factors such as problem complexity and available computational resources. Takagi-Sugeno (TS) models employ fuzzy sets and rules to approximate nonlinear functions, where each rule corresponds to a linear function of the input variables. These linear functions are commonly depicted as first-order or higher-order polynomials. The rules follow an “if-then” structure, wherein input variables are fuzzified using membership functions, and output variables are expressed as linear functions of these inputs [56, 57]. In the TS FIS model, the relationship between input variables $P_G(t-1)$, $P_L(t)$, and output variable $P_r(t)$ is incorporated.

2.3.1. Takagi-Sugeno fuzzy inference system (FIS)

TS method is a type of Fuzzy Inference System (FIS) that leverages fuzzy sets and rules to approximate non-linear functions. Here's a breakdown of its key aspects:

- **Fuzzy Sets and Membership Functions:** The TS method utilizes fuzzy sets to represent the input and output variables of the system. These fuzzy sets define the degree of membership for each input or output value. Membership functions map crisp input values to degrees of membership within the fuzzy sets,

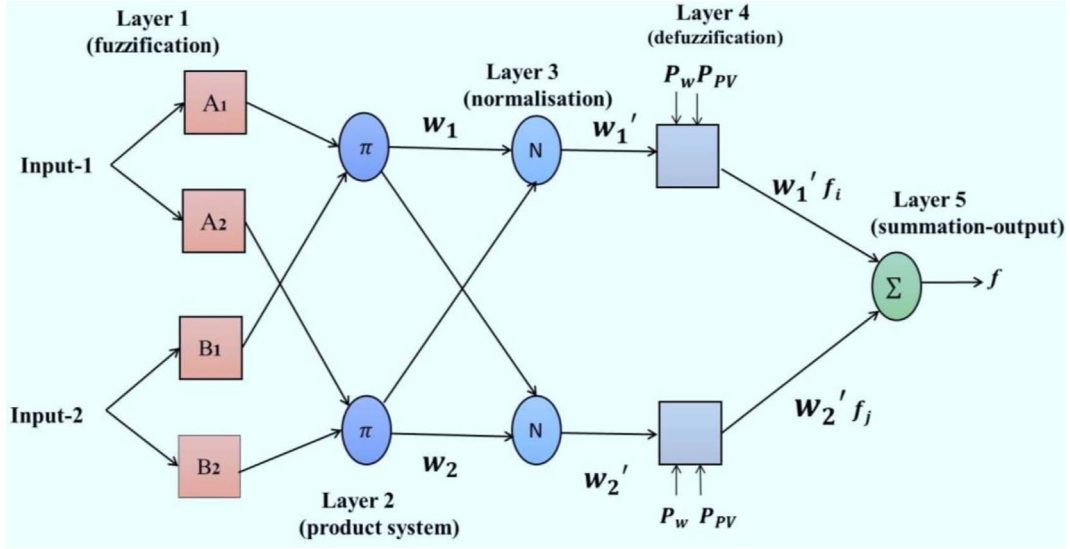


Fig. 4. Five layered architecture of ANFIS prediction model.

allowing for smooth transitions between membership levels [58, 59].

- **“If-Then” Rules:** The TS FIS employs a set of fuzzy rules that follow an “if-then” structure. These rules involve:

- **Antecedent (If Part):** The antecedent part of the rule defines the conditions based on the input variables. These conditions are expressed using fuzzy sets and their membership functions.
- **Consequent (Then Part):** The consequent part of the rule specifies the output based on the input conditions. Unlike Mamdani FIS (another common fuzzy inference system), the consequent in TS FIS is a linear function of the input variables (often first-order polynomials, but higher-order polynomials can also be used).

Benefits of TS method

- **Non-linear Function Approximation:** The TS method offers a powerful tool for approximating non-linear functions through a combination of fuzzy sets and linear functions. This makes it well-suited for modeling complex systems.
- **Interpretability:** While the TS method involves fuzzy logic, the use of linear functions in the consequents provides a degree of interpretability compared to “black-box” models. Understanding the contribution of each rule and its associated linear function can be beneficial for model analysis [60].

In the context of handling Hybrid Renewable Energy Systems (HRES), the suggested ANFIS method requires suitable sample data based on factors such as energy consumption and production at a given instant of time. This training dataset calculates the reference power as described by equations (7) and (8).

$$P_s(t) = P_G(t) \quad (7)$$

where, $P_G(t)$ represents total power produced and $P_S(t)$ represents the source power.

$$P_G(t) = P_{PV}(t) + P_W(t) \quad (8)$$

where, $P_{PV}(t)$ – solar PV instantaneous power, $P_W(t)$ – wind turbine instantaneous power.

To forecast the reference power outputs for both solar PV and WGS at a given time, it's essential to take into account variations in load demand. The reference powers for the solar PV and WGS at time “ t ” are represented as $P_{PV}^r(t)$ and $P_W^r(t)$, respectively. The Maximum Power Point Tracking powers for the Solar PV and WGS at same instant of time are denoted as $P_{PV-MPPT}$ and P_{W-MPPT} , with indicating the currents I_{PV} and I_W from the solar PV and wind sources, respectively.

This process of forecasting involves analyzing historical power generation data and current load demands, as summarized in Table 2, which includes data on previously generated power and current load requirements for accurate prediction.

By considering equation (7), the training set for ANFIS can be formulated according to equation (9).

$$\begin{bmatrix} P_G(0), P_L(1) \\ P_G(1), P_L(2) \\ \vdots \\ P_G(t-1), P_L(t) \end{bmatrix} = \begin{bmatrix} P_r(0) \\ P_r(1) \\ \vdots \\ P_r(t) \end{bmatrix} \quad (9)$$

The trained dataset is utilized to train the ANFIS, which subsequently controls energy consumption during testing stages. The predicted power generation is denoted as $P_G(t-1)$, while the load requirement is symbolized as $P_L(t)$, and the reference power as $P_r(t)$. The ANFIS system

Table 2. Reference power calculations.

Source power	Control power
PV system	$P_{PV}^r(t) = \frac{P_{PV-MPPT}}{I_{PV}}$
Wind system	$P_W^r(t) = \frac{P_{W-MPPT}}{I_W}$

features a single output, which corresponds to the reference power. In ANFIS, fuzzy rules serve to illustrate how input variables relate to output variables, employing an “if-then” format. In this structure, the “if” part delineates conditions based on input variables, while the “then” segment indicates the resulting outputs. Through this approach, ANFIS can comprehend intricate connections between inputs and outputs by establishing fuzzy logic-driven rules. These rules function as directives for the system to analyse and handle input data, thereby generating suitable output responses [61, 62].

Equations (10) and (11) define two fuzzy rules.

Rule 1: if $P_G(t-1)$ is A_1 and $P_L(t)$ is B_1 then

$$f_1 = p_1 P_G(t-1) + q_1 P_L(t) + k_1. \quad (10)$$

Rule 2: if $P_G(t-1)$ is A_2 and $P_L(t)$ is B_2 then

$$f_2 = p_2 P_G(t-1) + q_2 P_L(t) + k_2 \quad (11)$$

where, the parameters p_1, p_2, q_1, q_2, k_1 and k_2 represents the linear variable, while A_1, A_2, B_1 , and B_2 represent the non-linear variables. These parameters are utilized within the ANFIS model to capture the system’s behavior effectively. Table 3 illustrates the input variables utilized by the ANFIS, which are essential for the model’s decision-making process and inference generation.

The outcome of each rule is given by Equation (12).

$$f_i = p_i P_G(t-1) + q_i P_L(t) + k_i, \quad \text{where } i = 1, 2, 3. \quad (12)$$

By conducting a multiplicative process of the standard activation degrees of fuzzy rules with the individual outputs of each rule, the output f can be computed using equation (13).

$$f = \frac{\sum W_i f_i}{\sum W_i}, \quad \text{where } i = 1, 2, \quad (13)$$

where, W_i represents the standardized value. The five-layered structure of ANFIS is outlined as follows.

2.3.1.1 Fuzzification layer

In this layer, each predictive layer defines an input variable assigned to it. Expressions (14) and (15) describe the contribution of the fuzzy layer.

$$F_{L1,i} = \mu A_i(P_G(t-1)), \quad i = 1, 2, \dots \quad (14)$$

$$F_{L1,j} = \mu B_j(P_L(t)), \quad j = 1, 2, \dots \quad (15)$$

where, $F_{L1,i}, F_{L1,j}$, are the fuzzy layer outputs, and $\mu A_i(P_G(t-1)), \mu B_j(P_L(t))$, are the fuzzy layers of membership functions.

Table 3. Fuzzy input variables.

Predicted variable	Fuzzy set functions	
$P_{Gen}(t-1)$	High	Low
$P_L(t)$	High	Low

2.3.1.2 Product layer

The output at the product layer W_1 and W_2 represents the weighted input for the next node. This output can be described using equations (16) and (17) accordingly.

$$W_1 = F_{L2,i} = \mu A_i(P_G(t-1)) \mu B_i(P_L(t)), \quad i = 1, 2, \dots, \quad (16)$$

$$W_2 = F_{L2,j} = \mu A_j(P_G(t-1)) \mu B_j(P_L(t)), \quad j = 1, 2, \dots \quad (17)$$

2.3.1.3 Normalization layer

The third layer, which is known as the normalization layer, each node is considered a fixed node. This layer is responsible for executing the fuzzy “and” operation and effectively normalizing the input weights. The output’s W'_1 and W'_2 is determined by equations (18) and (19) respectively.

$$W'_1 = F_{L3,i} = \frac{W_i}{W_1 + W_2}, \quad i = 1, 2, \dots, \quad (18)$$

$$W'_2 = F_{L3,j} = \frac{W_j}{W_1 + W_2}, \quad j = 1, 2, \dots, \quad (19)$$

2.3.1.4 Defuzzification layer

This layer’s function is to execute an adaptive process that creates output fuzzy membership functions in accordance with established fuzzy rules. The performance of the defuzzification layer is delineated by the formulas designated as equations (20) and (21).

$$W'_1 f_i = F_{L4,i} = \frac{W_i}{W_1 + W_2} (p_1 P_G(t-1) + q_1 P_L(t) + k_1) \quad (20)$$

$$W'_2 f_j = F_{L4,j} = \frac{W_j}{W_1 + W_2} (p_2 P_G(t-1) + q_2 P_L(t) + k_2) \quad (21)$$

where, the defuzzy layer outputs are represented as $W'_1 f_i$ and $W'_2 f_j$ respectively.

2.3.1.5 Output layer

The expression given by equation (22) provides the total output of this layer by summing up the outputs of all nodes in the layer.

$$f = F_{L5,i} = \sum W'_i f_i = \frac{\sum W_i f_i}{\sum W_i}, \quad i = 1, 2, \dots \quad (22)$$

The overall output is denoted by “ f ”. Once the ANFIS training phase is concluded, it becomes capable of delivering the

Table 4. Fuzzy rules.

$P_{\text{Gen}}(t - 1)$	$P_L(t)$	Reference power
High	High	Low
High	Low	High
Low	High	Very low
Low	Low	Medium

reference power $P_r(t)$. Within this proposed framework, decisions regarding power allocation between the sources and the load are made based on the available power resources. The determination of reference power is guided by fuzzy rules, which are systematically outlined in Table 4, facilitating an efficient and balanced distribution of energy.

2.4 Power electronic converters

The power converters utilized in this system include three-phase diode rectifiers, which are responsible for converting AC-DC. Additionally, DC-DC converters are employed to adjust the DC voltage level to the desired value [63, 64]. Moreover, inverters are employed to convert the DC voltage into AC output with a specific power frequency. This enables the generation of a variable-frequency output voltage, which is then further processed to produce a sinusoidal AC voltage that aligns with the grid frequency.

In the solar PV system specifically, a DC-DC converter is employed to optimize the voltage and power levels generated by the solar panels. The switching signal utilized in the converter is carefully designed to ensure the efficient conversion of solar energy into electrical power while maintaining appropriate voltage levels for the desired application [65]. The switching signal employed in the converter undergoes the conversion of solar energy into electrical power, ensuring efficiency while also upholding voltage levels tailored to the specific application requirements. This process involves a sophisticated interplay of parameters and considerations, such as the characteristics of the solar PV array, the power electronics topology utilized in the converter, and the demands of the load or grid to which the electrical power is supplied [66]. The converter maximizes power transfer from the solar panels to the electrical system, mitigates losses, and maintains stability, ultimately enhancing the overall performance and reliability of the solar energy conversion system.

2.4.1 Modeling of DC/DC boost converter

In this system, the extracted maximum voltage and current from the solar PV module, obtained using the MPPT technique, are utilized as inputs to the boost converter. The duty cycle of the boost converter is designed based on various factors, including the MPPT, temperature, and irradiance of the PV module. The boost converter operates in a manner where the output voltage is higher than the input voltage. This process is commonly referred to as a step-up conversion. The output voltage and current of the boost converter can be described by equations (23) and (24) respectively. Equation (23) represents the output voltage of the boost converter, which is typically higher than the

input voltage due to the step-up operation. This output voltage is influenced by the duty cycle of the converter as well as other factors such as the input voltage, inductance, and switching frequency. Equation (24) describes the output current of the boost converter, which is dependent on the input current, duty cycle, and efficiency of the converter.

$$V_o = \frac{V_{\text{in}}}{(1 - D)} \quad (23)$$

$$I_o = \frac{I_{\text{in}}}{(1 - D)} \quad (24)$$

where, V_o – output voltage (V), I_o – output current (I), I_{in} – input current (A), V_{in} – input voltage, D – duty cycle.

2.4.2 Modeling of AC/DC converter

The diode rectifier is used in this work to convert the three-phase output voltage of the PMSG into a DC voltage. The rectified DC voltage (V_{rec}) is given by equation (25).

$$V_{\text{rec}} = \frac{3\sqrt{2}}{\pi} V_{\text{rms}} \quad (25)$$

where V_{rms} is the rms voltage applied to the three-phase rectifier. Even though the output voltage of the diode rectifier is unregulated, there are no extra losses stemming from the switching of power electronic components. By disregarding diode losses, we can assume that all the power obtained is fully converted from AC-DC [67].

2.5 Monitoring system using WSN

The adoption of WSNs is witnessing rapid growth across a wide array of applications. However, before these systems are released into the market, several critical factors must be carefully considered, including the design objectives of the application, system functionality, power efficiency, and overall cost [68, 69]. Compared to traditional sensors, WSN sensors are characterized by their lower cost, reduced weight, and lower processing and computational requirements. These sensors possess the capability to compute, detect, and collect data from their surroundings before encrypting it [70]. Each sensor node typically consists of three main components: the sensing unit, the processing unit, and the communication unit. A limited memory processing unit is employed to manage the gathered data, while a communication unit, usually in the form of a radio transceiver, facilitates the exchange of information between nodes to achieve specific objectives or retrieve relevant data. Estimating power production is an ongoing necessity, requiring a blend of technologies such as processing, analysis, data transmission, storage networks, sensors, and autonomous control. WSN offers a cost-effective, easy-to-implement, and low-power alternative compared to traditional monitoring techniques [71, 72]. WSN is frequently integrated into the IoT ecosystem to address complex challenges related to data transmission and storage. Within the realm of smart grids, the primary objectives encompass monitoring, control, and data analysis. Figure 5 illustrates the structure

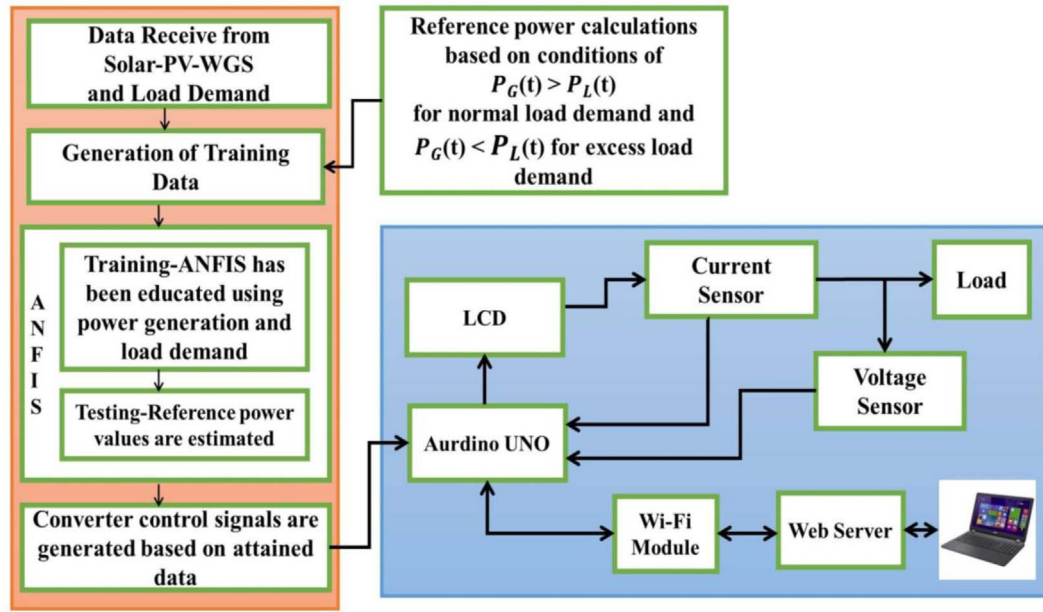


Fig. 5. Structure of controller and monitoring system with voltage and current sensors.

for monitoring and controlling techniques proposed in the system.

An IoT-based monitoring system typically comprises two key components: the first is analytic control systems, and the second is monitoring [73, 74]. In controlling setup, first-step data is received from Solar PV-WGS and loaded. In testing mode, reference power values are estimated, and at last, converter control signals are generated based on the attained data sets. Here the reference power is calculated based on the condition that $P_G(t) > P_L(t)$ for normal load demand and $P_G(t) < P_L(t)$ for excess load demand. In the monitoring setup, a voltage detection circuit and current sensors are connected to user loads [75, 76]. The Arduino UNO is one of the most popular and widely used microcontroller boards in the Arduino family. It is based on the ATmega328P microcontroller and is designed to be user-friendly and versatile for a wide range of applications, from simple hobby projects to more complex prototypes. The development process involves writing code in the Arduino IDE, compiling it, and uploading it to the board via USB, after which the microcontroller executes the program. The Arduino UNO receives data from these connected sensors and stores it in its internal memory. Communication between the web server and the monitoring units is facilitated through Wi-Fi modems. A local monitor displays the real impacts of the load via a Liquid Crystal Display (LCD), while the server receives load data from the Wi-Fi module.

3 Results and discussions

A solar PV-WGS combining both conventional and renewable energy sources was proposed. The most electricity

possible may be produced by this hybrid production system using wind and solar energy. Utilizing the ANFIS controller, the maximum power from solar PV-WGS systems is extracted to satisfy the power requirement. There are four membership functions divided into two inputs and outputs. The FIS block that was developed during the training has been applied to energy management. Figure 6 shows the MATLAB/Simulink Model, which analyzes the ANFIS controller with empirical data. Other advantages of the suggested controller included its ease of comprehension, adaptability, and lack of need for a control system or mathematical model. For real-time operation of the controller, the input data requires continual adjustments or modifications. The suggested method revolves around estimating the output power of sources by evaluating the demands or requirements of the load. Advancements in solar PV-WGS design aimed at improving power generation efficiency, monitoring capabilities, and security through the integration of IoT technologies and intelligent processes. This method essentially adapts and adjusts input data in real time to determine and regulate the power output from various sources based on the current load needs [77]. The solar PV-WGS powers are used to meet the necessary load requirement. The levels of irradiation and temperature for the PV module are 1000 W/m^2 and 25°C , respectively.

An on-site LCD is utilized as a local interface, presenting real-time updates and data regarding the loads' status. This arrangement enables direct monitoring and visualization of ongoing load outcomes via the LCD interface. The Wi-Fi module transmits load data to the web server, enabling easy access and analysis. This setup allows for monitoring various loads by capturing their current, voltage, and power parameters. Once the simulation software finishes its tasks, it retrieves data using the Message

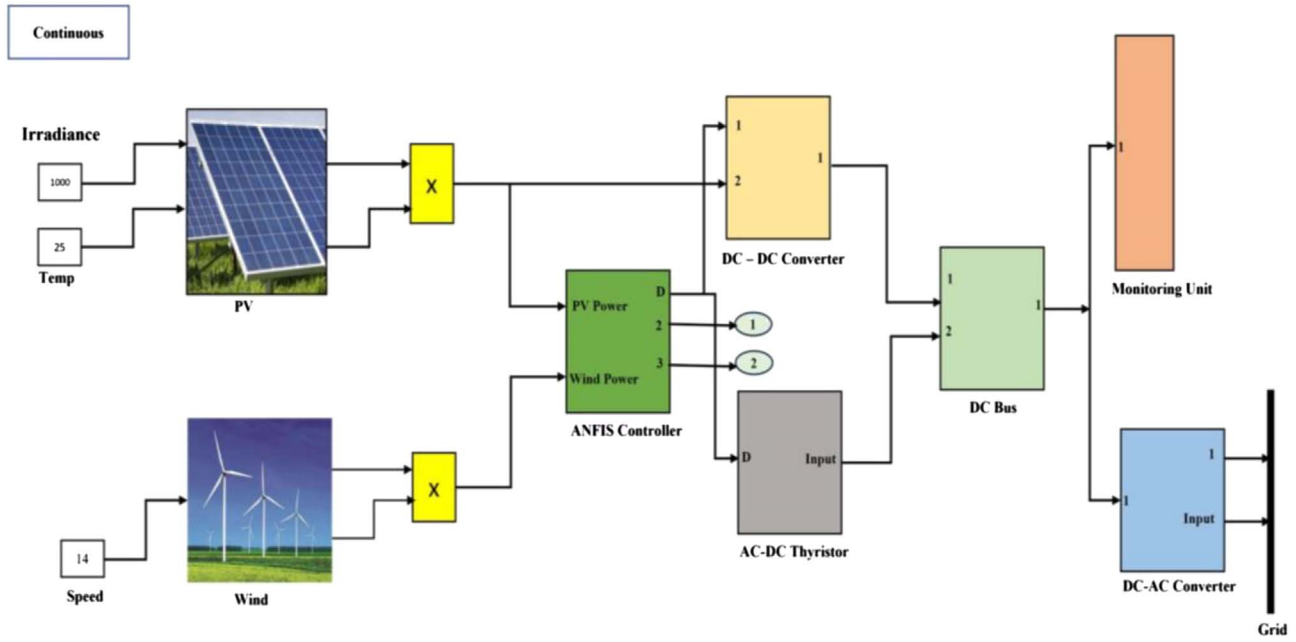


Fig. 6. Proposed Simulink model of solar PV-WGS with controlling and monitoring unit.

Queuing Telemetry Transport (MQTT) protocol, ensuring efficient transfer and analysis. The MQTT protocol is well-known for its efficiency in gathering data and smoothly transmitting it to server nodes. It focuses on collecting diverse electrical measurements from loads, such as current, voltage, real power, and reactive power. These measurements provide vital information for analysis and monitoring purposes. With MQTT, the data gathering and transfer process becomes seamless, guaranteeing that pertinent information reaches server nodes effectively. This feature is especially valuable in applications where real-time or periodic monitoring of electrical parameters is crucial for maintaining optimal system performance. This integration allows for the validation and analysis of the collected data from IoT devices within the MATLAB/Simulink environment using Thingspeak as a conduit. Thingspeak is a centralized platform for IoT data analytics, offering seamless integration of diverse IoT devices and efficient data management. Users can easily connect their devices to collect real-time data streams, including sensor readings and environmental metrics. Thingspeak provides powerful analytics tools for statistical analysis, trend prediction, and anomaly detection, enabling users to derive actionable insights and optimize processes. Its visualization features allow for customizable dashboards and graphs, facilitating real-time data monitoring and trend identification [78, 79].

The IoT devices will supervise and potentially control the data through Thingspeak, validating it within the MATLAB/Simulink platform for comprehensive analysis and management. Thingspeak processes the analytics of the data gathered through the IoT. In this instance, the analytics is configured so that poor efficiency data between generation and demand sends an alert signal to the controller, which then uses the data to make a highly efficient signal.

3.1 Simulation outcomes of the solar PV module integrated with a neuro-fuzzy MPPT technique

The Solar PV system consists of a PV array comprising 14 series and 1 parallel strings, capable of generating approximately 3.84 KW under full irradiance of 1000 W/m². In Figure 7 the relationship between V-I and P-V of the Solar PV modules is depicted. It is evident from the graph that the maximum power occurs near the open circuit voltage of the PV panel. The open-circuit voltage and the voltage at maximum power are noted as 36.6 volts and 29 volts, respectively. Similarly, the short-circuit current and the current at the maximum power point are recorded as 8.84 A and 8.35 A, respectively. The electrical specifications of the Solar PV module and boost converter can be found in Table 5. Both controllers are implemented in a simulation environment that models the behavior of a solar PV array. This environment includes the characteristics of the solar panels, environmental conditions (e.g., irradiance, temperature), and the power electronics interface.

Figure 8, as described, provides a clear visualization of the performance disparity between solar PV modules controlled by PI and ANFIS controllers. This visual evidence underscores the effectiveness of advanced control strategies in optimizing solar energy conversion. In the scenario shown in Figure 8a, the Solar PV module equipped with a PI controller achieves a peak power output of 3.2 kW within the first second. This result highlights the typical performance of PI controllers, which aim to minimize the error between the set point and the actual output by adjusting control inputs. While PI controllers are valued for their simplicity and reliability, their effectiveness in highly nonlinear systems, such as Solar PV modules subject to variable environmental conditions, can be limited. The fixed gains of a PI controller make it less responsive to rapid changes in

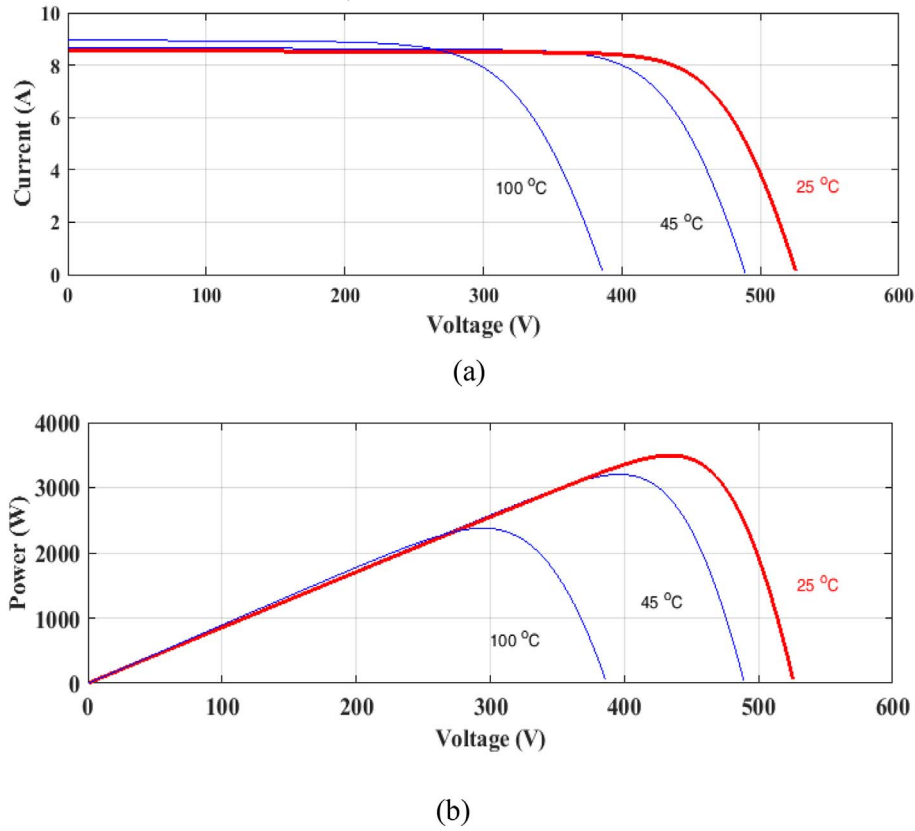


Fig. 7. Solar PV cell characteristics. a) $I-V$ characteristics, b) $P-V$ characteristics.

irradiance and temperature, which may result in less effective tracking of the maximum power point [80]. Conversely, Figure 8b demonstrates a notable improvement with the use of an ANFIS controller, where the maximum power output increases to 4.8 kW within the same timeframe. This enhancement is due to the adaptive and intelligent nature of the ANFIS framework. ANFIS controllers adjust their control strategy dynamically based on real-time data, allowing for more precise tracking of the MPP under changing conditions. This adaptability enables the ANFIS controller to optimize power output more effectively compared to the PI controller, showcasing its superior ability to handle the complexities of solar energy conversion.

The comparison underscores the significant impact of control strategy selection on the efficiency of Solar PV modules. While the PI controller provides a simpler and potentially more stable approach, its static nature may prevent it from fully exploiting available solar energy. In contrast, the ANFIS controller's dynamic and intelligent methodology significantly outperforms the PI controller, particularly in environments with fluctuating solar irradiance and temperature. This analysis highlights the value of advanced control techniques in renewable energy systems, as they can greatly enhance output and efficiency. The substantial improvement in power output achieved with the ANFIS controller demonstrates its effectiveness and makes a strong case for its use in optimizing solar PV module performance.

Table 5. Electrical specifications of solar PV module.

PV module	
Specifications	Rated values
Open circuit voltage V_{oc}	87.72 V
Short circuit current I_{sc}	2.66 A
Maximum voltage V_{mpp}	70.131 V
Maximum current I_{mpp}	2.448 A
Power rating	5 kW
Boost converter	
Parameter	Value
Inductor (L)	150 mH
Capacitor (C)	470 Mf

3.2 Simulation outcomes of wind generation system

The electrical parameters of WGS are shown in Table 6.

Figure 9 illustrates the power characteristics of a typical wind turbine operating with a blade pitch angle (β) of zero and variable speed operation.

Figure 10 in Simulink provides a visual representation of the output power generated by a WGS, under the influence of different control strategies, specifically PI and ANFIS

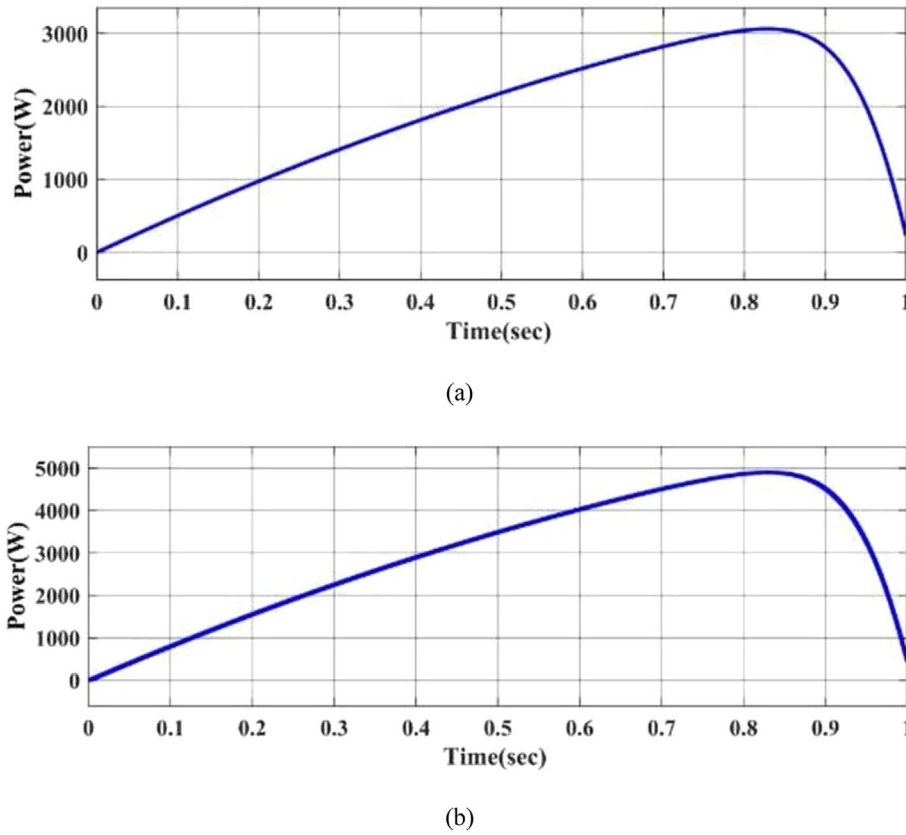


Fig. 8. Solar PV module output power characteristics. a) With PI controller, b) With ANFIS controller.

Table 6. Electrical parameters of WGS.

Wind generating system	
Specifications	Rated values
Wind Speed	14 m/s
Power rating	3 KW
Turbine Speed rating	360 RPM
Pitch angle	0°

controllers. This comparative analysis elucidates the impact of controller choice on the performance of the WGS, particularly concerning the power output achieved under specific wind speed conditions and load integration through an IoT setup. Within the time intervals from $t = 0$ to 2.5 s, the WGS, regulated by a PI controller, maintains a sustained wind power output of 2 KW, despite the wind speed set at 14 m/s. The PI controller, a conventional control strategy known for its simplicity and robustness, effectively adjusts the WGS operation to optimize power generation within this timeframe which is shown in Figure 10a. The fixed control parameters of a PI controller may limit its adaptability to dynamic environmental conditions and load variations, potentially restricting the overall performance of the Wind Generation System (WGS). In contrast, the use of an ANFIS

controller demonstrates significant improvements in WGS performance, as evidenced by an increase in wind power output to 2.5 kW, as illustrated in Figure 10b. The ANFIS controller enhances performance by dynamically adjusting its control strategy based on real-time data inputs, allowing it to better identify and utilize optimal operating points for the WGS [81, 82]. This results in improved power generation and efficiency. Furthermore, integrating IoT technology into the system facilitates a more connected environment, enabling advanced monitoring, control, and optimization of energy usage [83, 84]. The incorporation of IoT further enhances the WGS's efficiency and effectiveness through real-time data exchange and intelligent decision-making capabilities [85, 86].

The comparative analysis highlights the critical importance of choosing the right control strategy for optimizing the performance of WGS. Although the PI controller provides stable control, it is relatively static in its approach. In contrast, the dynamic and adaptive characteristics of the ANFIS controller allow it to more effectively capture and utilize wind energy, resulting in superior performance. Table 7 illustrates the metrics for the ANFIS Controller for simulation results. The performance improvements of an ANFIS controller for IoT monitoring systems, renewable energy integration, or smart microgrid systems, specific metrics can be used in simulations to quantify the enhancements.

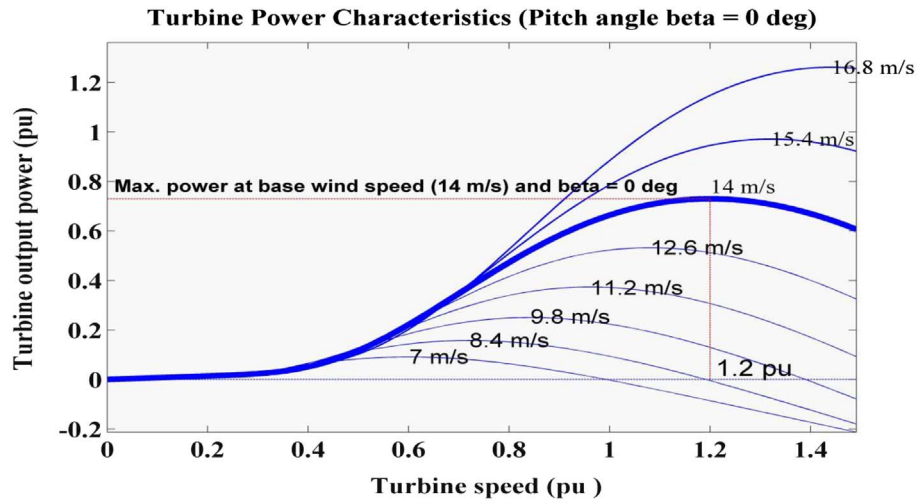


Fig. 9. Power characteristics of a wind turbine with constant pitch angle.

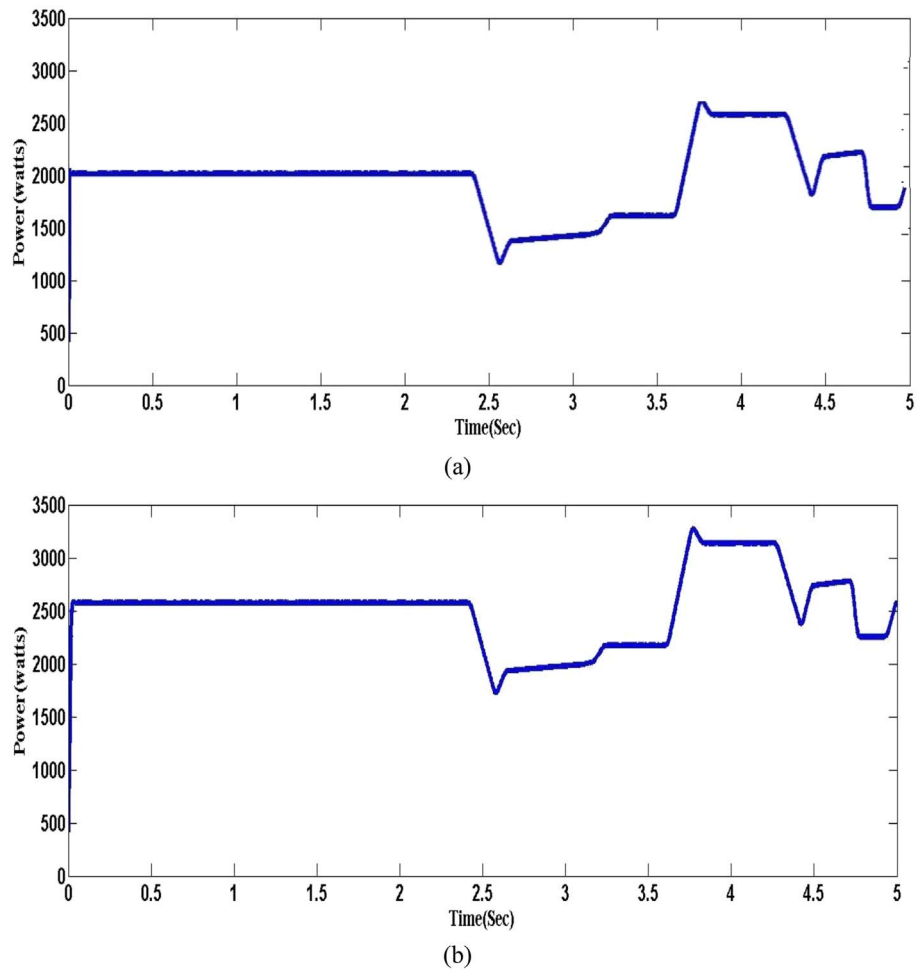


Fig. 10. Output power characteristics of WGS. a) With PI controller, b) With ANFIS controller.

Table 7. Metrics for ANFIS Controller for simulation results.

Metric	PI controller	ANFIS controller	IEEE standards	(%) improvement
Rise time (t_r)	2.8 s	1.5 s	<2 s	46.43%
Settling time (t_s)	4.6 s	2.7 s	<5 s	41.30%
Peak time (t_p)	3.5 s	1.8 s	<2 s	42.86%
Peak overshoot (M_p)	12%	5%	<10%	58.33%
Damping ratio (ζ)	0.35	0.7	≥ 0.4	100%
Number of oscillations	4	1	≤ 3	75%

Table 8. Grid monitoring unit specifications.

Grid specifications	Monitoring unit specifications
Grid current – 18.44 A	ACS712 Current sensor
RMS voltage – 232 V	ZMPT101B Voltage densor
Switching frequency – 100 KHz	SIM800 module, rs-232 gsm/gprs
Power factor – 0.909	MAX232 Dual driver/receiver
Bus voltage – 700 V _{dc}	16 × 2 Liquid crystal display
	ARDUINO UNO, ESP8266 WiFi module

3.3 Simulation results of monitoring unit using Proteous software

Table 8 gives the Smart grid and monitoring unit specifications.

Figure 11, as outlined, presents an insightful depiction of a smart grid monitoring system realized through Proteus simulation software, employing an Arduino Nano microcontroller to manage and display various electrical parameters under different load conditions [87]. This scenario effectively simulates a real-world application where integrating renewable energy sources, such as solar PV and WGS, with conventional grid infrastructure is crucial for optimizing energy consumption and enhancing grid stability.

- (a) Initial Condition with Non-Linear Loads (Fig. 11a) – The initial setup features two non-linear loads connected to an Arduino Nano, with the switches in the open position. In this configuration, the LCD display connected to the Arduino Nano shows a grid voltage of 232 volts and a current measurement of 18.44 A. This stage effectively captures the grid's operational status before integrating renewable energy sources, establishing a baseline for subsequent comparisons.
- (b) Integration of Solar PV-WGS (Fig. 11b) – When the switch is closed, the simulation shifts to a scenario where power from the Solar PV-WGS is integrated into the grid, demonstrating the Arduino Nano microcontroller's ability to process and transmit power data dynamically. The LCD display then shows a notable increase in overall active power to 4192.5 watts and apparent power to 4278.0 volt-amperes.

This surge illustrates the substantial contribution of renewable energy sources to the grid's total power capacity, highlighting the effectiveness of Solar PV and WGS in supplementing grid power.

- (i) Reactive Power Display (Fig. 11c) – Further exploring the grid's electrical characteristics, Figure 11c reveals the reactive power as 850.9 VAR (volt-amperes reactive). Reactive power is crucial for maintaining voltage stability within the grid, as it helps manage the voltage levels and supports the efficient distribution of active power. It is a key component in the power quality assessment, ensuring that the grid can deliver stable and reliable electricity by compensating for the energy stored in inductive and capacitive elements. By providing the necessary reactive power, the grid can avoid voltage drops and fluctuations, which enhances overall system performance and reliability. Understanding and monitoring reactive power are vital for optimizing power flow and improving the efficiency of power distribution systems.
- (ii) Activation SMS Alert for Grid Consumption (Fig. 11d) – Figure 11d illustrates an advanced feature of the system: an SMS alert mechanism that notifies users about the grid's total energy consumption. Utilizing WiFi and GSM technology, this feature marks a significant advancement in smart grid management, allowing users to receive real-time updates on energy usage and associated costs. It highlights the potential of IoT technologies to transform energy monitoring and billing, offering a user-friendly interface for tracking energy consumption and expenses.

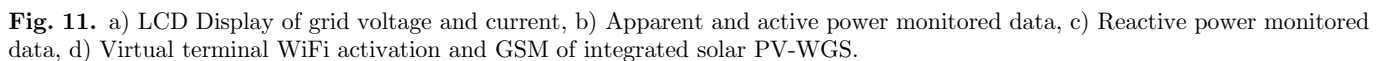


Table 9. Overall discussions and conclusion of existing solutions for frequency regulation in microgrid.

Reference	Discussion	Conclusion
Kamal <i>et al.</i> [47]	Reviews load flow and optimization strategies for smart grid integration	Advanced strategies enhance grid stability; future work on adaptive, scalable solutions needed
Tyagi <i>et al.</i> [48]	Analyzes control strategies for power quality in hybrid microgrids.	Control strategy improves power quality; real-world testing suggested.
Sharma <i>et al.</i> [49]	Reviews flexible power-point-tracking algorithms for photovoltaic systems.	Algorithms enhance photovoltaic efficiency; future research on adaptive solutions recommended
Xu <i>et al.</i> [50]	Discusses optimization for frequency regulation and economic dispatch in microgrids.	Strategy improves regulation and efficiency; applicable to diverse microgrids.
Ghafouri <i>et al.</i> [51]	Evaluates multi-function control for BESS in islanded microgrids	Control scheme enhances stability and regulation; further application in complex microgrids suggested.
Bhujel <i>et al.</i> [52]	Combines droop and MPC for voltage and frequency control in microgrids.	Combined approach enhances stability; scalability needs exploration.
Saxena <i>et al.</i> [53]	Analyzes load forecasting and renewable integration's impact on grid reliability	Strategies improve reliability; further research on forecasting methods suggested.
Xu <i>et al.</i> [54]	Optimizes frequency regulation and dispatch using distributed techniques.	Enhances regulation and efficiency in microgrids; real-world application needed.
Al-Salloomee <i>et al.</i> [55]	Evaluates control for voltage unbalance and harmonics in microgrids.	Control improves power quality; real-time testing recommended.
Javadi <i>et al.</i> [56]	Focuses on frequency stability in microgrid scheduling with islanding.	Method enhances stability during islanding; integration with other techniques advised.

The simulation depicted in [Figure 11](#) encapsulates the integration of renewable energy sources with smart grid technologies, facilitated by the Arduino Nano. It underscores the transformative potential of smart monitoring systems in enhancing grid efficiency, promoting sustainable energy utilization, and providing consumers with actionable insights into their energy consumption patterns. [Table 9](#) illustrates overall discussions and conclusion of existing solutions for frequency regulation in microgrid. Through the lens of this simulation, we witness the synergy between renewable energy integration and IoT-based monitoring systems, offering a blueprint for future advancements in energy management and grid modernization.

Implementing IoT monitoring systems, renewable energy integration, and smart microgrid systems presents several challenges, including technology integration complexity, interoperability, data security, and the variability of renewable energy sources. Additionally, scalability and robustness against failures or cyber-attacks are crucial. To address these challenges, validation methods like Hardware-in-the-Loop (HIL) simulations and pilot projects are essential. HIL simulations test system components and control algorithms in a virtual environment, helping identify and resolve issues before full-scale deployment. Pilot projects allow for smaller-scale implementation, gathering real-world performance data and user feedback. These approaches ensure that systems are reliable, efficient, and ready for broader use.

4 Conclusion and future scope

Conclusion

The effectiveness of modern grid systems relies heavily on the intelligent operation of power system infrastructure. Smart grids represent a significant improvement over traditional grids, offering enhanced reliability and efficiency while addressing various grid-related challenges. This paper presents the implementation of an IoT-enabled power monitoring system based on a neuro-fuzzy architecture. Within this system, an ANFIS serves as the controller for managing wind and hybrid solar power facilities within the smart grid framework. Leveraging Simulink software, the proposed approach integrates IoT and neuro-fuzzy concepts for power monitoring, focusing on parameters such as voltage, current, and power load. The IoT devices will supervise and potentially control the data through Thingspeak, validating it within the MATLAB/Simulink platform for comprehensive analysis and management. This integration allows for the validation and analysis of the collected data from IoT devices within the MATLAB/Simulink environment using Thingspeak as a conduit. Thingspeak processes the analytics of the data gathered through the IoT. In this instance, the analytics is configured so that poor efficiency data between generation and demand sends an alert signal to the controller, which then uses the data to make a highly efficient signal. The proteous simulation software is

used for monitoring and displaying results on an LCD. The proposed design aims to foster the development of cost-effective power sensing and monitoring devices. Its goal is to provide affordable solutions that seamlessly integrate into diverse user environments, thereby enhancing the accessibility and practicality of power monitoring and sensing for a wide array of applications.

Future scope

The potential future research directions for advancements in solar PV-WGS, particularly focusing on increasing power generation efficiency, enhancing monitoring capabilities, and improving security. Further research could explore the application of machine learning and artificial intelligence techniques for predictive maintenance, fault detection, and optimization of Solar PV-WGS in real time. These algorithms could dynamically adjust parameters such as panel orientation, tracking systems, and power distribution to maximize efficiency and output. Investigate the integration of energy storage technologies such as batteries or advanced capacitors with Solar PV-WGS. This would allow for better management of fluctuating power output and enable energy storage for use during periods of low sunlight or high demand. By focusing on these future research directions, scientists and engineers can continue to advance the field of solar PV-WGS technology, making it more efficient, reliable, and secure for widespread adoption and integration into the energy infrastructure.

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