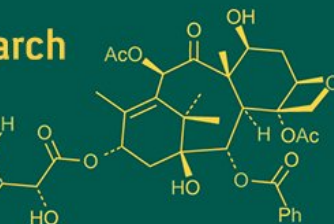
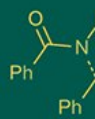
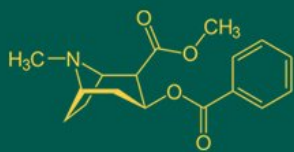


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Fuzzy logic systems in renewable energy: A comprehensive review

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Abstract

Fuzzy logic is an intelligent computational approach for handling uncertainty, ambiguity, and nonlinear system behavior. In recent years, fuzzy logic systems have gained significant attention in renewable energy applications due to their ability to manage the intermittent and dynamic nature of sustainable energy sources. This review presents an analysis of fuzzy logic systems and their applications in renewable energy technologies, including solar photovoltaic systems, hybrid renewable configurations, smart grids, and microgrid-based energy storage systems. The study discusses the fundamental architecture of fuzzy logic controllers, including fuzzification, rule-based inference, and defuzzification processes. It further examines the role of fuzzy logic in maximum power point tracking, energy management, load forecasting, battery management, power quality improvement, and grid stability enhancement. The paper highlights the advantages, limitations and future research directions of fuzzy logic applications in renewable energy. The findings suggest that fuzzy logic offers an effective, flexible, and reliable control strategy for improving the performance, efficiency, and sustainability of renewable energy systems.

Keywords: Fuzzy logic, renewable energy, intelligent control, solar photovoltaic systems, wind energy, hybrid energy systems, smart grid, maximum power point tracking (MPPT), battery management systems, optimization, Energy Storage Systems (ESS)

1. Introduction

Energy is a fundamental driver of economic growth and technological advancement in both developed and developing nations. At present, the global energy landscape remains heavily dependent on fossil fuels, with the 20th century witnessing an approximately twentyfold increase in their consumption. Coal and oil continue to dominate electricity generation systems, supporting critical applications such as lighting, heating, and cooling, while oil also remains central to transportation and industrial energy use. Global energy demand continues to increase due to rapid industrialization, urbanization, and electrification. Despite significant progress in clean energy deployment, fossil fuels still dominate the global energy mix. However, renewable energy technologies are experiencing unprecedented growth, particularly in the electricity sector. According to the International Energy Agency (IEA), renewable electricity is projected to increase from approximately 30% of global electricity generation in 2023 to nearly 46% by 2030, with solar Photovoltaic (PV) and wind energy accounting for the majority of this expansion ^[23, 24].

Recent global statistics indicate that renewable energy contributed approximately 32% of global electricity generation in 2024, highlighting the accelerating transition toward low-carbon energy systems ^[27]. Solar energy has emerged as the fastest-growing renewable technology, with global solar generation increasing by nearly 29% in 2024, while renewable electricity additions reached approximately 858 TWh, representing the largest annual increase recorded ^[27]. The International Renewable Energy Agency (IRENA) reported that global renewable capacity additions exceeded 585 GW in 2024, accounting for more than 90% of total global power expansion, with solar PV as the dominant contributor followed by wind energy systems (IRENA, 2024) ^[25].

Furthermore, global annual renewable capacity additions are projected to increase from approximately 666 GW in 2024 to nearly 935 GW by 2030, with solar PV and wind technologies representing approximately 95% of total capacity growth [23, 24]. Renewable energy systems are increasingly recognized as economically competitive alternatives to fossil fuel-based generation. The United Nations reports that more than 90% of newly installed renewable power projects are now cost-competitive or cheaper than fossil fuel alternatives, while solar and offshore wind technologies have become approximately 41% and 53% less expensive, respectively [26].

Despite these advancements, renewable energy systems remain highly dependent on environmental and climatic conditions, leading to intermittency, uncertainty, and nonlinear operational behavior. These challenges necessitate intelligent control and optimization strategies capable of enhancing energy efficiency, grid stability, and decision-making under dynamic operating conditions. In this context, fuzzy logic-based control systems have gained significant attention due to their ability to manage uncertainty and improve renewable energy system performance without requiring precise mathematical models [23, 24].

2. Fuzzy logic

Fuzzy Logic (FL), introduced by Zadeh [22], provides a mathematical framework for modelling uncertainty and

imprecision in complex engineering systems. Unlike classical binary logic, which assigns discrete truth values, fuzzy logic operates over a continuous range between '0' (completely false) and '1' (completely true), enabling the representation of nonlinear and ambiguous system behavior. This capability is particularly relevant in renewable and precision energy systems, where environmental variability and system nonlinearity limit the applicability of deterministic models. Consequently, fuzzy logic has been extensively applied in solar energy engineering for performance prediction, energy management, fault detection, degradation analysis, process control, optimization, and image processing tasks. The complexity of fuzzy logic-based models ranges from simple rule-based systems to advanced hybrid models integrating multiple computational intelligence techniques [20].

2.1. The architecture: The general architecture of Fuzzy Inference Systems (FIS), including Mamdani and Takagi–Sugeno models, follows a consistent structural framework [21]. As illustrated in Figure (1) and Figure (2), the system consists of three primary units: (i) input unit, (ii) processing unit, and (iii) output unit. These interconnected units enable the transformation of real-world inputs into interpretable control outputs through structured knowledge representation and inference mechanisms.

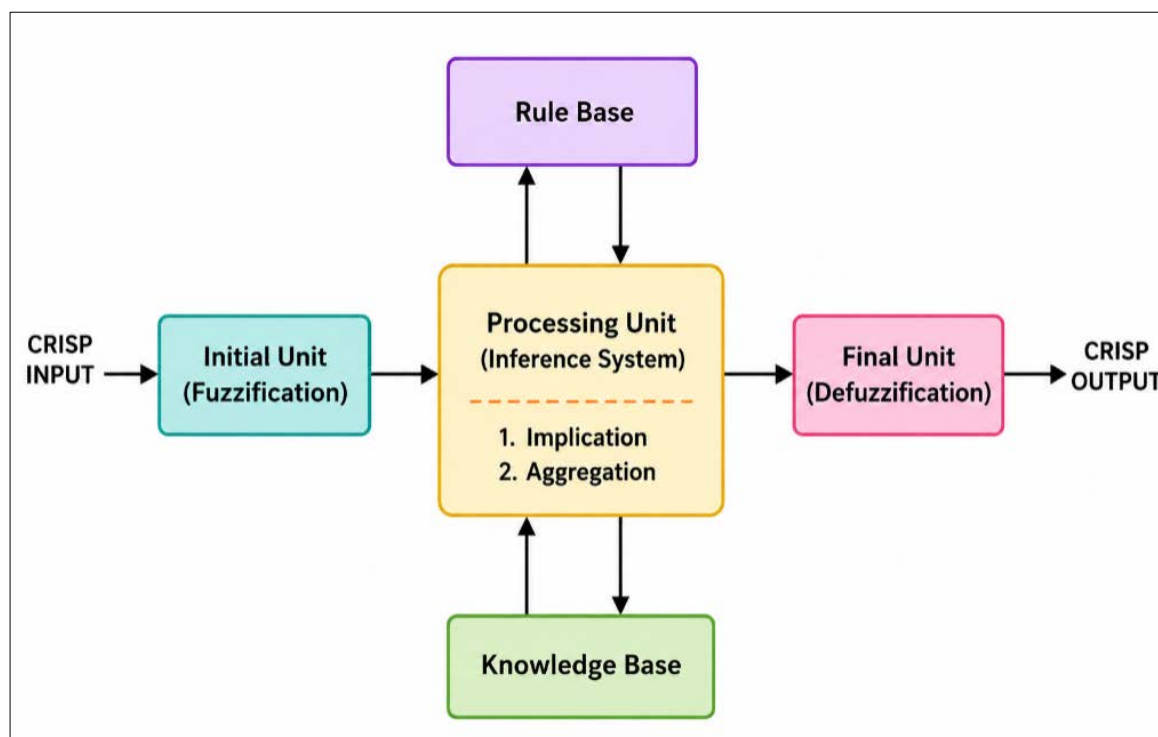


Fig 1: The general architecture of fuzzy logic expert system.

2.2. The fuzzy process

2.2.1. Initial unit or fuzzification unit

The fuzzification unit converts crisp inputs into fuzzy sets, forming the basis for approximate reasoning. This transformation is achieved using Membership Functions (MFs), which define the degree of membership of each input variable.

A fuzzy set A in the universe of discourse X is represented

as:

$$A = \{(x, \mu_A(x)) | x \in IR\} \dots\dots\dots(1)$$

Where $\mu_A(x) \in [0,1]$ denotes the membership value corresponding to element x [22]. The input domain represents the universe of discourse, while the output corresponds to the degree of membership.

Table 1: The general classifications of membership functions available for data conversion [28]

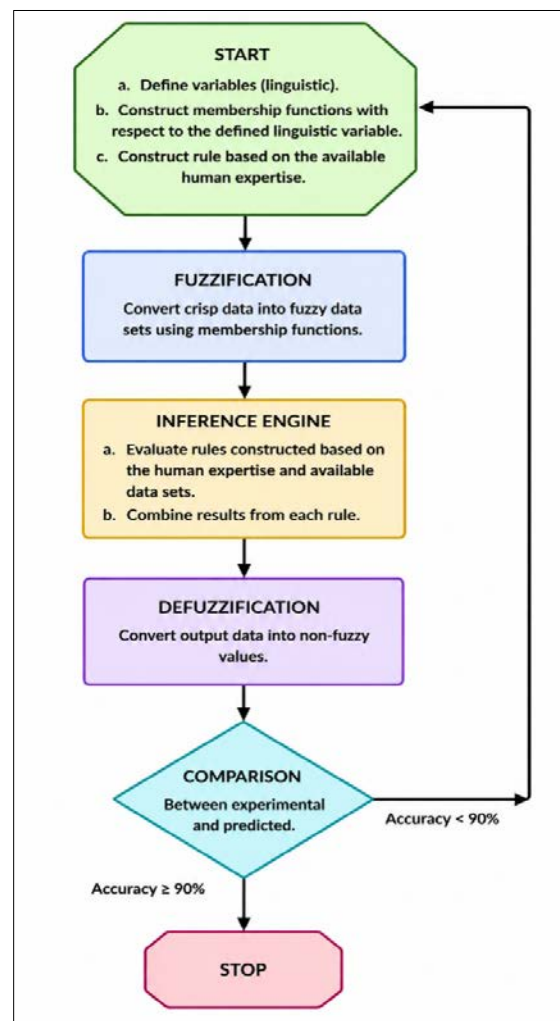
S. No.	Type of MF	No. of Parameters	Mathematical Expression	Applications	Output Prediction Syntax ($y = \text{typemf}(x, \text{params})$)	Graphical Representation
1	Gaussian	2	$f(x, c, \sigma) = e^{-\frac{(x-c)^2}{2\sigma^2}}$	SV, SPFHS, SDS	$y = \text{gaussmf}(x, [\sigma \ c])$	
2	Triangular	3	$f(x, a, b, c) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{c-x}{c-b} & b \leq x \leq c \\ 0 & x \geq c \end{cases}$	SI	$y = \text{trimf}(x, [a \ b \ c])$	
3	Trapezoidal	4	$f(x, a, b, c, d) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & x \geq d \end{cases}$	SI and SPFHS	$y = \text{trapmf}(x, [a \ b \ c \ d])$	
4	Bell-shaped	3	$f(x, a, b, c) = \frac{1}{1 + \left \frac{x-c}{a} \right ^{2b}}$	SPFHS	$Y = \text{gbellmf}(x[a \ b \ c])$	
5	Gaussian (2-type)	2	$f(x, c, \sigma) = e^{-\frac{(x-c)^2}{2\sigma^2}}$	SPFHS	$y = \text{gauss2mf}(x, [\sigma_1 \ c_1 \ \sigma_2 \ c_2])$	

SV: Solar Vehicle SPFHS: Solar Photovoltaic/Fuel Hybrid System SDS: Solar Drying System SI: Solar Irrigation

Table (1) presents commonly used membership functions in Solar Energy Conversion Devices (SECDs). Among these, Gaussian, triangular, and trapezoidal membership functions collectively referred to as polygonal functions are widely adopted due to their computational efficiency and adaptability. Their advantages include reduced data requirements, ease of parameter tuning based on measured system responses, capability to generate piecewise linear input-output mappings, and satisfaction of partition of unity conditions. Additionally, fuzzy logic models can achieve reliable prediction accuracy even with limited datasets compared to conventional data-driven approaches [21].

2.2.2. Processing unit or inference system

The processing unit, also known as the inference system, performs decision-making based on rule-based reasoning derived from empirical data and expert knowledge. FIS rules are typically expressed in the form of IF-THEN statements, where linguistic variables are used to categorize input parameters into qualitative ranges. These variables facilitate interpretability and adaptability in complex systems. Both Mamdani and Sugeno FIS architectures are commonly designed with multiple inputs (e.g., PV and FPC power) and a single output (e.g., PV/T system performance) [21]. The inference mechanism involves three key stages: implication, aggregation, and rule evaluation. Implication methods, such as product and minimum operators, determine the contribution of each rule, while aggregation methods such as summation, maximum, and probabilistic approaches combine individual rule outputs into a unified fuzzy set. The robustness of the inference process depends on the accuracy of the rule base and the selection of appropriate aggregation techniques.

**Fig 2:** The process flow chart through the fuzzy logic expert system.

2.2.3. Final unit or defuzzification unit

The defuzzification unit converts the aggregated fuzzy output into a crisp numerical value suitable for practical implementation. This step is critical for translating fuzzy reasoning into actionable control signals. Common defuzzification methods include centroid, smallest of maximum, largest of maximum, middle of maximum, and bisector approaches.

The final output is computed as:

$$\text{Final output} = \frac{\sum_{i=1}^N W_i Z_i}{\sum_{i=1}^N W_i} \dots\dots\dots(2)$$

Where Z_i represents the firing strength of the i^{th} rule and W_i denotes its corresponding weight [22]. This formulation ensures that the final output reflects the combined influence of all activated rules, enabling robust decision-making under uncertain and nonlinear conditions.

3. Fuzzy Logic in Solar Photovoltaic Systems

Energy demand has increased substantially with population growth, intensifying reliance on fossil fuels and accelerating greenhouse gas emissions, including carbon dioxide, methane, and nitrous oxide [12-14]. This has reinforced the transition toward renewable energy systems, which currently contribute approximately 16% of global energy consumption and are characterized by environmental sustainability and resource renewability [15]. Among these, solar energy defined as radiant energy emitted from the sun has emerged as a dominant and scalable solution due to its abundance, widespread availability, and declining cost trajectory [16]. Solar energy systems are primarily implemented through Photovoltaic (PV) and solar thermal technologies. PV systems directly convert solar radiation into electrical energy and contributed approximately 2% of global electricity demand in 2021 [17]. Advanced PV technologies, including multi-junction solar cells, concentrator photovoltaic systems, floating PV platforms, and photon down-conversion techniques, have significantly enhanced conversion efficiency and system adaptability [18]. In contrast, solar thermal systems convert radiation into heat energy for applications such as water heating, air heating, solar cooking, and Concentrating Solar Power (CSP) generation [19]. Despite these technological advancements, PV systems exhibit strong nonlinear behavior due to fluctuations in solar irradiance, ambient temperature, and load conditions, which limit the effectiveness of conventional control approaches [14].

To address these operational challenges, fuzzy logic has been increasingly adopted as an intelligent control and optimization framework. Fuzzy logic-based systems enable the modelling of uncertain and dynamic environmental conditions using linguistic variables and rule-based inference, thereby eliminating the need for precise mathematical models [12]. In solar PV applications, fuzzy logic has been effectively applied in performance prediction, energy management, fault detection, degradation assessment, and process control, improving decision-making under uncertainty [15]. The mechanism involves converting real-time input variables (e.g., irradiance, temperature, voltage, current) into fuzzy sets, applying inference rules derived from expert knowledge, and generating optimized control outputs through defuzzification [18]. From an optimization perspective, fuzzy logic plays a critical role in

enhancing system efficiency and operational stability. It is widely utilized in applications such as Maximum Power Point Tracking (MPPT), where continuous adaptation to varying environmental conditions is required to maximize energy extraction [17]. Compared to conventional deterministic and model-based techniques, fuzzy logic controllers demonstrate improved robustness, faster convergence, and reduced oscillatory behavior under rapidly changing operating conditions [16]. These characteristics make fuzzy logic particularly suitable for precision energy management in distributed and decentralized renewable energy systems.

However, despite its advantages, fuzzy logic implementation presents certain limitations. The development of an effective rule base requires domain expertise and careful tuning of membership functions, which may affect scalability and generalization across different system configurations [12]. Additionally, computational complexity may increase in large-scale or hybrid systems integrating multiple renewable sources [14]. Overall, the integration of fuzzy logic into solar PV systems represents a significant advancement in intelligent renewable energy management. Its ability to address nonlinearity, improve optimization, and enhance system reliability positions it as a key enabling technology for next-generation sustainable energy systems, particularly in precision agriculture and distributed energy applications [18].

4. Hybrid renewable energy systems and fuzzy logic-based optimization

The increasing cost of fossil fuels, coupled with their environmental impacts, has accelerated global interest in renewable energy technologies. Renewable energy systems are inherently clean, cost-effective, and require relatively shorter gestation periods compared to conventional power generation systems. However, systems based on a single renewable source often exhibit limitations in terms of efficiency, reliability, and economic viability due to their dependence on variable environmental conditions. To overcome these constraints, Hybrid Renewable Energy Systems (HRES), which integrate multiple energy sources such as solar Photovoltaic (PV) and wind energy, have been proposed as a viable solution [1]. From a system performance perspective, HRES configurations have demonstrated superior operational efficiency and reliability compared to standalone PV or Wind Energy Conversion Systems (WECS) [3, 4]. The complementary nature of solar irradiance and wind speed enables improved energy availability and load matching. However, the inherent intermittency of these resources introduces power fluctuations, which can adversely affect system stability and power quality. These fluctuations can be effectively mitigated through the integration of energy storage systems, which store surplus energy during periods of excess generation and supply power during deficits.

Despite these advantages, renewable energy systems remain challenged by discontinuous power generation due to their strong dependence on climatic and environmental conditions. This variability necessitates advanced optimization and control strategies to ensure efficient and reliable system operation. In this context, optimization algorithms have been widely explored for enhancing the performance of HRES. For instance, Nehrir et al. [5] employed computer-based modeling to evaluate standalone

PV/wind systems, while Bhandari ^[6] developed a mathematical model based on the Loss of Load Probability (LOLP) technique, demonstrating that optimal performance can be achieved when PV contributes approximately 75% of the total energy demand. Similarly, Afzal et al. ^[7] investigated system security using optimization techniques,

and Djamel and Abdallah ^[8] addressed power quality control in grid-connected hybrid systems using conventional MPPT approaches. Fathabadi ^[9] further proposed a universal MPPT technique for hybrid fuel cell/PV/wind systems to enhance power extraction efficiency.

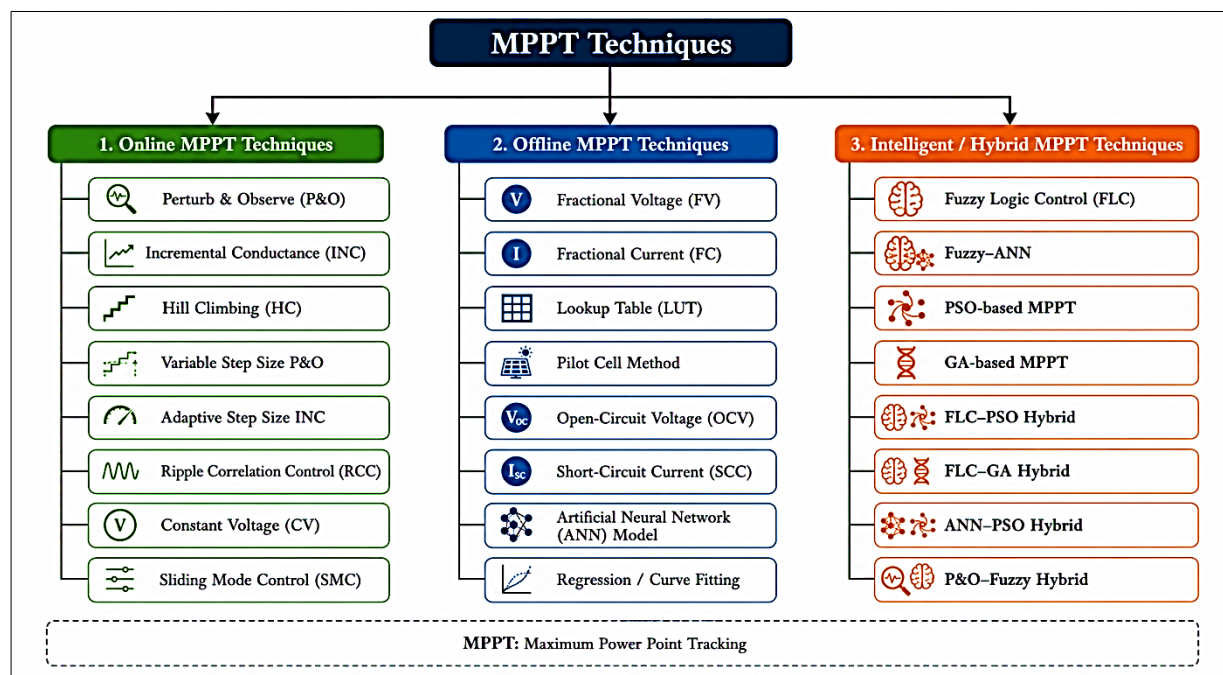


Fig 3: Classification of Maximum Power Point Tracking (MPPT) techniques for photovoltaic systems, categorized into online, offline, and intelligent/hybrid methods

However, conventional optimization methods, particularly those relying on probabilistic estimation and precise mathematical modeling, often exhibit limited accuracy in complex and nonlinear environments. These approaches require well-defined system models and may not adequately capture the uncertainties associated with renewable energy systems. Consequently, fuzzy logic-based control strategies have emerged as an effective alternative for handling system nonlinearity and uncertainty. Fuzzy Logic Controllers (FLCs) are particularly suitable for systems where accurate mathematical modeling is difficult or infeasible, as they rely on linguistic rules and approximate reasoning ^[2,10]. In the proposed framework, the FLC-based Maximum Power Point Tracking (MPPT) algorithm is designed to optimize energy extraction from both wind and solar subsystems. For wind energy systems, the controller ensures maximum power tracking under sub-rated wind speeds while limiting output power to rated levels at higher wind speeds, thereby preventing system overloading. For photovoltaic systems, fuzzy logic is employed to track the maximum power point under varying irradiance conditions, including partial shading scenarios, which are known to significantly affect system performance.

The overall system architecture integrates hybrid energy sources with intelligent control mechanisms to enhance operational efficiency and reliability. The modeling of system components and the implementation of fuzzy logic-based control strategies are presented in subsequent sections. Simulation results, discussed in Section IV, demonstrate the effectiveness of the proposed approach in improving power stability, energy efficiency, and adaptability under dynamic environmental conditions. From

an agricultural engineering and precision energy management perspective, the integration of fuzzy logic in HRES provides a robust framework for decentralized and on-farm renewable energy systems, where variability in environmental conditions is a critical challenge. This approach supports sustainable energy utilization, enhances system resilience, and contributes to the development of intelligent, adaptive energy infrastructures.

5. Smart grid applications

The transition toward sustainable energy systems has accelerated the deployment of smart grids, which integrate advanced communication, automation, and control technologies to enable efficient, reliable, and flexible power system operation. A smart grid facilitates the seamless incorporation of renewable energy sources such as solar, wind, and biomass, while ensuring real-time monitoring, adaptive control, and optimized energy distribution. However, the intermittent and stochastic nature of renewable energy introduces significant challenges related to grid stability, power quality, and demand-supply balancing, necessitating intelligent energy management strategies ^[29 - 33].

Conventional energy management approaches, including deterministic and model-based controllers; often exhibit limited adaptability under highly dynamic and uncertain operating conditions. In contrast, Fuzzy Logic Controllers (FLCs) provide a robust and computationally efficient framework capable of handling imprecise inputs and nonlinear system behavior. By utilizing linguistic variables and rule-based inference mechanisms, fuzzy logic enables adaptive decision-making for complex energy systems

without requiring explicit mathematical models. This characteristic makes FLCs particularly suitable for smart grid environments, where variability in renewable generation and load demand must be continuously managed. In this context, a fuzzy logic-based energy management model has been developed to optimize renewable energy integration within smart grids. The controller dynamically regulates energy flow by processing real-time inputs such as generation levels, storage status, and load demand. Simulation-based evaluation demonstrates that the proposed approach significantly enhances system performance across multiple operational metrics. Specifically, renewable energy utilization improved by approximately 20%, indicating more effective integration of variable energy sources. Grid stability was enhanced through a 15% reduction in frequency deviations, reflecting improved power quality and operational consistency. Furthermore, the reliability of energy storage systems showed a notable 25% improvement in State of Charge (SOC), suggesting optimized charge-discharge cycles and improved energy availability during peak demand conditions. The overall system efficiency increased by approximately 22% compared to conventional energy management methods. Comparative analysis with traditional control strategies, such as Proportional-Integral-Derivative (PID) controllers, further confirms the superiority of the fuzzy logic approach, with observed improvements including a 10% reduction in grid frequency fluctuations, a 15% enhancement in energy storage SOC, and a 12% increase in overall efficiency [34-38].

The effectiveness of the fuzzy logic-based model is further supported by sensitivity analysis, which demonstrates consistent performance under varying system parameters, highlighting its robustness and adaptability. Additionally, validation using real-world operational data confirms the practical applicability of the proposed approach in modern smart grid environments. Despite these advantages, certain limitations remain. The design of an effective fuzzy rule base requires expert knowledge, and system complexity may increase with large-scale grid integration involving multiple distributed energy resources. Nevertheless, the ability of fuzzy logic systems to manage uncertainty, enhance grid stability, and optimize energy utilization positions them as a critical enabling technology for next-generation smart grids. Overall, the integration of fuzzy logic-based energy management within smart grid infrastructure provides a scalable and adaptive solution for renewable energy integration. By improving efficiency, stability, and reliability, this approach contributes significantly to the development of sustainable and resilient energy systems, particularly in the context of decentralized and precision energy management applications.

6. Energy storage + battery (microgrid)

The global demand for electrical energy has increased steadily over recent decades, driven by heterogeneous growth across regions and the transition toward decentralized energy systems [39]. Since the early 1970s, electric utilities have progressively integrated battery technologies for large-scale energy storage, initially for load leveling and subsequently at transmission and distribution levels [36, 39, 40]. The increasing emphasis on climate change mitigation and energy security has accelerated the adoption of distributed generation, leading to the emergence of microgrids as resilient and flexible energy systems. These microgrids are particularly relevant in remote and off-grid agricultural regions, where access to centralized power

infrastructure is limited. Microgrids typically integrate Renewable Energy Sources (RES), primarily solar Photovoltaic (PV) and wind energy systems. However, the inherent intermittency and stochastic behavior of these sources pose significant challenges to maintaining voltage stability, frequency regulation, and overall power quality. To address these challenges, Energy Storage Systems (ESS) are incorporated to ensure reliable and stable operation under varying load and generation conditions. Energy storage technologies can be broadly categorized into high-energy-density systems for long-duration discharge and high-power-density systems for rapid response. Technologies such as Pumped Hydro Energy Storage (PHES), Compressed Air Energy Storage (CAES), and electrochemical batteries fall under high-energy systems, while supercapacitors represent high-power storage solutions.

Among ESS technologies, batteries are widely recognized for their high energy density, cost-effectiveness, compactness, and ease of deployment. Various battery chemistries, including lead-carbon batteries, lithium iron phosphate batteries, and vanadium redox flow batteries, have been employed to mitigate renewable energy fluctuations and enhance grid reliability [40,41]. However, reliance on a single energy storage system is often insufficient to meet the dynamic operational requirements of microgrids due to limitations in power density, response time, and lifecycle performance. Batteries alone are unable to efficiently handle rapid load variations or high transient power demands, such as those associated with motor-driven agricultural equipment, refrigeration systems, and irrigation pumps. Under such conditions, excessive current stress can reduce battery lifespan and compromise system reliability [40]. To overcome these limitations, Hybrid Energy Storage Systems (HESS) have been proposed, combining complementary storage technologies to exploit their respective advantages. Typically, HESS integrates high-energy-density batteries with high-power-density supercapacitors to simultaneously address long-duration energy requirements and short-term power fluctuations. Supercapacitors exhibit rapid charge-discharge capabilities, making them particularly effective for transient load compensation and voltage stabilization. The coordinated operation of HESS enables efficient energy balancing, improved transient response, and enhanced system stability under variable renewable generation conditions.

Energy Management (EM) in microgrids incorporating HESS and renewable sources requires advanced control strategies to optimize power flow, maintain stability, and ensure efficient utilization of storage resources [42]. In wind-integrated microgrids, the variability of wind speed further necessitates the use of storage systems to mitigate rapid power fluctuations and ensure reliable supply. Conventional optimization techniques, including game theory, evolutionary algorithms, dynamic programming, Model Predictive Control (MPC), and mixed-integer linear programming, have been widely applied for energy management. However, these methods are often computationally intensive, time-consuming, and dependent on precise mathematical models, limiting their real-time applicability in complex and uncertain environments [43-45]. In this context, fuzzy logic-based control has emerged as an effective alternative for microgrid energy management. Fuzzy Logic Controllers (FLCs) do not require explicit

mathematical modeling and are inherently capable of handling uncertainty, imprecision, and nonlinear system dynamics. These features make them particularly suitable for managing renewable energy variability and load fluctuations. FLC-based HESS management ensures optimal charge–discharge scheduling, thereby improving battery lifespan, reducing operational stress, and minimizing system costs ^[40].

The fuzzy logic-based energy management framework incorporates real-time monitoring of system parameters, including State of Charge (SOC), load demand, and generation variability, to maintain energy balance within the microgrid. Effective SOC control ensures that storage devices operate within safe limits, preventing overcharging, deep discharge, and excessive cycling, thereby enhancing system longevity and reliability ^[46]. Furthermore, fuzzy logic enables quantification of system uncertainties into actionable control decisions, improving overall operational efficiency and robustness. Despite the widespread deployment of microgrids combining PV systems with batteries or wind systems with diesel generators, limited research has focused on the integrated application of Hybrid Energy Storage Systems (HESS) with both solar PV and wind generation ^[47].

7. Advantages of fuzzy logic

Fuzzy logic-based control systems offer significant advantages in the context of renewable energy-integrated microgrids. A primary strength lies in their ability to effectively handle uncertainty, imprecision, and nonlinear system behavior without requiring detailed mathematical models. This characteristic is particularly beneficial in renewable energy applications, where environmental variability introduces complex and unpredictable dynamics. Furthermore, fuzzy logic controllers provide flexible and adaptive decision-making capabilities through rule-based inference systems, enabling real-time optimization of energy flow and storage utilization. This results in improved system stability, enhanced energy efficiency, and reduced computational burden compared to conventional optimization techniques. The capability to integrate expert knowledge into control rules further enhances interpretability and practical applicability.

Additionally, fuzzy logic facilitates efficient management of hybrid energy storage systems by dynamically coordinating battery and supercapacitor operation, thereby extending component lifespan and reducing operational costs. Its scalability and robustness make it suitable for deployment in distributed and precision energy systems, including agricultural microgrids where load variability and resource intermittency are significant challenges. However, despite these advantages, certain limitations persist. The design and tuning of fuzzy rule bases require domain expertise, and system performance may vary depending on membership function selection and parameter configuration. Moreover, as system complexity increases, the computational and structural complexity of the fuzzy system may also rise. Overall, fuzzy logic provides a robust, adaptive, and efficient control framework for modern microgrid energy management, offering a viable pathway toward sustainable, resilient, and precision-oriented energy systems.

8. Limitations

Despite the demonstrated effectiveness of fuzzy logic-based control in renewable energy systems, several limitations

constrain its large-scale deployment and generalization. A primary challenge lies in the design and tuning of the fuzzy rule base, which is highly dependent on expert knowledge and system-specific experience. The absence of standardized methodologies for rule formulation and membership function selection can lead to variability in system performance across different applications.

Furthermore, as system complexity increases particularly in Hybrid Renewable Energy Systems (HRES) and microgrid environments integrating multiple Distributed Energy Resources (DERs) the number of rules and variables grows significantly. This results in increased computational complexity and scalability issues, which may limit real-time implementation in large-scale power systems. In addition, fuzzy logic controllers do not inherently possess self-learning capabilities, making them less adaptive compared to advanced machine learning-based approaches unless integrated with hybrid techniques. Another limitation is the sensitivity to membership function design, where improper parameter selection can degrade control accuracy and system stability. Moreover, fuzzy logic systems may struggle to guarantee global optimality, particularly when compared with optimization-based techniques such as Model Predictive Control (MPC) or evolutionary algorithms. These limitations highlight the need for improved design methodologies and hybrid intelligent control frameworks.

9. Future scope

The future development of fuzzy logic-based control systems in renewable energy applications is expected to focus on hybridization with advanced Artificial Intelligence (AI) techniques, such as neuro-fuzzy systems, machine learning, and deep learning models. These integrated approaches can enhance adaptive learning, predictive capability, and real-time decision-making, thereby overcoming the limitations of conventional fuzzy systems.

In the context of smart grids and microgrids, future research should emphasize the development of real-time adaptive controllers capable of managing high penetration levels of renewable energy sources under dynamic environmental conditions. The integration of fuzzy logic with Internet of Things (IoT)-based monitoring systems and edge computing platforms will enable decentralized and intelligent energy management, particularly for precision agriculture applications where energy demand is spatially and temporally variable.

Additionally, advancements in Hybrid Energy Storage Systems (HESS), combining batteries, supercapacitors, and emerging storage technologies, require sophisticated control strategies. Fuzzy logic can play a critical role in optimizing State of Charge (SOC) control, energy balancing, and lifecycle management of storage systems. Future studies should also focus on scalability, standardization, and interoperability of fuzzy logic-based frameworks to facilitate their adoption in large-scale energy infrastructures. Moreover, the application of fuzzy logic in renewable-powered agricultural systems, such as solar-powered irrigation, autonomous farm energy management, and rural microgrids, presents significant opportunities for enhancing sustainability and energy efficiency. Integration with digital twins and predictive analytics can further improve system reliability and operational planning.

10. Conclusion

This review comprehensively examined the role of fuzzy logic systems in enhancing the performance, reliability, and efficiency of renewable energy systems, with particular emphasis on solar photovoltaic systems, hybrid renewable configurations, smart grids, and microgrid-based energy storage systems. The analysis demonstrates that fuzzy logic provides a robust and flexible control framework capable of effectively handling the inherent uncertainty, nonlinearity, and variability associated with renewable energy systems. Fuzzy logic-based controllers have shown significant improvements in key performance indicators, including maximum power extraction, grid stability, energy storage management, and overall system efficiency, when compared with conventional control strategies. Their ability to operate without precise mathematical models and to incorporate expert knowledge makes them highly suitable for complex and dynamic energy environments, particularly in decentralized renewable energy networks and precision agriculture applications. However, challenges related to rule base design, scalability, and computational complexity remain critical considerations for practical implementation. Addressing these limitations through hybrid intelligent systems and advanced computational techniques will be essential for future advancements. Overall, fuzzy logic systems represent a promising and enabling technology for next-generation renewable energy systems. Their integration with emerging technologies such as AI, IoT, and advanced energy storage solutions is expected to play a pivotal role in achieving sustainable, resilient, and intelligent energy infrastructures, particularly in the context of distributed energy systems and agricultural energy management.

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