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Intelligent Design of Hybrid Renewable Energy Systems Employing a Fuzzy Inference System Approach

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ABSTRACT

Objective: Off-grid renewable energy systems are essential for ensuring a sustainable and reliable electricity supply in regions where access to the conventional grid is limited or economically unjustifiable. Designing such systems requires systematic and efficient methodologies that can guide planners in selecting appropriate technologies under diverse environmental and consumption conditions. This study aims to develop an intelligent sizing framework for hybrid renewable energy systems by integrating expert knowledge with geographical, climatic, and load-related variables. The proposed model seeks to identify the optimal combination of photovoltaic panels, wind turbines, battery storage systems, and diesel generators for off-grid applications in Iran.

Methodology: The research methodology employs a two-stage approach. In the first stage, key variables influencing system sizing were identified through a comprehensive review of prior studies and structured interviews with academic and industrial experts. These interviews provided valuable operational insights, enabling the determination of qualitative ranges for model inputs and outputs. In the second stage, the collected expert knowledge was translated into fuzzy rules and implemented within a fuzzy inference system developed in MATLAB, forming an intelligent decision-support engine capable of evaluating multiple operational scenarios.

Results: The findings indicate that the proposed model accurately determines optimal configurations for various geographical locations and consumption profiles. Model outputs showed less than 10% deviation from 80% of expert assessments. Moreover, the model generates sizing recommendations within minutes, significantly improving the speed of decision-making.

Conclusion: In summary, the developed framework provides a practical and efficient tool for planners and stakeholders involved in designing off-grid hybrid renewable energy systems.

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Introduction

Global population growth—which has now reached 8 billion people (United Nations, 2022) — has inevitably increased energy demand. A significant portion of the world's population remains reliant on fossil fuels, including coal, natural gas, and petroleum products, for power generation and heating. Energy consumption is particularly high in the industrial, residential, and transportation sectors, which continue to rely heavily on petroleum products, natural gas, and coal (Salimian et al., 2018). According to the International Energy Agency, global energy demand is expected to grow by 33 percent between 2021 and 2030. In 2007, global energy demand was 145 billion megawatt-hours, and it is estimated to increase by 49 percent to reach 218 billion megawatt-hours by 2035 (Tahari Mehrjardi et al., 2024).

At the 2021 United Nations Climate Change Conference, held in Glasgow, ambitious goals were established to reduce greenhouse gas emissions to net zero and limit the global temperature rise to 1.5°C by 2030. These targets have intensified the search for cleaner and more sustainable energy resources. In general, sustainable energy generation involves producing energy without emitting greenhouse gases. Such systems include solar panels, wind turbines, hydropower, biomass, solar thermal systems, ocean thermal energy, and tidal energy (UNFCCC, 2021). Moreover, recent global reforms in the electricity sector have transformed the structure and operations of distribution companies, increasing the trend toward developing off-grid renewable energy systems. The fundamental importance of the distribution sector, combined with the operational diversity of distribution networks, has heightened the need for improved planning, operational mechanisms, and economic efficiency (Etezadi et al., 2023).

In recent years, renewable energy sources have accounted for a significant share of total energy production. Although the COVID-19 pandemic temporarily disrupted the development of renewable energies, their growth has remained strong and is expected to continue. For example, in 2021 alone, 314.5 GW of renewable energy capacity was added—an amount sufficient to supply all households in Brazil (Renewable Energy Secretariat, 2023). The primary goal of electricity generation is to ensure a reliable and uninterrupted supply to consumers. Nuclear, gas, fuel-based, and coal power plants are widely used due to their ability to provide a stable source of electricity. However, renewable sources such as solar panels and wind turbines cannot reliably meet demand on their own because of their intermittent nature. Consequently, hybrid renewable energy systems—combining multiple renewable sources and energy storage technologies—have been developed (Olatomiwa et al., 2016). The optimal configuration of such systems requires a deep understanding of energy generation, storage systems, technical characteristics, environmental conditions, and load profiles (Al-Falahi et al., 2017). According to electricity industry experts, off-grid renewable energy systems are essential for several reasons, including providing access to electricity in remote areas, reducing dependence on fossil fuels, enhancing energy sustainability, lowering operational and economic costs, and improving energy independence and security. Given the interconnected nature of the national power grid, an off-grid renewable energy system refers to a system that is fully independent of the national electricity network and relies entirely on renewable resources for power generation. Addressing these needs requires careful planning for the implementation of hybrid renewable energy systems, which also involves notable challenges (Ebadi, 2025).

Key challenges include optimal resource design (Bagheri et al., 2016), uncertainty in energy production due to environmental variability and economic and investment considerations (Bagheri et al., 2016), as well as issues related to energy storage (Gheyratmand et al., 2016). Proposed solutions include design optimization, exploring various resource combinations (Shahirinia & Moghadamjou, 2006), and deployment of advanced technologies, particularly in storage systems (Gheyratmand et al., 2016). Furthermore, in modeling problems where human judgment and decision-making form the core of the system, linguistic variables, fuzzy quantities, and ambiguous expressions are more applicable than crisp values. Human reasoning is inherently based on linguistic variables and their associated linguistic terms. These variables can be represented using fuzzy sets, and the relationships between them can be described using fuzzy operations (Khajavi et al., 2022).

Fuzzy inference systems are beneficial for developing models requiring evaluation. Such systems operate effectively with linguistic variables and have been employed in sustainability assessment models that can optimize cost management (Ebrahimi Kordlar et al., 2025). Accordingly, this study uses a fuzzy inference system to model the decision-making process given the nature of the problem. This research aims to address the key question of whether expert knowledge and experience can influence the sizing of energy resources in an off-grid renewable energy system. Additionally, the study investigates whether, assuming expert knowledge is sufficient for determining resource sizing, it is possible to develop a precise, fast, and generalizable model applicable nationwide. Research on renewable energy is highly essential. According to the annual report published by IRENA, installed renewable energy systems worldwide have grown by more than 117 percent from 2014 to 2023, highlighting the need for continued investigation in this field. Overall, the share of renewable energy in global power generation increased from 28.2% in 2014 to 43.2% in 2023. Moreover, solar and wind power generation have increased by more than 700 percent and 191 percent, respectively, over the past decade (International Renewable Energy Agency, 2023). Similarly, the number of research publications on renewable energy in Elsevier journals has grown by more than 1,980 percent between 2004 and 2024, underscoring the importance of ongoing research.

The remainder of this article is structured as follows: First, the theoretical literature is reviewed. Next, the methodology of the study is presented, including the interview procedures, identification of input variables, definition of their indicators, and the application of a fuzzy inference system as the decision-making tool employed in this research. After presenting the literature review and methodology, the research findings are evaluated, followed by the conclusions and recommendations.

Literature Background

In general, the existing literature on renewable energy sizing can be examined within the context of hybrid renewable energy systems. Prior studies in this domain have predominantly focused on sizing for specific conditions and have not always comprehensively accounted for climatic, geographic, and environmental variations. The following presents an overview of relevant studies and their methodologies.

Bukar et al. (2019) investigated the application of the Grasshopper Optimization Algorithm for optimal microgrid design. The primary objective was to determine an optimal configuration to supply power to five residential units in an off-grid area in Nigeria. The system comprised solar modules, wind turbines, battery storage, and a diesel generator. The study aimed to ensure a power supply at the minimum cost with a zero probability of load loss, and to compare the Grasshopper Optimization Algorithm with Particle Swarm Optimization and Cuckoo Search algorithms. The results demonstrated that the Grasshopper Optimization Algorithm significantly reduced both total capital cost and energy cost compared with the other algorithms.

Abd El-Sattar et al. (2022) proposed a novel Gradient Hummingbird Algorithm, which combines the artificial hummingbird algorithm with gradient-based optimization. The primary objective was to reduce energy costs and enhance the reliability of standalone hybrid renewable energy systems. The algorithm was applied to the optimal design of solar, wind, biomass, and battery storage systems for the New Taiba city in Egypt. It was compared with methods such as the Sine-Cosine Algorithm and the Whale Optimization Algorithm. The Gradient Hummingbird Algorithm proved to be an innovative and efficient approach for designing cost-effective and sustainable off-grid hybrid systems.

Maleki and Pourfayaz (2015) examined optimization of sizing for off-grid hybrid renewable energy systems comprising photovoltaic panels, wind turbines, diesel generators, battery storage, and fuel cells. They employed the Harmony Search Algorithm—a music-inspired optimization technique—to find optimal configurations of system components. Examined parameters included total system cost (installation, operation, and maintenance), system reliability in meeting load, emissions, and energy storage for covering generation outages. The findings indicated that hybrid renewable systems can sustainably supply remote areas and that the Harmony Search Algorithm yields near-optimal solutions for cost reduction and enhanced reliability.

Avril et al. (2010) studied multi-objective optimization of the size and mix of energy storage systems in standalone photovoltaic systems. Their goal was to identify an optimal blend of batteries and hydrogen storage that minimizes cost while maximizing reliability. By modeling storage systems mathematically and applying optimization algorithms, they showed that an optimal combination of batteries and hydrogen storage can reduce overall system cost and improve supply stability.

Brumana et al. (2022) analyzed the techno-economic optimization of hybrid power generation systems for a remote community in the MENA region with a peak demand of 10 MW. The objective was to achieve 90% annual load coverage by renewables. Three configurations were compared: (a) concentrated solar power with parabolic trough collectors, thermal storage, and a steam Rankine cycle; (b) an all-electric system with PV, wind turbines, and batteries; and (c) a hybrid of the two. The hybrid configuration attained the lowest levelized energy cost of $0.1364/kWh. Solutions based on a single technology incurred larger sizes and higher costs, while future economic scenarios suggested that integrating CSP and PV improves renewable penetration and grid resilience.

Carapellucci and Giordano (2012) designed and optimized an off-grid power system that combined renewable energy sources with hydrogen storage technologies to provide reliable energy for remote areas and islands. Components included PV panels, wind turbines, electrolyzers, hydrogen storage tanks, and fuel cells. Optimization sought to determine the size and composition that minimized total system cost while maximizing sustainability and reliability; the results showed that optimal technology mixes reduce overall energy costs.

Ghenai and Bettayeb (2019) designed and analyzed an optimized off-grid hybrid system to power a university building. Using modeling and simulation to evaluate daily and annual performance, they found that a combination of solar, fuel cells, and diesel generators reduced greenhouse gas and particulate emissions and was economically viable, reducing fossil fuel dependency.

Moghaddam et al. (2019) investigated optimal design and energy management of an off-grid hybrid system including PV, wind turbines, and fuel cells with hydrogen storage for northwestern Iran. They employed the Flower Pollination Algorithm to minimize the net present cost and compared it with Particle Swarm Optimization and learning-based optimization methods; the proposed method resulted in the lowest total net present cost. Al-Falahi et al. (2017) reviewed recent optimization methods for sizing standalone hybrid solar–wind systems. They analyzed evolutionary algorithms, artificial intelligence, and hybrid techniques, and compared software tools used in this field. They concluded that the appropriate optimization method depends on system structure, constraints, and project objectives, and that hybrid methods and specialized software can enhance system performance and efficiency.

Nordin and Rahman (2019) compared two standalone solar configurations—one using batteries alone and another combining batteries with hydrogen production to utilize surplus energy. Their iterative sizing technique evaluated technical and economic performance to identify optimal component sizes. Hatata et al. (2018) developed an optimization method for sizing a hybrid system of PV, wind, and batteries, aiming to reduce system costs and improve reliability. They utilized an Artificial Immune System algorithm inspired by the human immune system's search capabilities; the results showed precise sizing and cost reductions alongside improved reliability. Sanchez et al. (2014) optimized a standalone hybrid system comprising wind, PV, and hydrogen for southeastern Mexico, employing Particle Swarm Optimization to determine component sizes that minimize cost while ensuring reliable supply; the method produced accurate sizing solutions.

Khiareddine et al. (2018) proposed a comprehensive methodology for sizing a hybrid system including PV, wind, hydrogen storage, and batteries. They developed an energy management strategy to coordinate sources and storage, facilitating optimal sizing of components. Zhang et al. (2018) applied Simulated Annealing to optimize the sizing and performance of a hybrid renewable system containing PV, wind turbines, batteries, and hydrogen storage. The approach accurately determined optimal component sizes. N'Guessan et al. (2020) designed a hybrid system comprising wind turbines, fuel cells, electrolyzers, batteries, and supercapacitors for off-grid applications, utilizing mathematical modeling and Genetic Algorithms. By considering investment, maintenance, lifetime, and load patterns, the optimization reduced overall costs and extended component lifetimes. Recent studies (2025) further advanced methods and applications.

Verma et al. (2025) addressed optimal sizing and siting of renewable plants (e.g., solar and wind) within hybrid systems, combining Artificial Neural Networks for performance prediction with multi-objective Genetic Algorithms for simultaneous optimization of cost and efficiency. Their hybrid approach achieved accurate power forecasts and effective multi-objective optimization for placement and sizing. Al-Quraan et al. (2025) optimized an off-grid hybrid system comprising wind, PV, diesel generators, and batteries for a residential load using a bi-level optimization framework: the upper level performs sizing (number of units per resource), while the lower level manages daily operations via Model Predictive Control to minimize operational costs and battery degradation. Implemented as a mixed-integer nonlinear programming model, the approach minimized investment, operational costs, and emissions, demonstrating cost improvements, CO_2 reduction, and extended battery life. Kumar et al. (2025) presented an optimization model for hybrid renewable systems based on local resource assessment and demand-side management.

They utilized Particle Swarm Optimization and biogeography-based optimization for sizing, which was validated using HOMER software. PV–diesel–battery combinations were often the most economical under load transfer scenarios, and the approach reduced costs, emissions, and improved system efficiency. Khalil et al. (2025) introduced an innovative hybrid algorithm (Artificial Rabbits Optimization enhanced with adversarial learning) for optimizing the size and placement of PV and battery storage to improve voltage stability in radial distribution systems. Results showed that optimally sited PV and battery systems with appropriate power factors enhance voltage stability and reduce losses, outperforming alternative methods.

Zhang et al. (2025) proposed a Particle Swarm Optimization-based model for sizing PV and battery systems at power stations to mitigate solar generation intermittency, showing notable improvements in operational and economic performance. Keyvandarian et al. (2025) developed an adaptive robust approach for sizing off-grid hybrid systems (comprising wind, PV, battery banks, and diesel gensets) using dynamic uncertainty sets that capture temporal correlations in renewable energy outputs. An iterative column-generation-based solver effectively handled the adaptive robust optimization problem. The study found that dynamic uncertainty sets outperform conventional static robust models in terms of accuracy and performance, particularly for off-grid systems that require a reliable supply.

A comparative summary of the aforementioned studies is presented in the table below. This table provides a concise overview of the articles, summarizing methodologies, system components, optimization techniques, and principal findings.

Table 1. Summary of Studies Related to the Topic

Authors & Year	Research Objective	Energy Sources Examined	Variables Examined	Methodology
Keyvandarian, S. and Pelot (2025)	Optimization of sizing for off-grid hybrid renewable energy systems	Solar – Wind – Battery – Diesel Generator	Solar irradiation – Solar angle – Daylight hours & weather – Wind speed – Elevation – Slope – Proximity to sea/mountains	An iterative algorithm based on column-generation and constraint algorithms
Zhang et al. (2025)	Optimization of PV–battery system sizing and configuration	Solar, Battery	Solar radiation – Seasonal/diurnal variations – Daily energy demand – Load profile – Battery capacity – Temperature – Humidity – Cloud coverage	Particle Swarm Optimization
Khalil et al. (2025)	Optimal sizing and placement of PV and	Solar, Battery	Panel rated power – Panel location – PV efficiency – Battery capacity – Battery location –	Artificial Rabbit Optimization Enhanced with

	battery systems for voltage stability		Battery characteristics – Network voltage – Node voltages	Adversarial-Based Learning.
Kumar et al. (2025)	Optimal sizing of a hybrid renewable energy system	Solar – Wind – Battery – Diesel Generator	Solar radiation – Wind speed – PV and turbine output – Battery capacity – Load profile – Peak hours – Load shifting – Temperature – Weather	PSO + Biogeography-Based Optimization
Al-Quraan et al. (2025)	Optimization of a standalone hybrid energy system	Solar – Wind – Battery – Diesel Generator	Solar radiation – Wind speed – PV & wind power – Battery capacity – Load profile – Peak demand – Temperature – Humidity	Bi-level optimization framework
Verma et al. (2025)	Optimal sizing and siting of renewable power plants	Solar – Wind – Battery	Solar radiation – Wind speed – PV & wind power – Battery capacity – Load profile	Artificial Neural Network + Multi-objective Genetic Algorithm
N'guessan et al. (2020)	Optimal sizing of an off-grid hybrid energy system	Wind – Fuel Cell – Electrolyzer – Battery – Supercapacitor	Wind power – Battery capacity – Supercapacitor capacity – Electrolyzer capacity – Fuel cell capacity – Load profile – Wind speed	Genetic Algorithm
Zhang et al. (2018)	Optimization of sizing and performance of hybrid renewable systems	PV – Wind – Battery – Hydrogen Storage	Solar radiation – Wind speed – PV & wind power – Battery capacity – Hydrogen storage – Temperature – Humidity	Simulated Annealing
Khiareddine et al. (2018)	Optimal sizing of a hybrid energy system	PV – Wind – Battery – Hydrogen Storage	Solar radiation – Wind speed – PV & wind output – Battery capacity – Hydrogen storage capacity	Economic optimization – Energy management–based optimization – Hybrid optimization
Sanchez et al. (2014)	Technical and economic optimization of an off-grid hybrid system	Solar – Wind – Hydrogen	Solar radiation – Wind speed – PV & wind output – Hydrogen storage – Electrolyzer capacity – Fuel cell capacity – Peak load – Temperature – Pressure	Swarm Intelligence Algorithm
Hatata, O. and Aladl (2018)	Optimal sizing of a hybrid renewable energy system	Solar – Wind – Battery	Solar radiation – Wind speed – PV & wind output – Battery capacity – Load profile – Temperature – Pressure	Artificial Immune System Algorithm
Nordin and Rahman (2019)	Identification of optimal sizing	Solar – Battery – Hydrogen	Solar radiation – PV efficiency/lifetime – Battery type/capacity – Hydrogen storage – Electrolyzer capacity – Fuel cell capacity – Load profile	Simulation using HOMER Pro
Al-Falahi, J. & Enshaei (2017)	Optimization of sizing for standalone solar–wind hybrid systems	Solar – Wind – Battery – Diesel Generator	Solar radiation – Wind speed – PV efficiency – Turbine power curve – Battery characteristics – Diesel generator fuel use – Load profile – Temperature	Evolutionary algorithms, AI methods, hybrid techniques
Moghaddam et al. (2019)	Optimal design and energy management of a standalone hybrid system	Solar – Wind – Battery – Fuel Cell (Hydrogen Storage)	Solar radiation – Wind speed – PV & turbine parameters – Battery lifetime – Electrolyzer and fuel cell efficiency – Hydrogen storage – Load profile – Temperature	Flower Pollination Algorithm
Ghenai and Bettayeb (2019)	Optimal design and performance	Solar – Fuel Cell – Diesel Generator	Solar radiation – PV efficiency – Hydrogen storage – Fuel cell	HOMER Software

	analysis of an off-grid hybrid system		efficiency – Diesel generator fuel use – Load profile – Temperature	
Carapellucci and Giordano (2012)	Optimal sizing and configuration to minimize system cost and maximize reliability	Solar – Wind – Electrolyzer – Hydrogen Tanks – Fuel Cells	Solar radiation – Wind speed – PV/turbine specs – Hydrogen storage parameters – Load profile – Temperature	Mathematical programming + numerical optimization
Brumana et al. (2022)	Techno-economic optimization for a remote community in the MENA region	Solar – Wind – Battery – Thermal Systems	Solar radiation – Wind speed – PV/turbine specs – Battery capacity – Thermal system parameters – Load profile – Temperature	TRNSYS Software
Avril et al. (2010)	Optimal sizing of storage technologies in standalone PV systems	Solar – Battery – Hydrogen Storage	Solar radiation – Battery performance – Hydrogen system efficiency	Multi-objective optimization using Particle Swarm Optimization
Maleki and Pourfayaz (2015)	Sizing of standalone hybrid renewable energy systems	Solar – Wind – Diesel – Battery – Fuel Cell	Solar radiation – Wind speed – PV and turbine power – Electrolyzer and fuel cell parameters – Load profile – Diesel generator capacity	Harmony Search Algorithm
Abd El-Sattar et al. (2022)	Cost reduction and improved reliability in hybrid renewable systems	Solar – Wind – Biomass – Battery	Solar radiation – Wind speed – PV & wind output – Battery capacity – Biomass system capacity – Load profile – Temperature	Hybrid Artificial Hummingbird Algorithm + Gradient-based Optimization
Bukar et al. (2019)	Optimal configuration for supplying five off-grid residential units in Nigeria	Solar – Wind – Battery – Diesel Generator	Solar radiation – Wind speed – PV & turbine output – Battery capacity – Diesel generator specs – Load profile – Temperature	Grasshopper Optimization Algorithm

A comprehensive review of the existing literature in this field reveals that the majority of studies heavily rely on artificial intelligence algorithms to determine optimal sizing configurations. In fact, the commonality between this study and many previous works lies in the types of energy resources examined, which predominantly include solar, wind, battery storage, and diesel generators—resources widely used in renewable energy research. Another point of similarity concerns the input variables, which are largely consistent across most studies.

However, the primary distinction between the present research and the reviewed literature is the methodological approach. As shown in Table 1, none of the existing studies incorporated expert knowledge in their decision-making framework. This gap became evident after an extensive review of the literature. It is also important to note that the optimization approaches in prior studies were conducted for specific geographic conditions and lacked generalizability for decision-making in other settings. This research gap served as the primary motivation for the development of the present study, which aims to enable rapid decision-making within the context of energy management systems.

Materials and Methods

A fuzzy inference system (FIS) is a nonlinear decision-making system that utilizes fuzzy if–then rules to model the qualitative aspects of human knowledge. The FIS can be viewed as a function that utilizes human expertise to map a set of inputs to one or more outputs (Roshandel et al., 2024). Two main characteristics make the FIS an appropriate choice for this study:

(1) the essential role of human reasoning in understanding, expressing, and making decisions in socio-economic systems, and

(2) the ease of use and high accuracy of the system in mapping imprecise inputs to outputs (Nejatnia et al., 2023).

This research aims to develop a hybrid renewable energy configuration based on expert knowledge by employing a fuzzy expert system that accounts for geographic, climatic, environmental, and consumption conditions. The expert system considered in this study includes university faculty members in related engineering fields and practitioners from the electric power and renewable energy industries. Their collective expertise contributes to predicting the structure of the hybrid renewable energy system (i.e., the optimal sizing of each energy source). The identification of experts was carried out using the snowball sampling method. Initially, one faculty member and two industry professionals were interviewed; through snowball sampling, the pool gradually expanded to 16 experts. Most of these experts were active professionals in the renewable energy sector. To collect data, multiple in-person sessions were conducted over a six-month period with experts specializing in areas such as power engineering, control engineering, power electronics, and project management. These individuals possessed extensive hands-on experience in designing, implementing, and operating energy systems. Each interview session lasted approximately four hours, and several experts participated in multiple sessions.

A semi-structured interview approach was employed to elicit the experts' insights and practical experiences. Each session began with an overview of the current status of hybrid renewable energy system implementation and the associated challenges. Experts were then asked to propose optimal strategies for designing an off-grid hybrid renewable energy system. The collected data were documented and subsequently analyzed to extract appropriate fuzzy rules. Additionally, during the interviews, experts were presented with specific geographical scenarios and asked to explicitly determine the recommended hybrid energy configuration for each case. The key components of the fuzzy inference system in this study include membership functions, fuzzy rules, fuzzification, and defuzzification. A summary of expert characteristics is provided in the following table.

Table 2. Experts' Characteristics

No.	Educational Background	Occupation	Organizational Position	Area of Expertise in Renewable Energy
1	PhD – Power Engineering	University Professor	Professor	All renewable energy domains
2	PhD – Power Engineering	University Professor	Associate Professor	All renewable energy domains
3	PhD – Power Engineering	University Professor	Assistant Professor	All renewable energy domains
4	MSc – Power Engineering	Electrical Engineer	Project Manager	All renewable energy domains
5	MSc – Power Electronics	Electrical Engineer	Deputy of the Technical Department	Solar energy and battery systems
6	MSc – Power Electronics Engineering	Electrical Engineer	Hardware Technical Department Manager	All renewable energy domains
7	MSc – Control Engineering	Electrical Engineer	Project Manager	All renewable energy domains
8	MSc – Control Engineering	Electrical Engineer	Software Technical Department Manager	Wind, solar, and generator systems
9	MSc – Power Engineering	Electrical Engineer	Technical Project Engineer	Battery systems and diesel generator systems
10	MSc – Control Engineering	Electrical Engineer	Technical Project Engineer	All renewable energy domains
11	MSc – Power Electronics Engineering	Electrical Engineer	Technical Project Engineer	Solar and wind energy systems
12	BSc – Control Engineering	Electrical Engineer	Technical Project Engineer	Solar energy, diesel generator, and battery systems
13	BSc – Control Engineering	Electrical Engineer	Technical Project Engineer	Solar and wind energy systems
14	BSc – Power Engineering	Electrical Engineer	Technical Project Engineer	Solar and wind energy systems
15	BSc – Power Engineering	Electrical Engineer	Technical Project Engineer	Diesel generator systems
16	BSc – Control Engineering	Electrical Engineer	Technical Project Engineer	Solar energy and battery systems

As previously noted, the optimal design of an off-grid hybrid renewable energy system requires the collection of a set of input and output data derived from the knowledge and experience of domain experts. These input and output variables played a critical role in the decision-making process and in formulating the fuzzy inference system rules used to determine the optimal combination of energy resources. The input variables considered for analyzing and designing the off-grid hybrid renewable energy system included:

1. average solar irradiation,
2. average wind speed,
3. elevation above sea level,
4. average temperature,

5. average humidity,
6. number of cloudy days per year, and
7. Type of energy consumption (residential, commercial, or rural).

The subsequent section details the fuzzification process applied to each of these input variables. The fuzzy system also employed four output variables:

1. Capacity of the solar energy system (solar panels),
2. Capacity of the wind energy system (wind turbines),
3. |Battery storage capacity, and
4. Diesel generator capacity.

These outputs were ultimately determined through the defuzzification process. It is worth noting that MATLAB software was used for designing and implementing the fuzzy inference system.

Input Membership Functions

During the expert sessions, detailed discussions were held regarding the fuzzification approach for the input variables. Based on expert opinions and the aggregated mean values provided by them, the membership functions for the input variables were defined as follows. Since the linguistic variables used in this study exhibit full membership over relatively wide ranges, trapezoidal membership functions were adopted for all input variables except one.

It is worth noting that the membership functions for the variable type of energy consumption were modeled using triangular functions. This selection was made because the simulation results demonstrated that triangular membership functions provide more accurate and responsive behavior for this variable compared with other alternatives.

Table 3. Input Membership Functions

No.	Input Variable	Linguistic Variable	Fuzzy Model	Fuzzy Number
1	Number of Cloudy Days per Year	Low	Trapezoidal	(0, 0, 80, 120)
		Medium		(90, 110, 140, 160)
		High		(130, 170, 250, 290)
2	Average Wind Speed	Low	Trapezoidal	(0, 0, 13, 17)
		Medium		(12, 18, 27, 33)
		High		(28, 32, 43, 47)
3	Average Solar Irradiation	Low	Trapezoidal	(0, 0, 2, 3)
		Medium		(2, 3, 4.5, 5)
		High		(4.5, 5, 8, 8.5)
4	Elevation Above Sea Level	Low	Trapezoidal	(0, 0, 250, 350)

		Medium		(275, 325, 575, 625)
		High		(550, 650, 2450, 2550)
5	Average Humidity	Low	Trapezoidal	(0, 0, 0.25, 0.35)
		Medium		(0.275, 0.325, 0.675, 0.725)
		High		(0.65, 0.75, 0.85, 0.95)
6	Average Temperature	Low	Trapezoidal	(0, 0, 7.5, 12.5)
		Medium		(8, 12, 28, 32)
		High		(27.5, 32.5, 42.5, 47.5)
7	Type of Energy Consumption	Rural	Triangular	(0.95, 1, 1.05)
		Commercial		(1.95, 2, 2.05)
		Residential		(2.95, 3, 3.05)

The following figures illustrate the membership functions of the input variables, which were derived from discussions held with the experts.

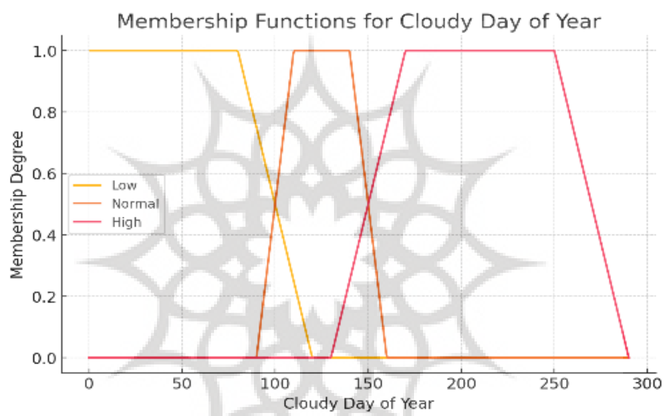

Figure 1. Membership Function of the Number of Cloudy Days per Year

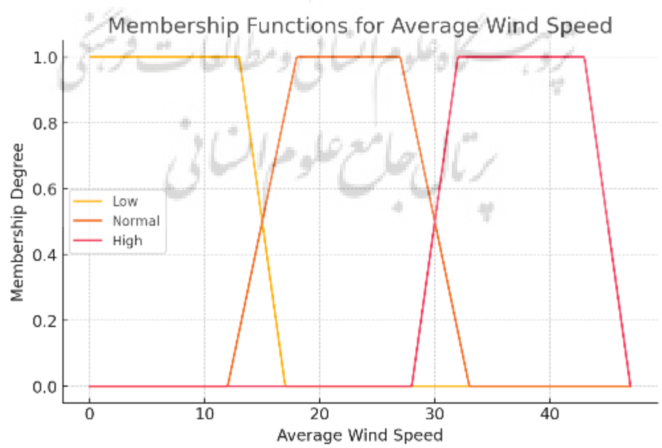

Figure 2. Membership Function of the Average Wind Speed

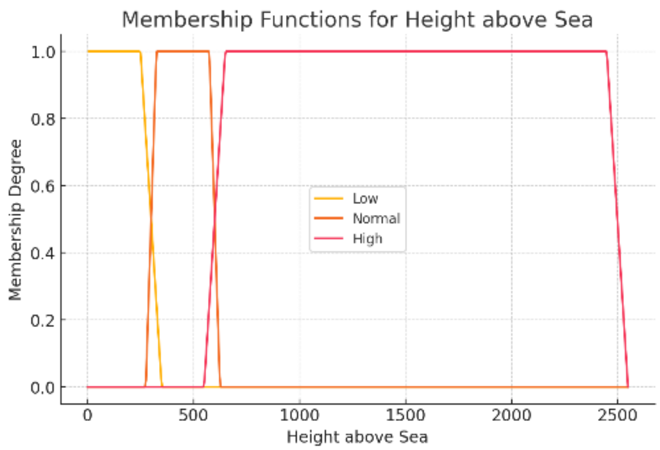

Figure 3. Membership Function of the Average Solar Irradiation

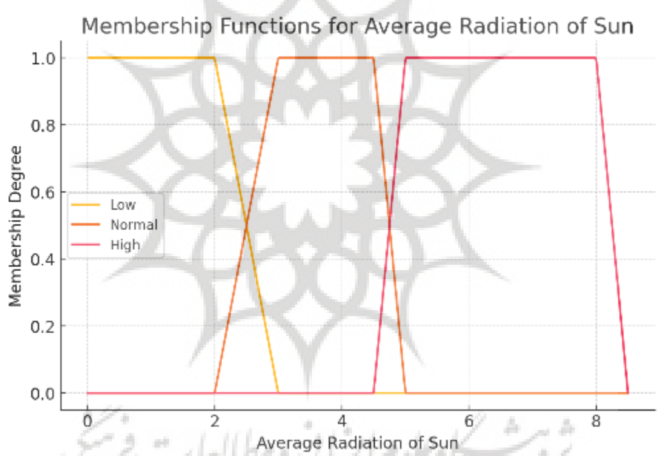

Figure 4. Membership Function of Elevation Above Sea Level

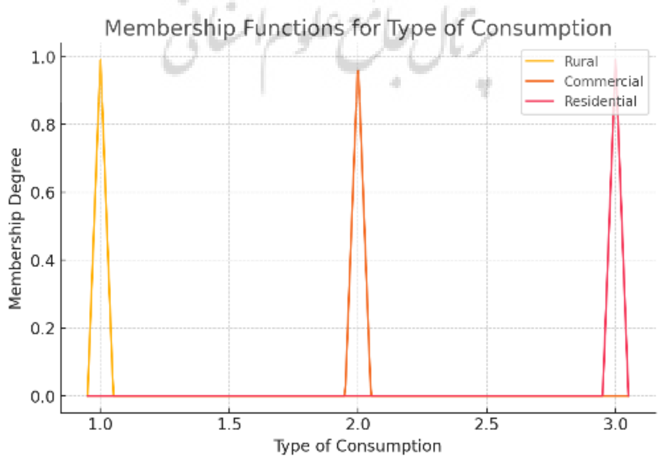

Figure 5. Membership Function of Humidity

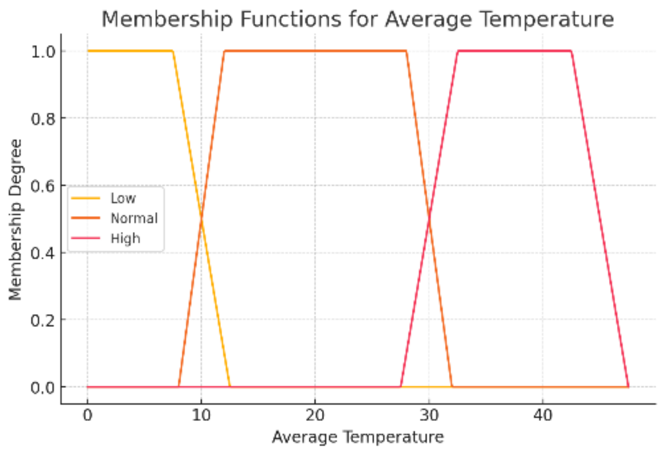

Figure 6. Membership Function of the Average Temperature

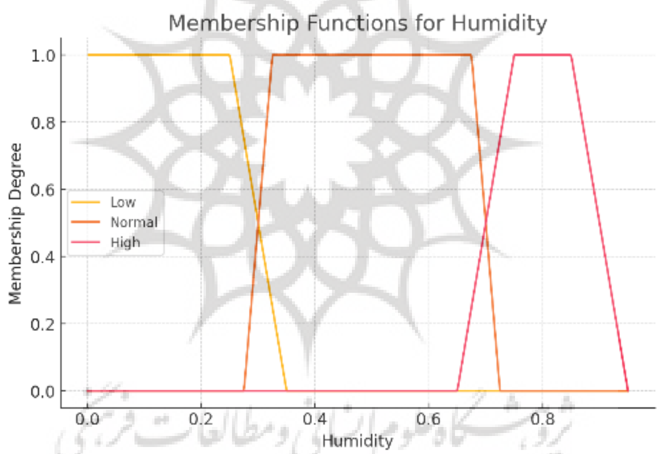

Figure 7. Membership Function of the Type of Energy Consumption

Sample Fuzzy Rules

Fuzzy rules form the foundation of the decision-making process within a fuzzy inference system. These rules, derived from the collective judgments of the experts, are expressed in the form of if–then statements and define the relationships between the input and output variables. They are formulated based on the expertise of experts and their practical experience. Given the number of experts participating in this study and the wide range of possible system states, a total of 2,187 fuzzy if–then rules were generated through the expert elicitation process. For each fuzzy rule, values are assigned to all four output variables, representing the required capacities of the energy resources to be installed in the hybrid renewable system. Below are five example fuzzy rules used in this study:

- Rule 1:

  If average solar irradiation is *Low*, average wind speed is *High*, elevation above sea level is *High*, average temperature is *Low*, average humidity is *High*, the number of cloudy days per year is *High*, and the type of energy consumption is *Residential*,

  then the solar energy capacity is *Medium*, the wind energy capacity is *Medium*, the battery storage capacity is *High*, and the diesel generator capacity is *High*.

- Rule 2:

  If average solar irradiation is *High*, average wind speed is *High*, elevation above sea level is *High*, average temperature is *Low*, average humidity is *Low*, the number of cloudy days per year is *Medium*, and the type of energy consumption is *Commercial*,

  Then the solar energy capacity is *High*, the wind energy capacity is *Medium*, the battery storage capacity is *High*, and the diesel generator capacity is *High*.

- Rule 3:

  If average solar irradiation is *High*, average wind speed is *High*, elevation above sea level is *Low*, average humidity is *Low*, the number of cloudy days per year is *Medium*, and the type of energy consumption is *Commercial*,

  Then the solar energy capacity is *Medium*, the wind energy capacity is *High*, the battery storage capacity is *Medium*, and the diesel generator capacity is *Low*.

- Rule 4:

  If average solar irradiation is *High*, average temperature is *High*, the number of cloudy days per year is *Low*, and the type of energy consumption is *Commercial*,

  Then, the solar energy capacity is High, and the battery storage capacity is Also High.

- Rule 5:

  If average wind speed is *High*, elevation above sea level is *Low*, and average humidity is *High*,

  Then, the wind energy capacity is High, and the diesel generator capacity is Also High.

Defuzzification of Outputs

In general, there are two main types of fuzzy inference systems: the Mamdani system and the Sugeno or Takagi–Sugeno–Kang (TSK) system. In this study, the Mamdani approach was employed. The reasons for selecting the Mamdani system over other approaches include its high interpretability, its superior ability to model nonlinear and complex relationships in problems involving multiple input and output variables, and the fact that Mamdani outputs are themselves fuzzy sets consistent with the fuzzy nature of the output variables defined in this research. Therefore, it is necessary to perform a defuzzification step at the end of the fuzzy inference process. Since the outputs of the fuzzy system in this study are quantitative indicators, appropriate membership functions were defined for each output variable to enable defuzzification. These membership functions were formulated based on the expertise gathered from the 16 specialists interviewed. The following table presents the membership specifications for each output variable.

Table 4. Output Defuzzification Functions

Row	Output	Linguistic Variable	Fuzzy Model	Fuzzy Number
1	Required Solar Energy Resources	Low	Trapezoidal	(18, 22, 30, 45)
		Medium		(32, 38, 47, 53)
		High		(45, 55, 80, 100)
2	Required Wind Energy Resources	Low	Trapezoidal	(10, 15, 26, 34)
		Medium		(25, 35, 45, 55)
		High		(40, 60, 90, 100)
3	Required Battery Capacity	Low	Trapezoidal	(50, 60, 90, 120)
		Medium		(85, 115, 135, 165)
		High		(140, 160, 185, 200)
4	Required Diesel Generator	Low	Trapezoidal	(10, 20, 45, 55)
		Medium		(42, 58, 67, 73)
		High		(65, 75, 90, 100)

It should be emphasized that all numerical values derived for the model outputs represent a percentage of the required peak demand. Accordingly, the recommended value required for structural formulation can be obtained by multiplying the actual consumption level by the defuzzified coefficients. The diagrams corresponding to the defuzzification functions of the output variables are presented hereafter.

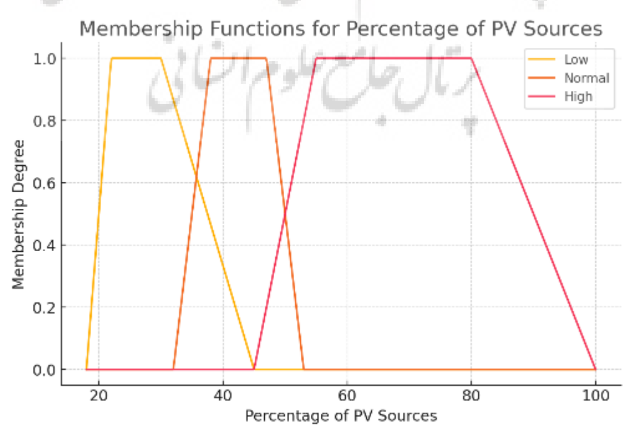

Figure 8. Defuzzification Function of the Solar Energy Source

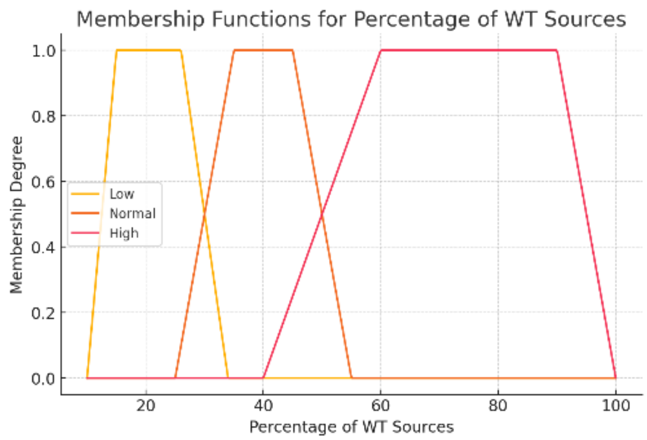

Figure 9. Defuzzification Function of the Wind Energy Source

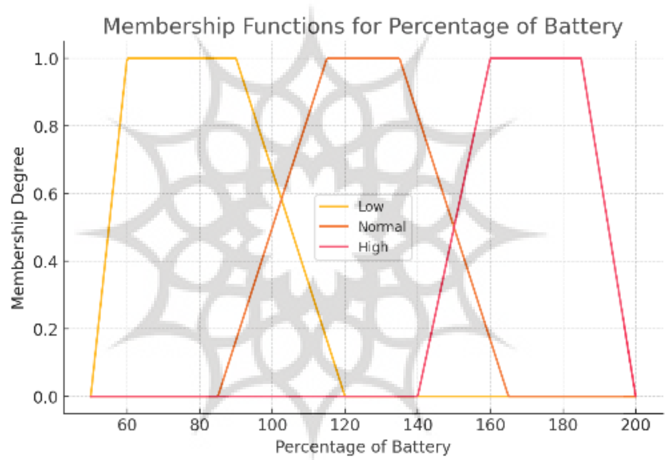

Figure 10. Defuzzification Function of the Battery Source

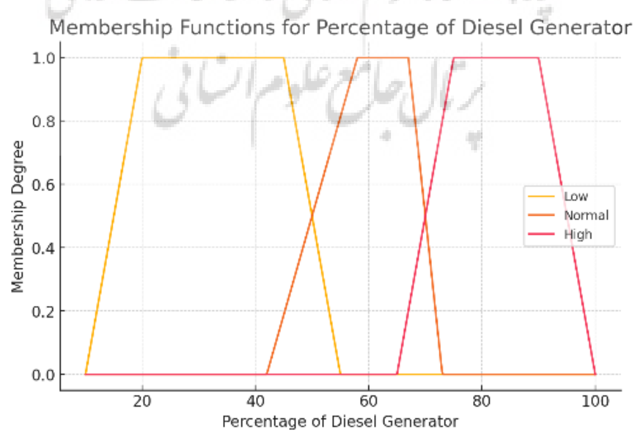

Figure 11. Defuzzification Function of the Diesel Generator Source

Based on the study's inputs and outputs, the architecture of the designed fuzzy system is illustrated as follows. The membership functions of the input variables, as well as the defuzzification functions of the output variables, can be observed in the following figure.

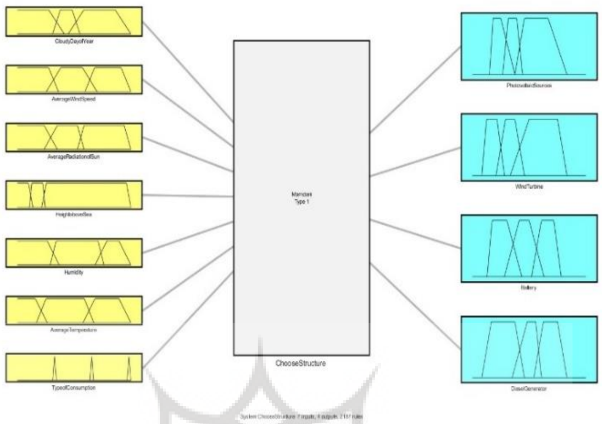

Figure 12. Architecture of the Fuzzy Inference System in MATLAB

Results

In this study, MATLAB software was used for the simulation process, and the data, consisting of seven inputs and four outputs, were implemented using command-based coding. Following the implementation, variations in each output with respect to changes in two selected inputs were recorded and analyzed. The initial state for all values, prior to varying the input variables, is presented in the following Table.

Table 5. Initial State of the Input Variables

No.	Input Variable	Initial Value
1	Number of cloudy days per year	125 days
2	Average wind speed	22.5 km/h
3	Average solar irradiation	3.75 kWh/m²/day
4	Elevation above sea level	450 m
5	Average humidity	50%
6	Average temperature	20°C
7	Energy consumption type	Residential

In each of these results, as is evident, changes in the input variables lead to variations in the output variable. Each of the generated plots illustrates the trend resulting from the variation of two input variables and, consequently, the corresponding change in a single output variable. A selection of these plots has been included in this study as representative examples. It should be noted that, during the plotting process, except for the two input variables under investigation, all other variables were fixed based on their initial values presented in Table 4.

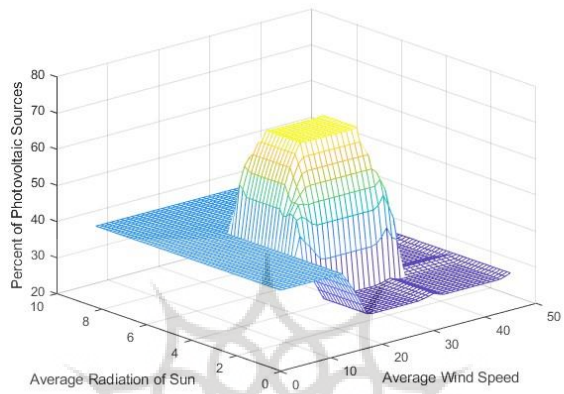

Figure 13. Variations in the size of the solar resource as a function of changes in the average wind speed and solar irradiance

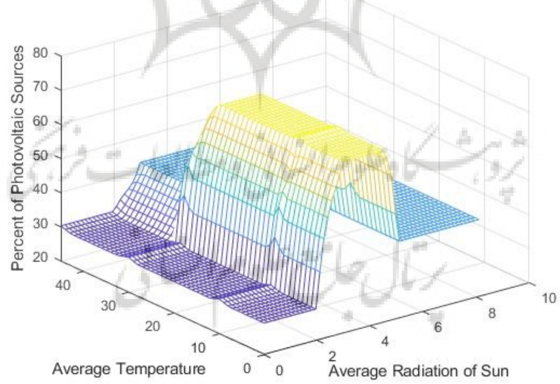

Figure 14. Variations in the size of the solar resource as a function of changes in solar irradiance and average temperature

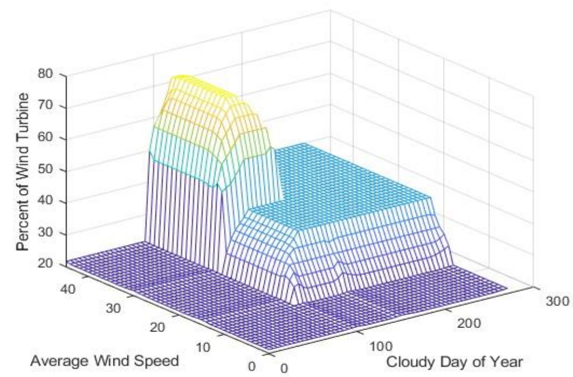

Figure 15. Variations in the size of the wind resource as a function of changes in average cloudy days and average wind speed

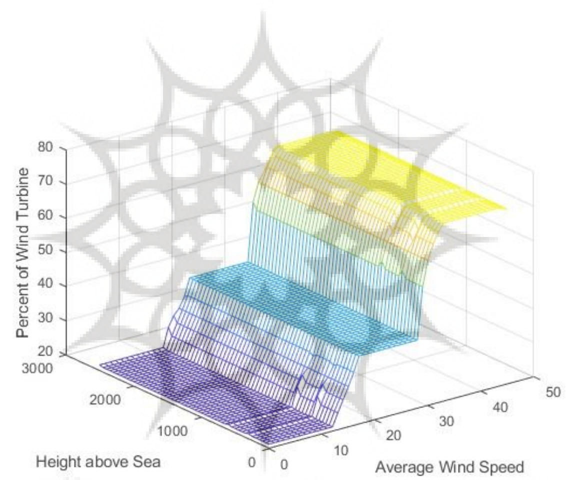

Figure 16. Variations in the size of the wind resource as a function of changes in average wind speed and altitude above sea level

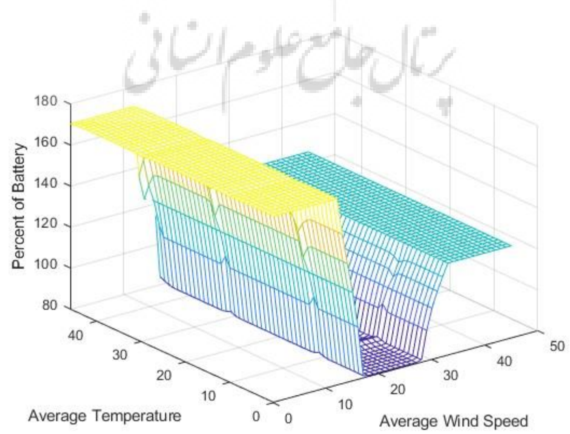

Figure 17. Variations in the size of the battery as a function of changes in average wind speed and solar irradiance

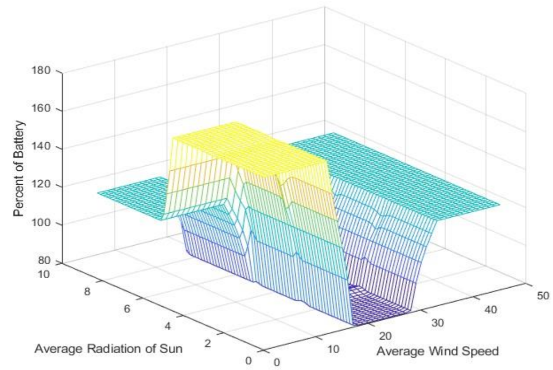

Figure 18. Variations in the size of the battery as a function of changes in average wind speed and average temperature

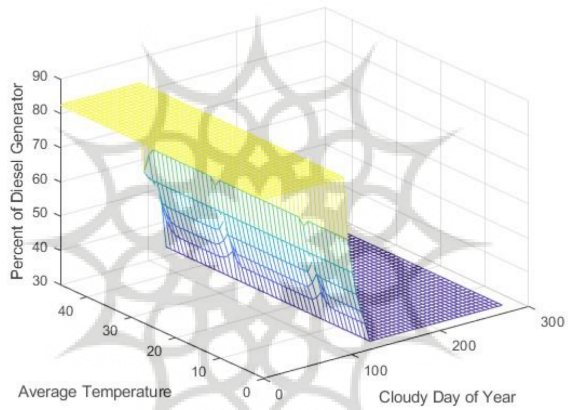

Figure 19. Variations in the size of the diesel generator as a function of changes in average cloudy days and average temperature

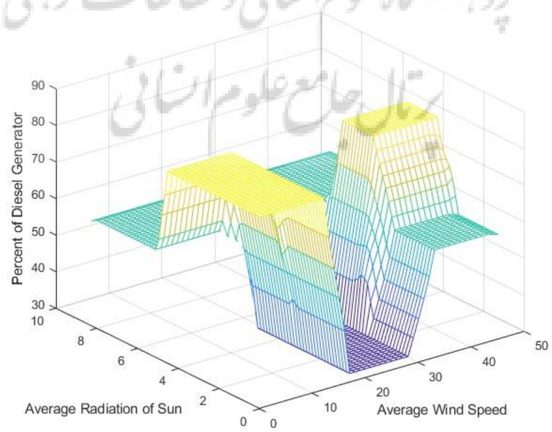

Figure 20. Variations in the size of the diesel generator as a function of changes in average wind speed and solar irradiance

For example, Table 6 presents several proposed regions based on their geographical characteristics and the required levels of energy resources. It should be noted that the geographical information, including the number of cloudy days, altitude above sea level, average humidity, and average temperature, was obtained from the Statistical Center of Iran. Data for average wind speed were extracted from the Iran Wind Atlas, and solar irradiance values were obtained from the Global Solar Atlas (globalsolaratlas.info) developed by the World Bank Group. The selected sample regions were chosen to represent the country's geographical diversity.

Accordingly, the cities of Zabol, Genaveh, Sarpol-e Zahab, Khoy, Kiasar, Ashkhaneh, and Yazd were selected. The selection also aimed to encompass a broad range of climatic and environmental conditions. After evaluating the model outputs for sizing renewable energy resources for these cities, chosen as representative points from different parts of Iran, the results were shared with experts in the field. Upon review, the experts expressed satisfaction with the model's accuracy. The evaluation process was conducted as follows: the geographical characteristics of the selected cities were provided to the experts, who were then asked to estimate the required size of renewable energy resources to meet consumer demand. A comparison of the expert estimates with the simulation results showed that the simulation outputs for 80% of the experts were within a 10% deviation from their assessments.

A 10% deviation is considered acceptable in mathematical and industrial computations, given that expert assumptions naturally vary from one specialist to another. Since the simulations were performed using MATLAB scripts, the model is inherently capable of accommodating various geographical conditions while maintaining full reproducibility. By selecting a wide range of cities for the sample set, the model's robustness and reliability were also examined. The subsequent section presents the table of input and output variables.

Table 6. Sample regions examined in the simulation

Row	City	Input Variables							Output Variables			
		Cloudy Days (days)	Average Wind Speed (km/h)	Average Solar Radiation (kW/m²/day)	Elevation (m)	Average Humidity (%)	Average Temperature (°C)	Energy Consumption Type	Solar Energy (%)	Wind Energy (%)	Battery (%)	Diesel Generator (%)
1	Zabol	10	30.6	5.7	489	28.91	22.4	Residential	43	43	160	73
2	Genaveh	72	14.4	5.5	4	66.81	22	Residential	42	21	140	69
3	Sarpol Zahab	26	21.6	5.1	545	40.05	20.3	Rural	41	21	125	50

4	Khoy	71	14.4	4.9	1103	50.16	12.6	Commercial	61	49	130	38
5	Kiasar	102	14.4	3.9	1294	65.75	13.4	Rural	36	30	105	44
6	Ashkhaneh	44	18	4.9	762	51.19	16	Residential	43	21	171	83
7	Yazd	14	14.4	5.7	1216	28.03	20	Commercial	64	55	125	35

Based on the conducted analyses and simulations, it was determined that certain input variables have a greater influence on the output variables, resulting in more significant variations. In this study, solar radiation intensity has the most significant impact on the amount of solar energy required. In contrast, wind speed has the most significant effect on the required wind energy. Additionally, the type of energy consumption plays the most influential role in determining battery and diesel generator usage. Overall, average humidity shows the least impact on variations in the output components.

One of the key findings extracted from the simulations is that the decision-making speed for selecting a suitable geographical location is reduced to only a few minutes using this model. In contrast, the conventional calculations required by consulting companies, policymakers, and decision-makers may take several days. The use of a fuzzy inference system as a decision-support tool yields a substantial reduction in the time required for informed decision-making.

Conclusion

As demonstrated in the research findings, each renewable energy system is designed based on specific climatic, geographical, and environmental conditions. The proposed model developed in this study is capable of providing appropriate sizing recommendations for renewable energy systems utilizing four energy sources—solar, wind, battery, and diesel generator—based on expert knowledge and tailored to specific situations. The results obtained from seven geographical regions in Iran, presented as case examples, show a deviation of only 10% from the opinion of 80% of the experts, confirming the high accuracy and efficiency of the designed model. The high inference speed and acceptable precision are among the key strengths of this model, which significantly reduce the time required for analysis and cost estimation compared with classical sizing methods or simulation-based models. Furthermore, the study's broad geographical coverage within Iran is another significant aspect.

Clients can utilize the findings of this research, supervisory engineering firms in the field of renewable energy, consulting companies involved in hybrid renewable energy system design, and private firms that design and implement hybrid renewable energy systems. The outcomes may also be integrated into standalone software tools or incorporated into larger digital platforms. Additionally, the results can serve as a decision-support instrument for national energy policymakers, enabling optimal and targeted planning for investment and development of renewable energy infrastructure through the use of fuzzy inference systems. In the context of national policy-making, incorporating cost-calculation modules into the model could turn it into an effective tool for cost estimation. All potential users can leverage this tool to rapidly and accurately determine the optimal renewable energy system configuration based on geographical characteristics. Moreover, companies can utilize real-world operational data to calibrate the fuzzy inference rules proposed in this study, thereby further enhancing the model's performance.

Since the integration of industrial expert knowledge with model development in the energy sector via a fuzzy inference system is relatively uncommon, this research can serve as a guiding framework for other researchers. It highlights how accumulated expert knowledge can be employed to develop practical and cost-reducing models, even across other industries. For more rigorous analysis, it is recommended that the fuzzy inference system be combined with other decision-making tools such as machine learning algorithms or multi-objective optimization methods. Several avenues exist for extending the research, including:

a) Integration with Geographic Information Systems (GIS);

b) Inclusion of future climate scenarios considering climate change;

c) Increasing the number of national and international experts participating in the study; and

d) Incorporating economic and social factors into the model.

This study benefited from the involvement of industrial experts, ensuring the tool's practical applicability. Including academic experts could further enhance the theoretical depth of the model. The research also faced certain limitations, one of which was the lack of access to comprehensive international datasets and the technological differences that exist across other countries, which could potentially affect the model's accuracy outside Iran. To address this limitation, the development of international databases and cross-border collaborations is recommended.

Overall, this research, through the application of a fuzzy inference system and expert knowledge, takes a significant step toward simplifying and accelerating the decision-making process for sizing renewable energy resources. With model development, expansion of datasets, and the use of complementary analytical tools, its effectiveness and comprehensiveness can be further enhanced at regional and international scales.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors have witnessed various ethical issues, including plagiarism, failure to obtain informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

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Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work.

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