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Article

Intelligent Management of Alternative Energy Sources through a System Based on Fuzzy Logic

Gestión inteligente de fuentes alternativas de energía mediante un sistema basado en lógica difusa

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Abstract: This research explores the application of computational intelligence techniques, specifically fuzzy logic, in the management of alternative energy sources such as wind, solar, and fuel cells. It proposes a hybrid energy generation system and evaluates its performance by considering factors like availability, reliability, and responsiveness to energy demand and environmental conditions. The study emphasizes the use of fuzzy logic-based control systems to optimize energy distribution, enabling efficient utilization of renewable energy sources. Furthermore, the management system is tested under various scenarios to determine how it can adapt to different energy needs. The goal is to demonstrate that intelligent management can lead to better energy efficiency in hybrid renewable energy systems. The computational tool developed for this purpose simulates the system's behavior and allows for detailed analysis, making it a valuable resource for optimizing renewable energy management in diverse contexts, particularly in countries like Colombia.

Keywords: Alternative Energy; Hybrid Generation; Fuzzy Logic; Power Management; Renewable Energy Systems; Intelligent Systems; Wind Energy; Solar Energy; Fuel Cells; Energy Demand

Resumen: Esta investigación explora la aplicación de técnicas de inteligencia computacional, específicamente la lógica difusa, en la gestión de fuentes alternativas de energía como la eólica, solar y las celdas de combustible. Se propone un sistema híbrido de generación de energía y se evalúa su rendimiento considerando factores como la disponibilidad, confiabilidad y la respuesta a la demanda energética y las condiciones ambientales. El estudio destaca el uso de sistemas de control basados en lógica difusa para optimizar la distribución de energía, lo que permite una utilización eficiente de las fuentes de energía renovables. Además, el sistema de gestión se prueba bajo diversos escenarios para determinar cómo puede adaptarse a diferentes necesidades energéticas. El objetivo es demostrar que la gestión inteligente puede conducir a una mayor eficiencia energética en los sistemas híbridos de energía renovable. La herramienta computacional desarrollada para este propósito simula el comportamiento del sistema y permite un análisis detallado, lo que la convierte en un recurso valioso para optimizar la gestión de energías renovables en contextos diversos, especialmente en países como Colombia.

Palabras clave: Energía Alternativa; Generación Híbrida; Lógica Difusa; Gestión de Energía; Sistemas de Energía Renovable; Sistemas Inteligentes; Energía Eólica; Energía Solar; Celdas de Combustible; Demanda Energética

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1. Introduction

As human needs grow increasingly complex, so do energy consumption patterns. Awareness of the environmental damage caused by the human footprint has become a prominent topic of discussion in contemporary society [13].

Regarding renewable energy generation, a common global challenge is the intermittent and disruptive nature of these sources. For example, wind energy is only available when the wind is blowing, and photovoltaic energy is only available under adequate sunlight conditions [8]. Hydroelectric power, on the other hand, is considered a reliable source for meeting large-scale, short-term power demands. Its significance lies in its ability to adjust water flow through turbines to match changing loads, thereby reducing reliance on coal-fired and nuclear plants, which have slower response times [1]. However, hydroelectric power poses significant environmental challenges during the construction of its infrastructure, making it less favorable as a "clean" energy alternative compared to solar and wind sources. Research efforts have focused on mitigating these weaknesses primarily through sophisticated software solutions and smart grid technologies that enable real-time power supply management based on end-user demand.

In Bilacenge, Southwest Sumba, Northeast Timor, Indonesia [8], the use of a smart microgrid integrating both solar and wind energy sources has been investigated. A demonstration plant was designed to rely on a battery system and a PLC-based Energy Management System (EMS) that ensures stability amid fluctuations caused by natural variations in wind and sunlight. The EMS operates by processing data collected from various control units and issuing directives to maintain energy balance. This data collection system comprises three main components: Smart Meter Control (SMC), Smart Power Manager (SPM), and Battery Monitoring Unit (BMU). The SMC facilitates bidirectional communication, transmitting power supply and demand information to the EMS and regulating load input and output based on EMS commands.

In Europe, the implementation of artificial intelligence (AI) in the smart renewable energy sector is under study. Specifically, the focus is on envisioning intelligent agents powered by smart grid technologies and AI algorithms, which must consider not only technical capabilities but also social and economic factors. By leveraging different AI approaches, such as managing structured data, utilizing data mining, and employing machine learning techniques, an AI ecosystem can be established within the energy sector. This advancement promises to revolutionize energy management and distribution through an AI-powered smart energy grid [20].

In Colombia, the adoption of renewable energy is relatively recent, especially considering that hydroelectric power accounts for approximately 60% of the total electricity supply, while fossil fuels cover about 30%. However, there is still significant progress to be made to establish a robust renewable energy foundation [4], particularly if the goal is to implement smart software solutions that require structural changes in legislation, operation, and energy policies [14].

This study proposes the design and implementation of a fuzzy logic controller for an alternative energy plant comprising three generation sources: wind, photovoltaic, and fuel cells. By operating these sources in parallel, the aim is to enhance the reliability of energy supply. Additionally, through fuzzy logic-based system management, the goal is to improve overall system efficiency by prioritizing the use of less expensive sources, wind and photovoltaic, while activating the fuel cell only when demand cannot be met by these sources alone. This work is intended to set a precedent and pave the way for future implementations of smart software-based technologies to optimize and promote renewable energy systems in Colombia.

In Section 2, the key contributions of this research are presented, highlighting the design and implementation of the fuzzy logic-based management system, the integration of a hybrid renewable energy plant, and the development of a computational tool for evaluation. Section 3 discusses the state-of-the-art in renewable energy systems, focusing on combinations of source types, control software, and smart power grids. Section 4 details the rationale for selecting wind energy as the primary focus, provides a descriptive model of the proposed plant, and outlines the parameters used to assess the model's efficiency. Section 5 presents an overview of the software interface along with descriptions of its key features and functionalities. Section 6 synthesizes the overall performance and behavior of the proposed model based on the experimental results. Finally, Section 7 discusses expectations for practical implementation and suggests potential strategies to further optimize system performance.

2. Contributions

This study presents several novel contributions to the intelligent management of alternative energy sources through a system based on fuzzy logic:

1. Development of a Fuzzy Logic-Based Management System (GLD): A key contribution of this research is the design and implementation of a Mamdani-type fuzzy inference engine that dynamically manages three clean energy sources—wind, solar photovoltaic, and fuel cells. The system uses environmental and demand variables to optimize energy distribution, enhancing the autonomy and reliability of the hybrid power plant.
2. Integration of a Hybrid Renewable Energy Plant: The proposed model integrates wind turbines, monocrystalline solar panels, and solid oxide fuel cells, each modeled according to real-world parameters. This hybrid approach leverages the strengths of each energy source to ensure consistent power supply under varying environmental conditions.
3. Scenario-Based Management Strategies: The study defines and implements multiple management scenarios: Profitability, Reliability, Priority, and Percentage, to showcase the system's flexibility in adapting to different operational goals. Each scenario allows customized decision-making for energy distribution based on user-defined criteria or system performance.
4. Creation of a Computational Tool with Graphical Interface: A user-friendly software tool was developed to simulate and evaluate the system. This tool allows users to define subsystem parameters, select demand profiles based on real-time criteria, and observe system behavior through intuitive graphical outputs.
5. Adaptation to Colombian Context: The research contextualizes the model for Colombia's energy matrix, which currently depends heavily on hydroelectric and fossil fuel sources. By demonstrating the feasibility and advantages of intelligent renewable energy management, this study sets a foundation for future implementation of smart grid technologies in the country.
6. Validation through Simulation: The proposed model is tested across different demand scenarios using historical data and environmental conditions, validating its capability to balance energy supply efficiently, minimize reliance on costly sources, and respond adaptively to fluctuations.

3. Related Works

The state-of-the-art research in alternative energy management covers various dimensions, including technological advancements, grid integration challenges, and optimization strategies.

In [19], Zhao et al. propose a novel hybrid system combining solar-assisted methanol reforming and fuel cell power generation to address the hydrothermal management limitations of proton exchange membrane fuel cells (PEMFC). By using methanol both as a coolant and as a source for hydrogen production via solar-assisted reforming, the system achieves enhanced efficiency. Simulation results demonstrate controlled temperature, improved power density, and significant increases in energy and system efficiency compared to conventional approaches.

The integration of renewable energy sources into smart grids presents considerable challenges, as discussed by Khalid in [10]. Smart grid technologies are essential in facilitating this transition by automating and digitizing grid operations, thereby enhancing flexibility and reliability. The review highlights the importance of addressing user acceptance, operational flexibility, and regulatory frameworks to fully realize the potential of smart grids in accommodating variable renewable energy sources and transforming electricity markets.

Yan et al. [17] focus on the operational costs caused by wind power fluctuations, employing a data-driven model to accurately estimate power system operating costs under various wind scenarios. By clustering different fluctuation patterns and leveraging deep neural networks, the study offers insights into optimizing system operations and mitigating additional costs, demonstrating high accuracy and effectiveness in cost analysis.

Zhang et al. [19] address the optimization of wind power consumption in district heating systems by proposing a mathematical model and scheduling strategy that maximizes wind power utilization while maintaining system reliability. Taking into account the dynamic characteristics of cogeneration components, including thermal inertia and load demand, the study provides practical solutions for efficient integration of wind power into heating systems.

Renewable energy supply chain management is explored by Sarkar and Seo [15], who model the conversion of waste into renewable energy to sustainably meet increasing demand. Their energy supply chain model encompasses waste collection and energy generation, considering scenarios with both unequal and equal power distribution among supply chain participants. Using game theory and coordination policies, the research demonstrates how cooperation maximizes profits and underscores the importance of flexibility and automation in production systems.

Taken together, these studies reveal a thorough exploration of methods to optimize alternative energy management, addressing technological, operational, and economic challenges to facilitate efficient integration into existing energy systems.

4. Methodology

Selection of Alternative Energy Sources

In selecting alternative energy sources for evaluation in the fuzzy logic-based management system, considerations were made regarding technological development, cost, and future prospects within the renewable energy sector. As previously mentioned, wind energy is widely adopted in China due to its simplicity, efficiency, and rapid return on investment [18], making it highly competitive compared to combustion-based generation methods. Wind energy was chosen in this study because of its technological maturity and, in most cases, cost-effective implementation.

Although solar photovoltaic energy involves a relatively high initial investment, ongoing scientific and economic efforts continue to improve its viability and prominence [6]. Predicting the performance of such installations is feasible, thanks to existing studies on solar irradiation patterns.

Lastly, hydrogen-derived energy used in fuel cells, while not entirely new, has gained considerable momentum recently, particularly in the automotive sector. Its appeal lies in its relative simplicity and controllable power generation, which depends on hydrogen flow within the system. This energy source, combined with the autonomy of photovoltaic systems and the reliability and continuity of fuel cell systems, offers promising benefits [5;7].

This research employs generic models of a vertical-axis wind turbine, commonly used in wind farms; monocrystalline silicon solar panels, prevalent in medium- to large-scale photovoltaic installations; and solid oxide fuel cells (SOFC), selected for distributed generation. The core contribution of this work lies in the integration of these alternative energy sources, harnessing their individual strengths synergistically to mitigate challenges that arise when operating in isolation. Consequently, the system achieves a balance by combining the robustness and high power capacity of the wind system, the storage capacity and autonomy of the photovoltaic system, and the reliability and continuous operation of the fuel cell system.

Alternative Energy Plant Modeling

Figure 1 illustrates the block diagram of the alternative energy plant, which includes its subsystems of wind, photovoltaic, and fuel cell, for which energy management is desired.

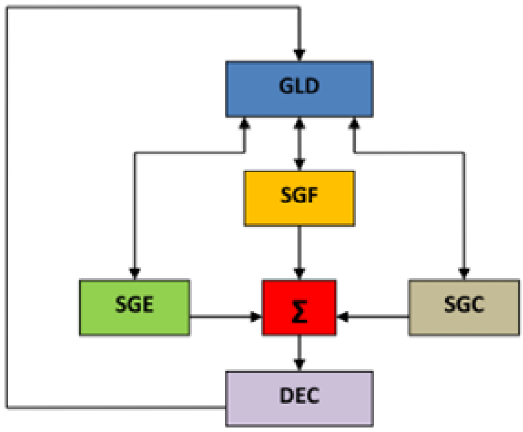

Figure 1. Block diagram of the proposed system.

The arrows illustrate the types of communication between the systems, showing that the fuzzy logic-based management system (GLD) receives information from the wind generation system (SGE), photovoltaic system (SGF), and fuel cell system (SGC). Simultaneously, it sends back information regarding the percentage of their required power, indicating bidirectional communication. The management system maintains unidirectional communication only with the load, from which it requests data on electrical demand. After completing the management process, the energy supplied by each system is aggregated through the summing block, with the goal of meeting the electrical demand of the load (DEC).

Wind Generation System (SGE)

The Wind Generation System (SGE) primarily consists of the wind turbine model [20], which includes parameters such as the number of turbines, blade length, high and low cut-in speeds, power coefficient, generator efficiency, and multiplier efficiency. Together, these factors determine the system's nominal power. However, the available energy depends on the wind speed incident on the turbine blades, which will be modeled based on different wind profiles, as detailed in Table 1.

Not all the energy is captured by the generator due to losses during the energy conversion process, associated with both mechanical and electrical components. Therefore, it is crucial to consider the mechanical multiplier efficiency (η_{mec}) and the electrical generator efficiency (η_{elec}).

For modeling the incident wind on the system, wind standards provided by the meteorological service of Ernesto Cortissoz International Airport in Barranquilla, Colombia, were used. These standards are summarized in Table 1.

Table 1. Wind Speed Classification

TYPE	SPEED KM / H	SPEED KNOTS
Breeze	1 – 5	0.5 – 2.7
Light	6 – 11	3.2 – 5.9
Gentle	12 – 19	6.5 – 10.3
Moderate	20 – 28	10.8 – 15.1
Fresh	29 – 38	15.7 – 20.5
Strong	39 – 49	21.1 – 26.5
Gale	50 – 61	27.0 – 33.0
Storm	62 – 74	33.5 – 40.0

Wind system model structure can be seen in Figure 2. This shows as well the inputs and outputs of the wind system.

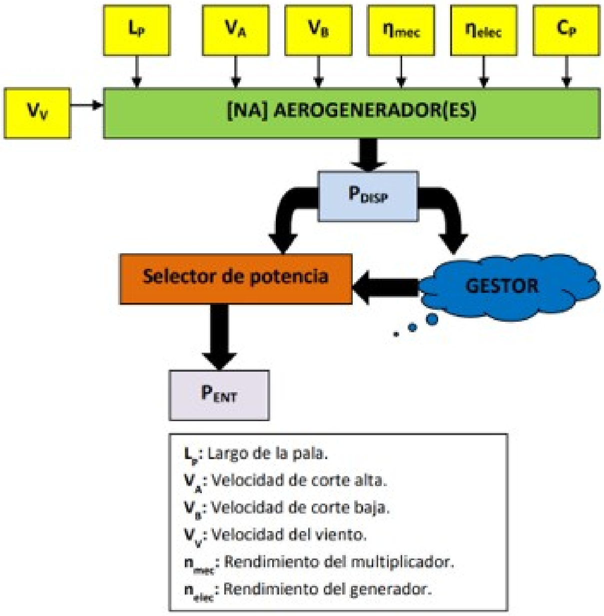

Figure 2. Block diagram of the proposed system.

Photovoltaic Generation System (SGF)

The Photovoltaic Generation System (SGF) comprises solar panels and a battery bank, as detailed in studies such as [3] and [11]. Key parameters, including the number of panels, panel power, battery capacity, voltage, and losses in converters and self-discharge, play an integral role in determining the system's nominal power. However, the actual energy output depends on incident solar irradiation and the stored energy within the battery bank. The modeling process accounts for overall system efficiency, incorporating losses from components such as the battery bank, power converter, and self-discharge. Autonomy time is influenced by battery capacity, nominal voltage, and the power generated by the panels, as discussed in [16].

Calculations of available energy require ensuring that energy production sufficiently compensates for system losses so that usable energy exceeds these losses. Nominal energy is computed considering factors such as the number of panels, energy provided per panel, and the peak solar hours at the installation site. Solar irradiation, which measures the power received per unit area from sunlight, plays a crucial role, as explained in [2]. Modeling approaches include varying weather conditions—sunny, cloudy, and rainy—using solar irradiation data to reflect changes in irradiation levels.

Figure 3 illustrates the photovoltaic system model structure, outlining its inputs and outputs, thereby providing a visual representation of the system's configuration and operational dynamics, as discussed in the referenced studies.

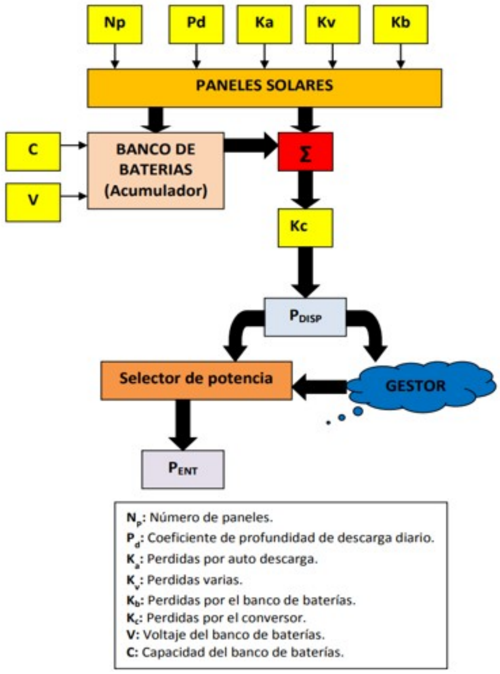

Figure 3. Block diagram of the photovoltaic system.

Fuel Cell Generation System (SGC)

The Fuel Cell Generation System (SGC) is based on the Solid Oxide Fuel Cell (SOFC) model, commonly used in distributed energy systems, as described in [9]. This model considers parameters such as the number of fuel cells and their intrinsic characteristics, including utilization factor, activation losses, ohmic losses, and concentration losses. These factors, combined with hydrogen flow, determine the system's nominal power, which remains available as long as the system operates.

In the initial modeling phase of the SOFC, accurately accounting for the chemical reactions within the cell is critical. Not all hydrogen entering the cell reacts with oxygen; therefore, a utilization factor coefficient is introduced. This coefficient increases with the amount of hydrogen undergoing the reaction and decreases inversely with the total hydrogen input to the cell.

Calculating the power output of the fuel cell system requires knowledge of the cell's DC voltage. Given the inherent losses within the fuel cell, these must be incorporated into calculations in accordance with Kirchhoff's laws. The research treated the available power of the SOFC as a controlled variable dependent on hydrogen flow, which is assumed to be constant. Figure 4 illustrates the model structure of the fuel cell system, providing an overview of its inputs and outputs.

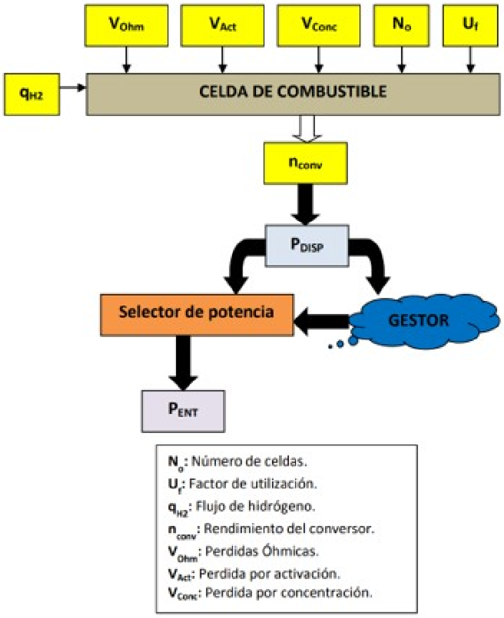

Figure 4. Block diagram of the fuel cell system.

Electric Demand Models (DEC)

The modeling of Electric Demand (DEC) is based on accumulated knowledge of electricity consumption patterns in the traditionally recognized residential, commercial, and industrial sectors. This demand model is developed using historical data obtained from [12], which characterize these demand types.

In the residential sector, demand peaks occur during family-oriented hours, specifically between 7:00 PM and 9:00 PM.

The analysis also revealed that the commercial sector experiences its peak consumption during typical working hours, approximately from 8:00 AM to 8:00 PM, reaching up to 10,000 kW around 10:00 AM.

The industrial sector shows a longer duration of high energy consumption due to the continuous and energy-intensive nature of industrial processes, with demand peaking at about 4,000 kW around 1:00 PM.

Fuzzy Logic-Based Management System (GLD)

For the design of the Fuzzy Logic-Based Management System (GLD), the general structure of fuzzy logic-based systems (Figure 5) was used as a reference model. This figure illustrates the fundamental components of such systems. In this research, a Mamdani-type model was employed.

The system includes an input block containing the most relevant information about the system to be controlled. In this case, the inputs consist of meteorological variables such as wind speed and solar irradiation, the available hydrogen quantity from the fuel cell system, and the electrical demand curve (DEC) that the system aims to satisfy.

These GLD inputs are converted into fuzzy values using input membership functions, which can be of various types. For this study, triangular and trapezoidal membership functions were selected due to their simplicity and practical implementation.

The inference block uses a set of "if-then" rules that define the conditions the GLD must meet. The output block employs output membership functions, also triangular and trapezoidal, that convert the fuzzy decisions into specific numerical values using the center of gravity method.

In this research, the outputs correspond to the autonomy percentages (demand satisfaction) for each subsystem (SGE, SGF, and SGC) relative to the electrical demand curve. Once the autonomy values for each system are determined, simple management rules are applied to coordinate system operation under different scenarios, as described later.

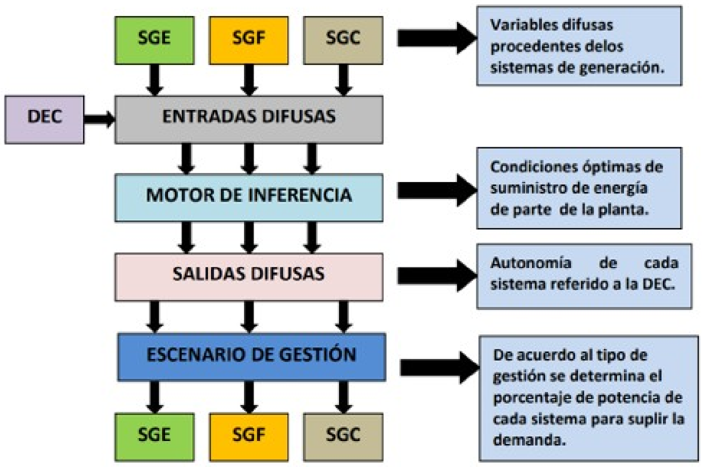

Figure 5. Block model of the proposed GLD.

Inputs for the Fuzzy Logic-Based Management System (GLD)

In the design of the GLD, the operational variables of the hybrid alternative generation plant were used as inputs. These variables include wind speed, solar irradiation, and the available quantity of hydrogen, all of which directly affect the amount of electrical power each system can generate. Together with the electrical demand, these variables are fed into the GLD and converted into fuzzy values using membership functions, as illustrated in Figures 6 and 7.

The membership function for the input from the Wind Generation System (SGE) is defined based on the parameters described in Table 1, which outlines wind types and their corresponding speeds. With appropriate adjustments to the measurement system, the same methodology can be applied to the Photovoltaic Generation System (SGF), which is modeled considering the daily solar radiation curve, and to the Fuel Cell Generation System (SGC), where the input is determined by the hydrogen storage level, expressed as a percentage of the fuel content in the tank.

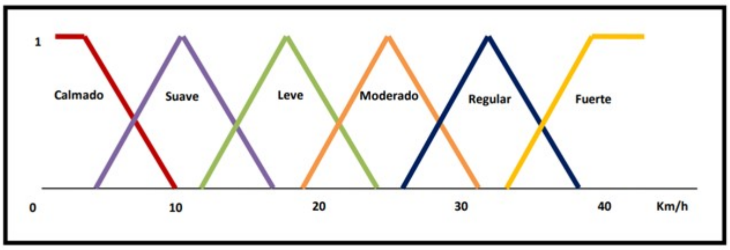

Figure 6. GLD input membership function (WIND SPEED).

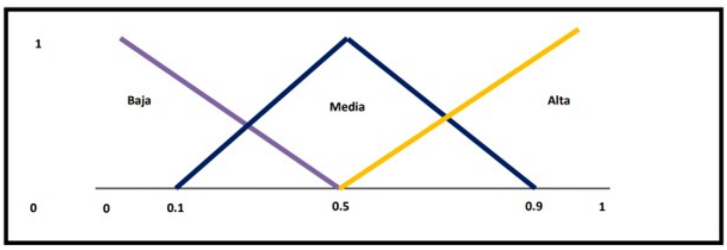

Figure 7. GLD entry membership function (DEMAND).

The membership function for the Electrical Demand Curve (DEC) input is normalized with respect to the maximum and minimum values of the demand curve. This normalization ensures that the fuzzy values derived from electrical demand are bounded and can be applied to any type of demand curve.

Inference Engine of GLD

The inference engine of the Fuzzy Logic-Based Management System (GLD) operates using a set of "if-then" rules designed to optimize the operation of the proposed alternative energy generation plant. The system aims to:

- Fully satisfy the Electrical Demand Curve (DEC), thereby increasing the autonomy and reliability of the proposed system.
- Determine the required power output for each subsystem of the alternative energy plant based on the selected management scenario, providing high flexibility and efficiency.
- Permit the use of energy from the electrical grid only when the hybrid alternative energy system is unable to meet the DEC.

To achieve these objectives, a rule base was developed based on accumulated operational experience from each generation subsystem. Each subsystem has an associated fuzzy inference engine that calculates the autonomy or demand satisfaction level specific to that subsystem. This inference engine estimates, based on fuzzy variables related to each subsystem (wind speed, solar irradiation, and hydrogen level) and the inherent capacity of each subsystem (defined by the model parameters), the percentage of demand satisfaction for each subsystem.

This enables the GLD to determine, through straightforward rules and according to the specified management criteria, the operational percentage for each subsystem. For the Wind Generation System (SGE), 16 rules were implemented, using the membership functions depicted in Figures 6 as inputs and Figure 9 as the output. Figure 8 illustrates the response surface, showing the relationship between demand and wind inputs and the SGE's demand satisfaction percentage output.

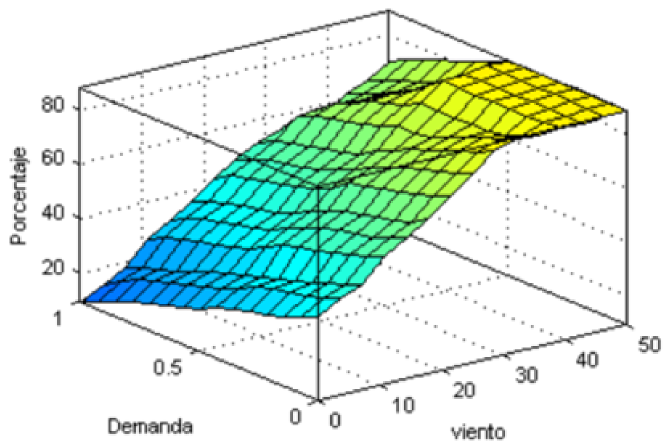

Figure 8. Work area generated by the GLD for the satisfaction of the SGE.

Observing Figure 8, the system's behavior can be described by the rules associated with the Wind Generation System (SGE). These rules are as follows:

- If WIND is *CALM* and DEMAND is *HIGH*, then SATISFACTION is *NONE*.
- If WIND is *CALM* and DEMAND is *MEDIUM*, then SATISFACTION is *LOW*.
- If WIND is *CALM* and DEMAND is *LOW*, then SATISFACTION is *MEDIUM*.
- If WIND is *GENTLE* and DEMAND is *HIGH*, then SATISFACTION is *LOW*.
- If WIND is *GENTLE* and DEMAND is *MEDIUM*, then SATISFACTION is *MEDIUM*.
- If WIND is *GENTLE* and DEMAND is *LOW*, then SATISFACTION is *HIGH*.

- If WIND is *LIGHT* and DEMAND is *HIGH*, then SATISFACTION is *MEDIUM*.
- If WIND is *LIGHT* and DEMAND is *MEDIUM*, then SATISFACTION is *HIGH*.
- If WIND is *LIGHT* and DEMAND is *LOW*, then SATISFACTION is *VERY HIGH*.
- If WIND is *MODERATE* and DEMAND is *HIGH*, then SATISFACTION is *HIGH*.
- If WIND is *MODERATE* and DEMAND is *MEDIUM*, then SATISFACTION is *VERY HIGH*.
- If WIND is *MODERATE* and DEMAND is *LOW*, then SATISFACTION is *TOTAL*.
- If WIND is *STRONG* and DEMAND is *NOT HIGH*, then SATISFACTION is *TOTAL*.
- If WIND is *STRONG* and DEMAND is *HIGH*, then SATISFACTION is *HIGH*.
- If WIND is *VERY STRONG* and DEMAND is *NOT HIGH*, then SATISFACTION is *TOTAL*.
- If WIND is *VERY STRONG* and DEMAND is *HIGH*, then SATISFACTION is *VERY HIGH*.

Similarly, to determine the satisfaction level of demand for the Photovoltaic Generation System (SGF), 11 rules were implemented, taking into account the membership functions and comparing demand and solar irradiation inputs with the SGF satisfaction percentage output. Likewise, to assess the demand satisfaction for the Fuel Cell Generation System (SGC), 9 rules were established.

GLD Outputs

In the design of the Fuzzy Logic-based Management System (GLD), the outputs were taken as the autonomy or percentage of satisfaction of the DEC for each subsystem. Figure 9 displays the membership functions used to determine the output or response of the GLD. This is similarly employed to obtain autonomy in each subsystem.

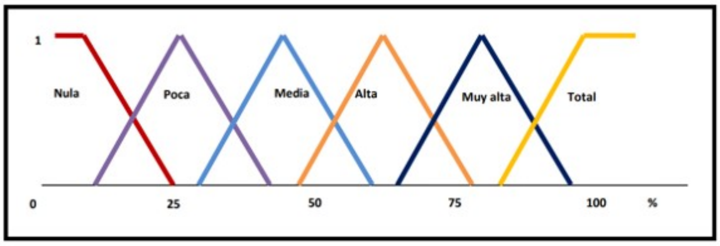

Figure 9. Membership function of the outputs to the GLD.

As can be seen, the GLD output provides a percentage from 0 to 100% of the demand satisfaction that each subsystem can handle on its own.

GLD Management Scenarios

For this research, the management scenarios were defined as follows. These scenarios are designed to demonstrate the flexibility of the GLD in achieving different management objectives. The scenarios are:

- PROFITABILITY: In this scenario, the objective is to meet the demand using the most cost-effective subsystem. Currently, wind generation systems are more economical than photovoltaic systems, which in turn are more cost-effective than fuel cell systems, considering both efficiency and operational costs.
- RELIABILITY: Here, the management system prioritizes the subsystem generating the highest power output for a given Electrical Demand Curve (DEC).
- PRIORITY: In this mode, the operator specifies the order of energy supply from each subsystem according to their own criteria.
- PERCENTAGE: This selection requires the operator to set maximum operation percentages for each subsystem. It should be noted that the plant as a whole can deliver between 0% and 100% of the power required by the DEC.

5. Implementation

Computational graphical tool

To implement the proposal, a computational tool with a graphical user interface was developed. This tool incorporates models for the subsystems SGE, SGF, and SGC, including all adjustable parameters and fuzzy input variables necessary for managing the hybrid alternative energy generation system. The tool's main features are:

1. Selection of Demand Curve: The user begins by selecting the demand curve on which the system will operate. This curve is generated through a fuzzy inference system that takes inputs such as sector, month, day, and time to produce the corresponding demand profile for those parameters.
2. Subsystem Parameters: Users can input the operational parameters for each subsystem (SGE, SGF, and SGC), which are then used to calculate the nominal power of each. Users can also select which subsystems are enabled for management. With three systems available, seven possible subsystem combinations exist, but at least one subsystem must be enabled alongside the grid for the management system to function.
3. Execution and Analysis: The tool can be executed for a specific point on the demand curve or, if desired, can analyze the entire curve multiple times, enabling the generation of various scenarios for the same demand profile.
4. Graphical User Interface: The interface provides controls for selecting energy sources, monitoring system management according to specified criteria, and evaluating results. It allows for evaluating individual cases or performing batch analyses for a given daily demand curve. Results controls enable selection of response curves representing electrical power for each system and the demand. Graphs display the percentage of demand satisfaction and the operation percentage determined by the GLD for each subsystem and the grid, based on the chosen management criteria.

The tool (Figure 10) offers a comprehensive platform for experimenting with and analyzing the performance of the GLD under various scenarios and input conditions.

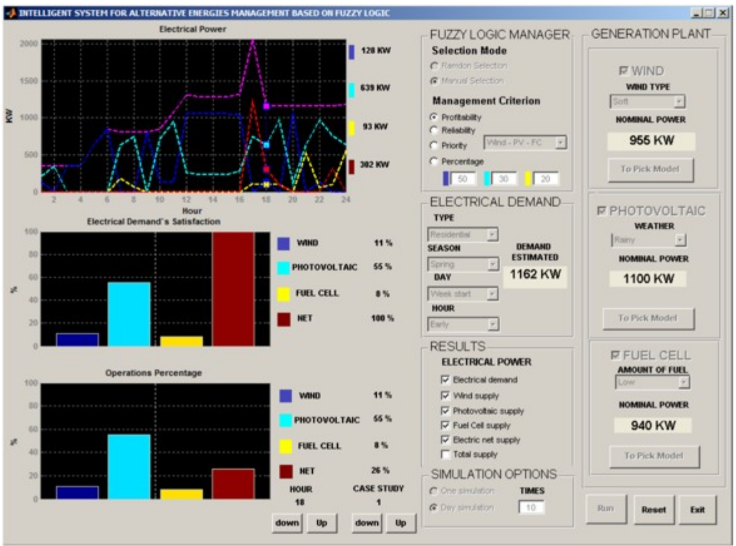

Figure 10. Interface implemented for the evaluation of the GLD.

Obtaining electricity demand curves

The implemented system for this research establishes and weights the demand curve on which it operates. This curve incorporates essential temporal variables, including sector, season, day of the week, and time of day. Different combinations of these inputs produce various demand curves used for management purposes. These curves are derived from historical demand data corresponding to the specified sectors.

Additionally, the system allows users to input a predefined demand curve for further analysis. The manager can work with any established curve and determine the appropriate management strategy for each scenario. The resulting electric demand curves conform to the format described earlier in this chapter.

Figure 11 shows the control panel used to enter parameters for generating the demand curve. Each parameter features a dropdown menu containing descriptive options, including:

- Sector: Residential, commercial, and industrial.
- Season: Summer, spring, autumn, and winter.
- Day of the week: Beginning of the week, midweek, and weekend.
- Hour of the day: Early morning, morning, afternoon, and evening.

Users can select values for each parameter, and the system generates the corresponding electric demand curve based on historical usage patterns.

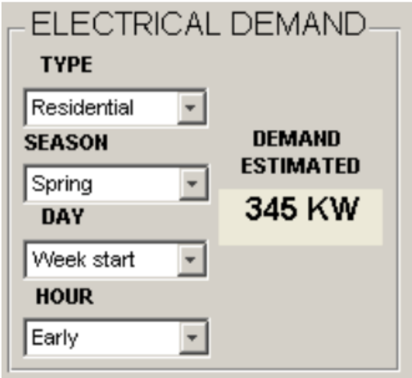

Figure 11. Electrical demand control panel.

Rated power of the alternative energy plant

Using the models described in the previous chapter, the nominal power of each subsystem is calculated based on its operating parameters. The actual operating power of each subsystem depends on the values of its respective operating variables. For the wind subsystem, this variable is wind speed; for the photovoltaic subsystem, it is solar irradiation; and for the fuel cell subsystem, it is the hydrogen level. The combined nominal power of these three subsystems constitutes the nominal power of the alternative energy plant.

Figures 12, 13, and 14 show the control panels for each subsystem, as detailed in Section 4 of this chapter. These panels display the various parameters that determine the nominal power of each subsystem.

Figure 12. Wind system control panel.

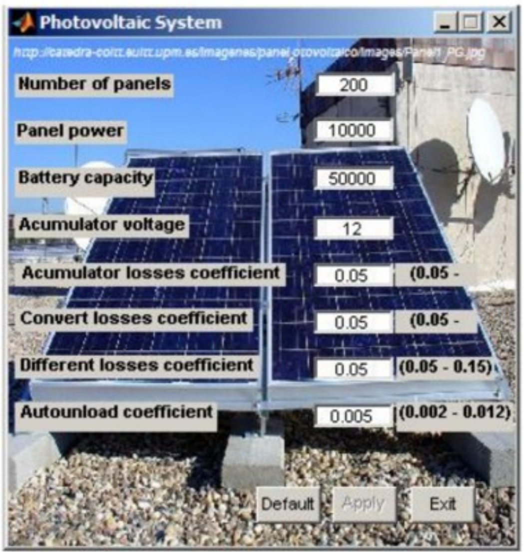

Figure 13. Photovoltaic system control panel.

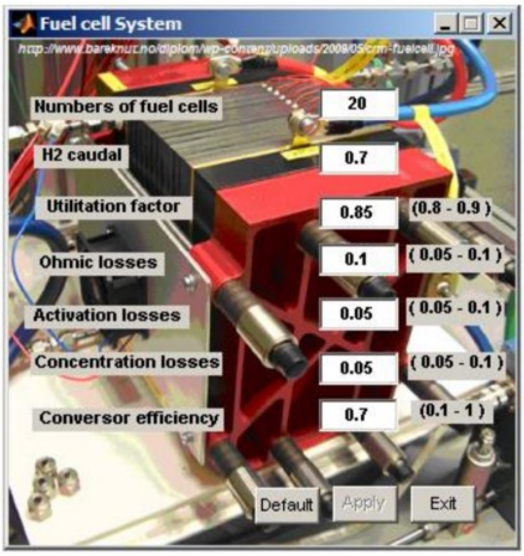

Figure 14. Fuel cell system control panel.

Figure 15 illustrates the hybrid system as a whole. The nominal power of each subsystem is displayed based on the parameters shown in the previous figures. Additionally, this panel allows for manual adjustment of the fuzzy inputs for each system, using the descriptors for the GLD inputs as described in Section 4.

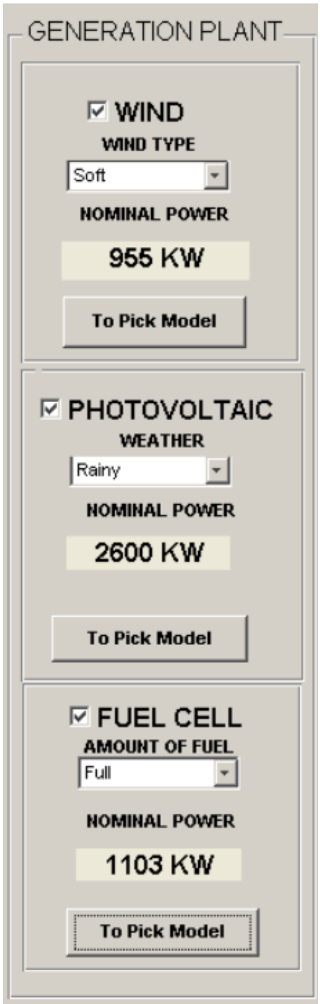

Figure 15. Hybrid alternative generation plant selection panel.

Management of the energy generated by the plant

The management of the energy generated by each subsystem of the plant is handled by the GLD. Using the fuzzy logic inference engine described in Section 4, the GLD determines the demand satisfaction level for each subsystem based on the input random variables. It then specifies the percentage of electrical power required from each subsystem according to the selected management scenario.

6. Conclusions

After implementing a hybrid electrical power generation system model based on three clean alternative sources and developing a management system capable of optimizing the energy produced under various conditions, the analysis of results leads to the following conclusions:

The hybrid approach, integrating wind, photovoltaic, and fuel cell technologies, has proven to be an effective strategy for enhancing both the reliability and autonomy of the power system. By diversifying energy sources, the system achieves greater adaptability to fluctuating environmental conditions, mitigating the intermittent nature of renewable resources.

The fuzzy logic-based management system demonstrates significant capability in optimizing plant operation by dynamically adjusting the contribution of each energy source according to real-time environmental inputs and electrical demand. The developed computational tool, featuring an intuitive graphical interface, offers a versatile platform for parameter tuning and scenario testing, facilitating comprehensive evaluation and validation of the management strategy. This tool effectively maximizes the utilization of available energy, providing a viable and sustainable solution for hybrid renewable energy systems.

Among the subsystems analyzed, the Solid Oxide Fuel Cell (SGC) stands out as the most reliable, due to its power output being directly controllable via hydrogen flow. Unlike wind and photovoltaic sources, whose outputs naturally fluctuate with uncontrollable environmental factors, the fuel cell system maintains power output close to its nominal capacity, ensuring system stability. However, this advantage is offset by higher operational costs associated with its raw materials, which affects overall profitability compared to the other subsystems.

7. Future works

Future investigations present a compelling opportunity to enhance the robustness of these findings by employing more detailed measurement methods. While the current study offers valuable insights into the reliability, profitability, and autonomy of a hybrid renewable energy system, further research could explore specific aspects more deeply to achieve a comprehensive understanding.

One direction for future work involves refining the data collection process. Utilizing advanced sensing technologies and precise instrumentation can provide more granular data on the performance variables of each energy subsystem, such as wind speed, solar irradiance, and hydrogen flow. This increased level of detail will not only improve the accuracy of the conclusions but also offer a more nuanced perspective on the complex interactions within the hybrid system.

Furthermore, expanding experimentation across diverse environmental conditions and geographical locations would generate a broader dataset. This geographical variability could include regions with distinct weather patterns, enabling a comprehensive analysis of the system's performance under various climatic scenarios. Such an approach would be invaluable for tailoring the system's design and management strategies to different environmental contexts, ultimately enhancing its adaptability and reliability.

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Meglys Pérez: Investigation, Resources, Writing – review & editing.
All authors have read and agreed to the published version of the manuscript. Please refer to the CRediT taxonomy for the definitions of the terms. Authorship is limited to those who have made substantial contributions to the reported work.

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Conflicts of Interest: Under the authorship of this research, it is declared that there is no conflict of interest with the present research.

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