Fuzzy Decision-Making for the Optimization of Off-Grid Multisource Power Generation Systems

Ammar Ali Mohammed Quran[1], Róbert Szabolcsi[2]

[1]Óbuda University, Doctoral School on Safety and Security, Népszínház u. 8, 1081 Budapest, Hungary, engammar@stud.uni-obuda.hu

[2]Óbuda University, Kandó Kálmán Faculty of Electrical Engineering, Tavaszmező u. 17, 1084 Budapest, Hungary, szabolcsi.robert@kvk.uni-obuda.hu

Abstract: The search for alternative energy sources has become critical in a time of increasing energy demand and awareness of environmental practices. The increasing demand for energy worldwide may be met effectively and sustainably with the help of Off-grid multisource power generating systems, or OMPGS. The primary objective of this article is to optimize the OMPGS's design and functionality for usage in rural communities. Taking into account local climatic conditions, demand data, and technical specifications, a size optimization model is created using the innovative Particle Swarm Optimization (PSO) approach, which minimizes the Levelized Cost of Electricity (LCOE). Furthermore, a Fuzzy Logic Controlled Energy Management System (EMS) is suggested to guarantee ideal power regulation and energy retention in the system. By taking this method, the system's overall resilience, efficiency, and responsiveness to fluctuating energy needs are improved.

Keywords: Fuzzy control; Renewable energy; Multiresoure ; Decision making; Off-grid

1 Introduction

The majority of countries' electricity, heat, and natural gas energy supply systems are independently planned, designed, and operated due to historic development; [1] [2] [3]. this lack of coordination and control amongst systems results in low overall energy utilization efficiency and makes it difficult to ensure energy reliability [4].

Supplying these places with energy is one of the biggest issues facing the world's off-grid and isolated communities. These regions are expensive to connect to the grid, and in certain situations, it is not physically feasible [5] [6] [7]. Thus, based on the installation area's parameters (such as radiation intensity, ambient temperature, wind speed, etc.), several hybrid system modes may be chosen for these regions [8] [9] [10].

In order to achieve total energy design planning and optimal operation, it breaks the current method of independent design and operation of each energy system and combines a range of energy systems. A multi-energy complementary energy system can be constructed through the coordinated optimization control of the integrated energy system in order to improve the consumption of renewable energy, support the reform of the energy structure, and accomplish the goals of energy conservation and emission reduction. This is possible because different resource conditions and energy needs necessitate different energy systems. But because different energy sources might interact, a single energy system's ability to function is limited by its coupling system. The energy flow of the energy systems can also be impacted by the connection apparatus in the interim. The development of microgrids has been spurred in recent years by energy systems' environmental concerns, and their quick deployment has sped up the integration of distributed energy, renewable energy, and distributed energy storage systems into contemporary power systems [4] [11].

The optimum regulation of the power networks in light of the connectivity with large-scale renewable sources has been adequately covered by the studies that are now available [1] [2] [3]. In contrast, to large-scale renewable energy operational scenarios, microgrids with a high proportion of distributed renewable power lower operating costs and carbon dioxide emissions, while simultaneously lowering dependency on fossil fuels. The recovery and use of waste heat from cogeneration units has increased fuel usage efficiency overall and has increased microgrids' viability economically [12] [13] [14].

Table 1 lists some recent study projects in the area of off-grid multisource power generation that combines renewable energy sources with fuel cell supplies [15].

The intermittent and unpredictable nature of renewable power generation presents significant obstacles to the power balance control and dependable operation of microgrids, despite the numerous advantages of distributed renewable generating [11] [16]. Figure 1 shows Sustainable Energy Sources that can be used for Off-Grid Multisource Power Generation Systems.

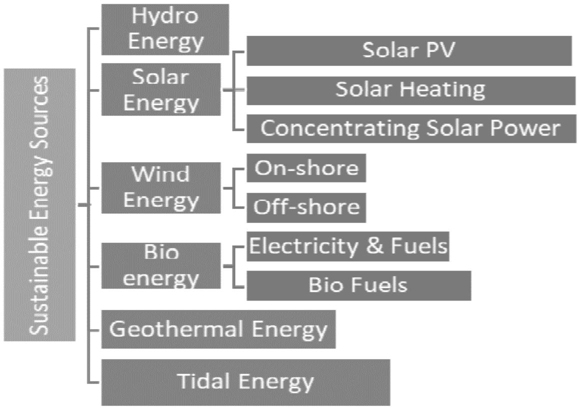

Figure 1
Sustainable Energy Sources [17].

Table 1
Recent studies on off-grid multisource power generation using renewable energies in conjunction with fuel cells

Reference, Year	Renewable energy used	Location	Purpose	Connection mode	Sensitivity analysis	LCOE (S/kWh)	Electricity demand (kWh/day)
[18],2019	PV	Egypt	Reverse osmosis desalination	Off-gri	Yes	0.062	110
[19],2020	Wind	China	Residential house	Off-grid	Yes	1.278	10
[20],2020	PV, wind, biomass	Iran	Rural electrification	Off-grid and on-grid	No	0.164-0.233 (off-grid), 0.096-0.125(on-grid)	361
[21],2020	Biomass	Egypt	Small tourist village	Off-grid	Yes	0.335	92.2
[22],2021	PV, wind	Turkey	Electric vehicle	Off-grid	Yes	0.685	11.27
[23],2021	PV, wind, tidal	Iran	Remote application	Off-grid	No	O.4477— 1 O.864	20—40
[24],2021	PV, wind	Pakistan	Co-generation of electricity, heat, and hydrogen	Off-grid	Yes	0.965	15

1.1 Fuzzy Logic in Decision Making

A mathematical framework for handling ambiguity, imprecision, and uncertainty in decision making is offered by fuzzy logic. Fuzzy logic enables the depiction of degrees of truth, in contrast to classic binary logic, which functions in a clear true/false paradigm. Because of its versatility, it is especially well-suited for modeling and regulating systems that have inherent uncertainty and inaccurate information, such as off-grid multisource power generating systems.

Fuzzy decision-making is used to optimize these kinds of systems and takes into account a number of factors, including as energy output from renewable sources, energy storage capacity, load demand forecasts, and system dependability. To deal with the linguistic variables and uncertainties related to these factors, fuzzy sets and fuzzy rules are used. Fuzzy logic makes it possible to integrate qualitative evaluations into quantitative decision-making processes by using language concepts like "high," "medium," and "low."

For example, think about the choices made while choosing the best combination of renewable energy sources for an off-grid system. The integration of disparate and sometimes unclear data on the dependability, accessibility, and effectiveness of solar, wind, hydro, and other renewable energy sources is made possible using fuzzy logic. Decision-makers may better understand real-world circumstances and make decisions that are in line with the unique requirements and features of the off-grid site by describing these variables as fuzzy sets [25].

Moreover, fuzzy decision making works wonders when handling energy systems' dynamic nature. The stability and dependability of off-grid multisource power generating systems are constantly challenged by fluctuations in the output of renewable energy, fluctuating load demands, and the intermittent nature of renewable sources. Fuzzy logic allows rules to be created that take the system's changing conditions into account, which makes it excellent at managing real-time modifications and flexibility.

Fuzzy logic and decision making together provide a potent toolkit for managing the intricacies of off-grid multisource power generation. In the parts that follow, we will delve deeper into the subtleties of fuzzy decision making and examine its applications in system optimization. Specifically, we will look at how fuzzy decision making might help achieve the delicate balance between energy generation, storage, and consumption in an off-grid setting. We want to shed light on the revolutionary potential of fuzzy decision making in influencing the development of resilient and sustainable energy solutions in the future through this investigation [11] [26].

1.2 Research Contribution

Two essential elements of off-grid multisource power generation systems (OMPGS) are optimal size and control. Even with the ideal system size, ineffective operation is inevitable in the absence of effective control. Optimal control guarantees lower operating costs and consistent energy supply, while optimal size lowers implementation costs and increases energy affordability. The majority of research, according to a survey of the literature, only consider system sizing or energy control. Nonetheless, an integrated strategy is necessary due to the interdependence of OMPGS's size, cost, control, and dependability. In order to improve energy scheduling during OMPGS operation in an off-grid community, this project intends to design an optimal sizing model that determines the OMPGS's most cost-effective configuration. The model will then be integrated into an Energy Management System (EMS).

The study develops a complete model that guarantees energy dependability and cost efficiency by combining these two factors. The best equipment size is determined using the Particle Swarm Optimization (PSO) approach for dependability and cost-effectiveness. Meanwhile, an EMS that keeps supply and demand energy balanced throughout OMPGS operation is developed using a Fuzzy Logic Controller.

2 Fuzzy Decision-Making Applications in Off-Grid Multisource Power Generation Optimization

2.1 Configuring the System and Choosing its Components

The Off-grid multisource power generating systems (OMPGS) that is being considered is seen in Figure 2 in its standard form. The system combines a wind turbine and solar photovoltaic panels, two sustainable energy sources. A diesel generator supplies emergency power, while batteries are used as a backup power source. To convert direct current (DC) to alternating current (AC) and vice versa, an inverter is provided. The community's energy consumption is a good indicator of the consumer load. It is also presumed that the inverter has an energy management system that controls the flow of power between the different energy sources and the load. Below is a full description of each component's mathematical model.

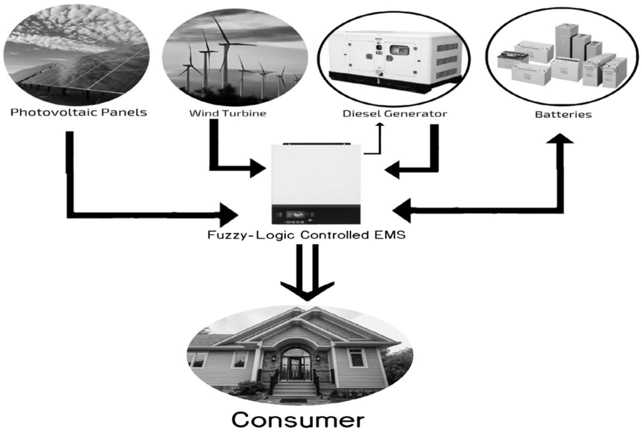

Figure 2
Structure of a OMPGS system

2.1.1 Solar PV Model

A number of variables, such as sun irradiation, seasonal fluctuations, ambient temperature, PV module type, and tilt angle, affect the output power of solar photovoltaic (PV) systems. A basic simulation model is used to determine the power output, P_{pv}, as indicated by the following equations [28] [29]:

$$P_{PV} = N_{PV} \times \eta_{PV} \times A_m \times G_t \tag{1}$$

$$\eta_{PV} = \eta_{ref} \times \eta_{pc}[1 - \beta(T_c - T_{cref})] \tag{2}$$

$$T_c = T_a + \frac{NOCT - 20}{800} \times G_t \tag{3}$$

In this case, the number of PV panels is denoted by Npv, the panel efficiency is represented by η_{pv}, the total surface area of the panel is denoted by A_m,. Additionally, the global solar irradiance (W/m^2) is indicated by G_t. Furthermore, the nominal operating cell temperature (°C) is NOCT, while the ambient temperature is T_a.

2.1.2 Wind Turbine Model

Local wind speeds and the turbine's specifications affect a wind turbine's power production. The power output of the wind turbine was calculated using the following formulas [30]:

$$P_w(V) = \begin{cases} \frac{P_r(V - V_{CIN})}{V_{rat} - V_{CIN}}, & V_{CIN} \leq V \leq V_{rat} \\ P_r, & V_{rat} \leq V \leq V_{CO} \\ 0, & V \leq V_{CIN} \text{ or } V \geq V_{CO} \end{cases} \tag{4}$$

$$V = V_{ref} \left(\frac{H}{H_{ref}} \right)^{\alpha} \tag{5}$$

The reference height in this model is denoted by H_{ref}, the wind speed at the reference height is represented by V_{ref}, and the wind shear exponent is denoted by α. The turbine's height is represented by H. V its wind speed at height H, its rated wind speed by V_{rat}, its rated power by P_r, its cut-in speed by V_{CIN}, and its cut-out speed by V_{CO}.

2.1.3 Battery Model

When the production of renewable energy is inadequate, batteries store electrical energy in chemical form and provide electricity. The following formula [31] is used to determine the battery's capacity, C_B.

$$C_B = \frac{E_L \times SD}{V_B \times DOD_{max} \times T_{cf} \times \mu_B} \tag{6}$$

The operating voltage is represented by V_B, the energy demand (Wh) is represented by E_L The temperature correction factor is represented by T_{cf}, the number of autonomy days is represented by SD, the maximum depth of discharge is represented by DOD $_{max}$. Also, the battery efficiency is represented by μ_B.

The ratio of the battery's available capacity to its rated capacity, measured in ampere-hours (AHr), is known as the state of charge (SOC) and may be written as follows [31]:

$$SOC = \frac{\text{Available Capacity (AHr)}}{\text{Rated Capacity (AHr)}} \times 100 \tag{7}$$

In cycles of charging and discharging, the SOC at time t is calculated as follows:

$$SOC(t) = SOC(t-1) \times (1-\sigma) + \frac{[E_{Gen}(t) - E_{Load}(t)]}{\mu_B} \tag{8}$$

$$SOC(t) = SOC(t-1) \times (1-\sigma) + \frac{[E_{Load}(t) = E_{Gen}(t)]}{\mu_B} \tag{9}$$

where the energy generated is represented by E_{Gen}, the load demand is represented by E_{Load}, and the self-discharge rate per hour is represented by σ. Equation (8) is used to charge batteries, and Equation (9) is used to discharge them. The battery functions within the permitted discharge limitations, which are represented as SOC_{max} and SOC_{low}, respectively.

2.1.4 Diesel Generetor Model

When battery storage and renewable energy sources are not enough to fulfill demand, a diesel generator in a hybrid renewable energy system (HRES) steps in to provide electricity. The generator should run between 70% and 89% of its rated capacity for maximum efficiency [32]. The following equation [33] represents the diesel generator's fuel consumption:

$$D_f(t) = \alpha_D P_{DG}(t) + \beta_D P_{Dr} \tag{10}$$

where the fuel consumption is expressed as $D_f(t)$ (liters/hour), the diesel generator's power is expressed as $P_{DG}(t)$ (kW), and the rated power output is expressed as P_{Dr} (kW). The fuel consumption curve factors are denoted by the coefficients α_D and β_D, respectively, and are set as 0.2461 l/kWh and 0.08415 l/kWh [36]. Fuel costs can be stated as follows:

$$C_g = \frac{D_f(t)C_f}{P_{DG}} = C_f(\alpha_D + \beta_D P_{DG}/P_{Dr}) \tag{11}$$

The diesel generator's depreciation cost is computed as:

$$C_{DW} = \frac{MT}{20000} C_{\text{initialDG}} \sum_{t=T_0}^{M} P_{DG}(t) \tag{12}$$

where the total operating hours (MT) and The initial cost of purchasing the diesel generator is shown by $C_{\text{initialDG}}$. The fuel and depreciation charges added together represent the total cost of running the diesel generator:

$$C_{DG} = C_g + C_{DW} \tag{13}$$

Determining the ideal design for off-grid multisource power generating systems is made possible by fuzzy decision making. Through the use of fuzzy rules that take into account variables like system cost, resource availability, and geographic location, decision-makers may arrive at configurations that are both technically and financially sound. Fuzzy sets are an excellent way to handle the imprecision that comes with variables like wind speed and solar radiation. This allows for more nuanced judgments that accurately reflect the dynamic nature of renewable energy sources [28].

2.1.5 OMPGS system Strategy

The power flow must be adjusted to maximize the use of renewable energy sources while guaranteeing that there is always energy available to power the load in order to determine the ideal size of the OMPGS system using the PSO. The PV, wind turbine, battery, DG, and load are the components of the OMPGS taken into account in this study. A balance between the energy supplied and the energy demanded is maintained by the PSO's power management. The PSO program determines whether to charge the battery or discharge the battery. As an alternative start the diesel engine based on the conditions at each hourly timestep after comparing the load and renewable energy (solar and wind).

The extra energy is used to charge the battery when the load can be powered entirely by renewable energy. Energy is drawn from the battery to power the load when the renewable energy is insufficient to power it and the battery's state of charge is higher than its lowest state. The diesel generator is turned on to power the load when the RE is not enough to do so and the battery's state of charge is lower than its lowest point. The extra energy from the diesel generator is then used to charge the battery. Figure 3 shows the power flow strategy's flow chart.

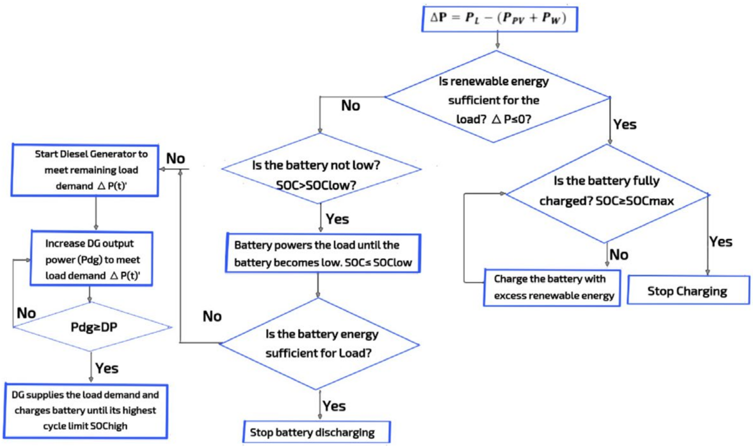

Figure 3

Diagram representing the Off-grid Multuble power supply design optimization process

2.2 Demand Management and Load fForecasting

For off-grid systems to maintain a balance between energy output and consumption, accurate load forecasting is essential. Decision-makers may include expert knowledge and qualitative judgments into load forecasting models with the use of fuzzy logic, which makes it easier to incorporate linguistic factors. As a result, demand management is able to be more flexible and responsive, guaranteeing that the system can instantly react to shifting energy needs.

Controlling the distribution of electricity from each energy source to fulfill load demand is the main function of the energy management system (EMS) in an Off-grid multisource power generating systems (OMPGS). A properly tuned energy management system (EMS) maximizes the utilization of renewable energy sources while maintaining a balance between energy supply and demand. In order to keep the system's components in equilibrium while the OMPGS is operating, the EMS continuously controls the energy flow, as shown by the following equation:

$$P_{pv}(t) + P_w(t) + P_{batt\_discharge}(t) + P_{DG}(t) = P_l(t) + P_{batt\_charge}(t) \tag{14}$$

The renewable energy input in this EMS configuration is represented by wind energy (Pw) and solar photovoltaic (Pv) power. The system prioritizes fulfilling the load demand via renewable sources, taking power from the battery only when renewable energy is inadequate. The diesel generator kicks in as a backup if renewable energy sources are not available and the battery's charge is either below the minimum state of charge (SOC) or not enough to fulfill demand. The power differential (ΔP) is the difference between the renewable energy supply and the load demand (P_L).

$$\Delta P = P_L(t) - (P_{pv}(t) + P_w(t) \tag{15}$$

2.3 Optimization of Energy Storage

The important field of energy storage optimization is impacted by fuzzy decision making. The choice of suitable storage technologies, like pumped hydro storage or batteries, depends on a number of important factors, such as cycle life, cost, and round-trip efficiency. Decision-makers may more easily identify storage solutions that meet the unique requirements and limitations of off-grid locations by using fuzzy logic to navigate the trade-offs included in these factors.

Using the formula from [34], the battery's State of Charge (SOC) for the Fuzzy Logic Controller (FLC) is expressed as follows:

$$SOC\ (t) = \frac{P_{batt}(t-1) + C_{batt}[P_{RE}(t) - P_L(t)] + \{P_{DG}(t) - (1 - C_{batt})[P_L(t) - P_{RE}(t)]\}}{P_{batt}} \tag{16}$$

where P_{batt} (t-1) is the amount of battery energy left over from the previous hour. The expression C_{batt} $[P_{RE}(t)\ - P_L\ (t)]$ represented the current charging or discharging power of renewable energy. The generator's charging power is represented by $\{P_{DG}\ (t\ ) - (1 - C_{batt})\ [P_L\ (t\ ) - P_{RE}\ (t)]\}$. The rated battery capacity is represented by P_{batt} in this instance.

The battery stops charging if the supply of renewable energy (RE) is sufficient to satisfy the load demand (ΔP≤0) and the battery is fully charged (SOC > SOCmax). When the load (ΔP≤0) can be met by renewable energy and the battery is not fully charged (SOC < SOCmax), the extra renewable energy charges the battery until it reaches its maximum capacity (SOCmax).

The battery drains to meet the load until it hits the lower limit (SOC ≤ SOClow) when renewable energy is inadequate for the load (ΔP>0) and the battery is sufficiently charged (SOC > SOClow). Discharging ceases if there is enough energy in the battery to match the requirement. The diesel generator kicks in to cover any leftover demand (ΔP′) if the battery is too low (SOC ≤SOClow) or cannot provide the load. It modifies its output appropriately. When the battery reaches full charge (SOC ≥ SOCmax), the generator powers, the load, and continues to charge it.

2.4 Fault Tolerance and Resilience

Off-grid systems are frequently installed in isolated or hostile areas, where system performance may be impacted by things like severe weather or equipment failure. By taking into consideration fuzzy rules that take uncertainties in system resilience and reliability into account, fuzzy decision making aids in the design of fault-tolerant systems. By doing this, off-grid power generating systems are guaranteed to be flexible enough to adjust to unanticipated events, reducing downtime and increasing overall resilience.

2.5 Assessment of Environmental Impact

Fuzzy decision making takes environmental aspects into account in addition to technical concerns. Fuzzy logic is a tool that decision-makers may use to evaluate the environmental effects of various system configurations and energy sources while taking ecological sensitivity, land usage, and carbon footprint into account. By taking a comprehensive approach, off-grid systems are guaranteed to fulfill energy demands and make a positive contribution to environmental conservation, which is in line with the larger objective of sustainable energy solutions.

3 Formulating Fuzzy Decision Making Mathematically

The optimization of off-grid multisource power production systems involves the mathematical formulation of fuzzy decision making, which combines components of fuzzy logic and decision theory to describe the inherent uncertainty and imprecision of the system. In this context, the following mathematical ideas and symbols are frequently used.

The connection between the FLC-based energy management system and the Off-grid multisource power generating systems (OMPGS) is shown in Figure 4. The OMPGS provides signals to the FLC system that indicate solar, wind, load demand, and battery condition. Two fuzzy logic controllers (FLCs), FLC1 and FLC2, are used in this investigation.

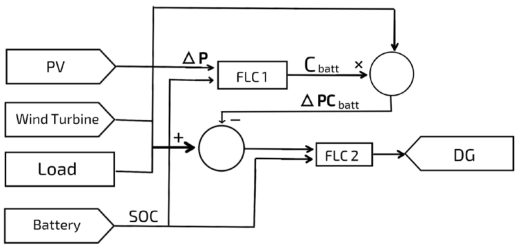

Figure 4
The Fuzzy Logic Controllers' signal flow

3.1 Membership Functions and Fuzzy Sets

Consider the universe of discourse X, which stands for a certain parameter (wind speed, sun radiation, etc.). The membership function $\mu_A(x)$ of a fuzzy set A in X gives each element x in X a degree of membership between 0 and 1. The membership functions for high, medium, and low solar radiation levels, respectively, might be represented by the functions $\mu_{High}(x)$, $\mu_{Medium}(x)$, and $\mu_{low}(x)$, if X represents the amounts of solar radiation. Figure 5 shows membership functions.

$$\mu_{High}(x) + \mu_{Medium}(x) + \mu_{low}(x) = 1 \quad (17)$$

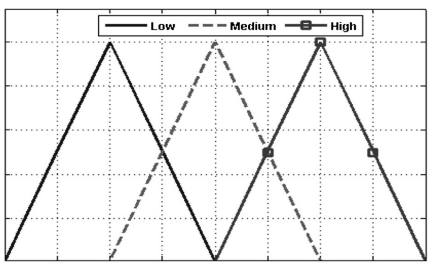

Figure 5
Membership functions

3.2 Fuzzy Rules

The connections between the input and output variables in a fuzzy system are defined by fuzzy rules. They are represented using linguistic variables and take the form of "IF-THEN" sentences.

The knowledge and expertise of operators or experts is the foundation upon which the fuzzy logic rules are built. The acronyms in the membership functions stand for different terms: " V " denotes "very," " L " denotes "low," " H " denotes "high," " S " denotes "standard," " M " denotes "much," " P " denotes "positive," and " N " denotes "negative."

Battery State of Charge (SOC), the initial input to FLC1, consists of seven membership variables with a range (universe of discourse) from 0 to 1. The second input is composed of six membership variables and varies between 80 kW and 60 kW in differential power (ΔP). These inputs provide 42 fuzzy logic rules when combined. The output has seven membership variables and also varies from 0 to 1, as shown by the battery multiplier constant (C_{Batt}).

3.2.1 Fuzzy Logic Controller 1 (FLC1) Rules

Table 2 lists the fuzzy logic rules for FLC1. The power differential (ΔP) between the available renewable energy and the current energy demand is the first input to FLC1, and the battery's state of charge (SOC) is the second. Whether to charge or discharge the battery is determined by the controller based on the values of ΔP and SOC at any given moment. The amount of energy allotted for charging or draining the battery is determined by the correction power factor (C_{batt}), which is the output of FLC1.

Table 2
lists the fuzzy logic rules for FLC1

ΔP(t)'/SOC	$P_{DG}(t)$						
	ML	L	SL	S	SH	H	MH
NH	VL	VL	VL	VL	VL	VL	VL
NL	VL	VL	VL	VL	VL	VL	VL
NS	VL	VL	VL	VL	VL	VL	VL
PL	VL	VL	VL	VL	VL	VL	VL
PS	S	S	S	VL	VL	VL	VL
PH	H	H	MH	MH	VL	VL	VL
PMH	VH	VH	VH	MH	VL	VL	VL
PVH	VH	VH	VH	MH	VL	VL	VL
PMVH	VH	VH	VH	MH	VL	VL	VL

3.2.2 Fuzzy Logic Controller 2 (FLC2) Rules

In Table 3, the fuzzy logic principles for FLC2 are explained. When to turn on the diesel generator (DG) to generate electricity for the extra load is decided by FLC2. FLC2 receives two inputs: the prior battery state of charge (SOC(t-1)) and the power differential (ΔP), which indicates the remaining load after taking into account battery draining power. The FLC2 determines whether to initiate the DG based on these inputs. The controller starts the DG if there is an excess load and a low SOC. Nonetheless, the DG stays off if the SOC is low and there is an abundance of renewable energy. In a similar vein, the DG is not initiated when SOC is high and there is extra load. When there is more renewable energy and SOC, the DG will turn on.

Table 3
lists the fuzzy logic rules for FLC2

ΔP(t)'/SOC	$P_{DG}(t)$						
	ML	L	SL	S	SH	H	MH
NH	VL	VL	VL	VL	VL	VL	VL
NL	VL	VL	VL	VL	VL	VL	VL
NS	VL	VL	VL	VL	VL	VL	VL
PL	VL	VL	VL	VL	VL	VL	VL
PS	S	S	S	VL	VL	VL	VL
PH	H	H	MH	MH	VL	VL	VL
PMH	VH	VH	VH	MH	VL	VL	VL
PVH	VH	VH	VH	MH	VL	VL	VL
PMVH	VH	VH	VH	MH	VL	VL	VL

3.3 Fuzzy Inference System

Fuzzy rules are combined in a fuzzy inference system as shown in Figure 6, to produce clear decisions. Fuzzy rules are applied to input variables in the Mamdani model, a popular fuzzy inference method, and the results are combined to provide a fuzzy output. To generate a crisp number and defuzzify the fuzzy output, the centroid approach is frequently employed.

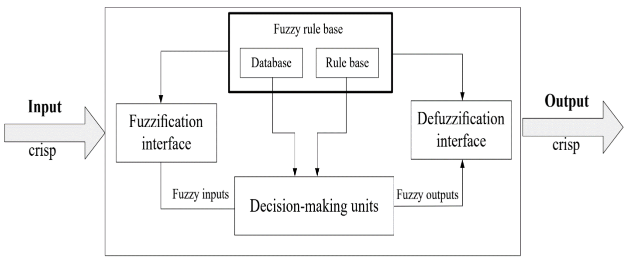

Figure 6
Generic fuzzy inference system

The output produced by the FLC1 and FLC2 controller is shown in three dimensions in Figure 7, respectively.

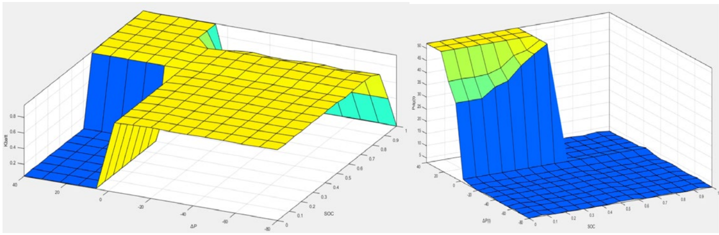

Figure 7
Plot of the FLC1 and FLC2 Rules in three dimensions, respectively

3.4 Constraints and Decision Variables

Let the decision variables for the off-grid multisource power generating system be represented by the variables X1, X2, …, and Xn. These variables' constraints, which include those related to resource availability, system cost, and environmental effect, are quantitatively represented.

$$X1 + X2 + \cdots + Xn \leq System\ Capacity \tag{18}$$

3.5 Objective Function

The aim of the optimization problem is represented by the objective function. A mathematical expression is usually what has to be maximized or reduced. When it comes to off-grid power generation, the target function might stand for total cost, environmental effect, or both.

$$Min\ f(X1, X2, \dots, Xn) \tag{19}$$

3.6 Optimization Algorithms

Optimization algorithms are frequently used in fuzzy decision making to determine the ideal values for decision variables. To find answers inside the fuzzy decision space, heuristic techniques such as simulated annealing, genetic algorithms, and particle swarm optimization can be used.

$$Optimal\ Soluation : X *= argminf(X1, X2, \dots., Xn) \tag{20}$$

The Off-grid multisource power generating systems (OMPGS) was optimized using the Particle Swarm Optimization (PSO) method using data from sun irradiation, temperature, wind speed, energy consumption, and equipment specifications. The output power of diesel generators, wind turbines, solar panels, and batteries were all calculated with the aid of these inputs.

Technical Analysis: To estimate the energy production from the solar panels, wind turbines, battery storage, diesel generator, and the algorithm considered technical data. Additionally, the analysis considers weather patterns and the features of the OMPGS equipment. For the purpose of forecasting system performance, this data was essential.

Economic Analysis: To calculate the total capital expenditure of the OMPGS, the algorithm took into account not only the technical data but also the economic factors, such as the cost per kilowatt-hour for each component. To cover recurring expenses

PSO Algorithmin in Figure 8, calculated important performance metrics such as the Levelized Cost of Energy (LCOE) and Loss of Power Supply Probability (LPSP) by analyzing the meteorological, technical, and economic data. In addition, it ensured that the system maintained a sufficient State of Charge (SOC) by optimizing the sizes of the diesel engine, wind turbines, batteries, and solar PV. Finding the most effective OMPGS arrangement to satisfy energy demands at the lowest cost and with the maximum dependability was the aim.

To summarize, fuzzy decision making in off-grid multisource power production systems is mathematically based and combines classic optimization methods with fuzzy logic notions. Decision-makers may understand and manage the complexity and uncertainties inherent in renewable energy systems, resulting in more resilient and adaptable solutions, by leveraging fuzzy sets, rules, and inference algorithms.

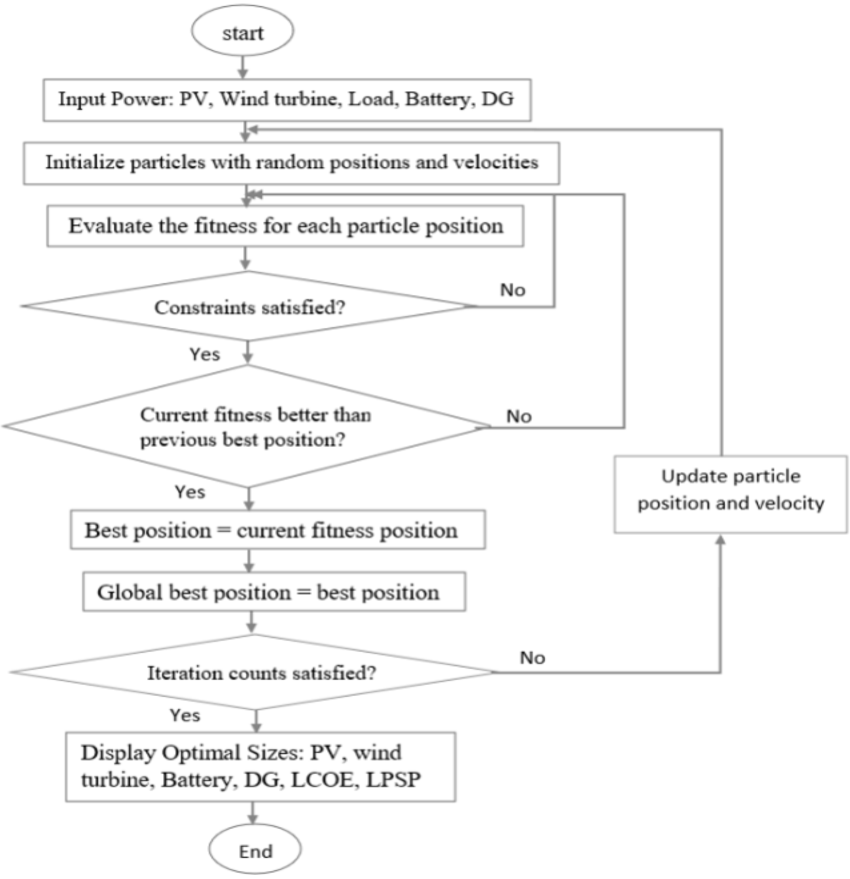

Figure 8

Particle Swarm Optimization (PSO) Algorithm flow chart [27]

4 Case Studies and Practical Implementations

In order to provide a strong theoretical foundation for fuzzy decision making in off-grid multisource power production system optimization, case studies and real-world applications must be looked at.

4.1 Island Microgrid Optimization

Consider residing on an isolated island where the only energy sources are hydro, wind, and sun. In response to shifting weather patterns and energy demand, fuzzy decisionmaking may dynamically distribute resources. The island community will always have a steady and dependable supply of electricity thanks to the use of fuzzy logic controllers. This control allows the system to adjust to fluctuations in the output of renewable energy.

4.2 Projects for Rural Electrification

Including fuzzy decision making into the design of electrification initiatives might be crucial in off-grid environments, especially in rural regions. When choosing the best possible mix of energy sources, storage options, and demand management techniques, fuzzy logic can help. This guarantees that the electrification system satisfies the community's unique requirements while accounting for resource availability risks.

4.3 OMPGS System Size Optimization

The best size for each component in hybrid power generating systems that include solar, wind, and other sources can be difficult to determine. The use of fuzzy decision making enables the evaluation of imprecise criteria like equipment efficiency and load fluctuation. The system may optimize overall efficiency by dynamically adjusting the size of energy storage devices, wind turbines, and solar arrays through the formulation of fuzzy rules.

4.4 Fuzzy Decision Making in Smart Grids

In the creation of smart grids, where prompt and flexible decision making is required, fuzzy logic plays a key role. Fuzzy controllers are effective in managing dispersed energy supplies, anticipating demand patterns, and optimizing energy flow. This flexibility is especially important in off-grid situations, where the topology of the grid may dynamically alter in response to local patterns of generation and consumption [35].

Conclusion

Although fuzzy decision making has demonstrated its effectiveness in improving off-grid multisource power production systems' optimization, difficulties still exist. The creation of precise fuzzy models, the requirement for reliable data collecting, and the incorporation of real-time feedback into decision making processes are some of these problems.

In order to increase the precision of decision making models, future research paths may examine OMPGS systems that blend fuzzy logic with machine learning methods.

Furthermore, improvements in data analytics and sensor technologies can help provide fuzzy systems with more accurate inputs, which will improve their performance even more in dynamic contexts. In conclusion, one of the most important steps toward developing resilient and sustainable energy solutions is the inclusion of fuzzy decision making in the optimization of off-grid multisource power generating systems.

Decision makers are empowered to navigate complicated decision spaces by fuzzy logic, which embraces the inherent uncertainties of renewable energy sources and dynamic system circumstances. The future of decentralized, ecologically conscientious, and adaptable off-grid power systems will probably be greatly influenced by fuzzy decision making, especially as technology advances and our knowledge of renewable energy grows.

References

[1] Al-Masri, H. M. and Ehsani, M. (2015) Feasibility investigation of a hybrid on-grid wind photovoltaic retrofitting system. IEEE Transactions on Industry applications, 52(3): 1979-1988

[2] Al-Janahi, S. A., Ellabban, O., and Al-Ghamdi, S. G. (2020) Techno economic feasibility study of gridconnected building-integrated photovoltaic system for clean electrification: A case study of Doha metro. Energy Reports, 6: 407-414

[3] Al-Sharafi, A., Sahin, A. Z., Ayar, T., and Yilbas, B. S. (2017) Techno-economic analysis and optimization of solar and wind energy systems for for power generation and hydrogen production in Saudi Arabia. Renewable and Sustainable Energy Reviews, Elsevier, Vol. 69(C), pp. 33-49, DOI: 10.1016/j.rser.2016.11.157

[4] Injeti, S. K., and Thunuguntla, V. K. (2020) Optimal Integration of DGs. 5 (1), 21-35.doi:10.1186/s41601-019-0149-x

[5] Alayi, R. and Rouhi, H. (2020) Techno-economic analysis of electrical energy generation from urban waste in Hamadan, Iran. International Journal of Design and Nature and Ecodynamics, 15(3): 337-341

[6] Pahlavan, S., Jahangiri, M., Alidadi Shamsabadi, A., and Khechekhouche, A. (2018) Feasibility Study of Solar Water Heaters in Algeria, a Review. Journal Solar Energy Research, 3(2): 135-146

[7] Alayi, R., Kasaeian, A., and Atabi, F. (2020) Optical modeling and optimization of parabolic through concentration photovoltaic/thermal system. Environmental Progress and Sustainable Energy, 39(2): e13303

[8] Alayi, R., Khan, M.R.B., and Mohmammadi, M.S.G. (2020) Feasibility study of grid-connected PV system for peak demand reduction of a residential building in Tehran, Iran. Mathematical Modelling of Engineering Problems, 7(4), pp. 563-567

[9] Mustafayev, R. I., Hasanova, L. H., and Musaev, M. M. (2018) Using regulated electrical machines in small hydropower plants operating in a power network. Russian Electrical Engineering, 89(5): 322-327

[10] Alayi, R., Ahmadi, M. H., Visei, A.R., Sharma, S., and Najafi, A. (2020) Technical and environmental analysis of photovoltaic and solar water heater cogeneration system: a case study of Saveh City. International Journal of Low-Carbon Technologies. ctaa077

[11] Gao, Q., Zhang, X., Yang, M., Chen, X., Zhou, H., & Yang, Q. (2021) Fuzzy decision-based optimal energy dispatch for integrated energy systems with energy storage. Frontiers in Energy Research, 9, 809024

[12] Wang, Q. and Wang, L. (2020) Renewable energy consumption and economic growth in OECD countries: A non-linear panel data analysis. Energy, 207: 118200

[13] Alayi, R. and Jahanbin, F. (2020) Generation Management Analysis of a Stand-alone Photovoltaic System with Battery. Renewable Energy Research and Application, 1(2), 205-209

[14] Wojuola, R. N. and Alant, B. P. (2019) Sustainable development and energy education in Nigeria. Renewable Energy, 139: 1366-1374

[15] Alayi, R., Seydnouri, S. R., Jahangeri, M., & Maarif, A. (2022) Optimization, sensitivity analysis, and techno-economic evaluation of a multi-source system for an urban community: a case study. Renewable Energy Research and Applications, 3(1), 21-30

[16] Gu, W.,Wu, Z., Bo, R., Liu,W., Zhou, G., Chen,W., et al. (2014) Modeling, Planning and Optimal Energy Management of Combined Cooling, Heating and Power Microgrid: A Review. Int. J. Electr. Power Energ. Syst. 54, 26-37, doi:10.1016/j.ijepes.2013.06.028

[17] Saleh, A. M., & Mahmood, T. (2022, October) Integration of Sustainable Energy Sources in Yemen Benefits, Challenges, and a Sample of Design. In 2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA) (pp. 1-6) IEEE

[18] Rezk, H., Sayed, E. T., Al-Dhaifallah, M., Obaid, M., Abou Hashema, M., Abdelkareem, M. A., and Olabi, A. G. (2019) Fuel cell as an effective energy storage in reverse osmosis desalination plant powered by photovoltaic system. Energy, 175: 423-433

[19] Li, C. (2021) Technical and economic potential evaluation of an off-grid hybrid wind-fuel cell-battery energy system in Xining, China. International Journal of Green Energy, 18(3): 258-270

[20] Rad, M. A. V., Ghasempour, R., Rahdan, P., Mousavi, S., and Arastounia, M. (2020) Technoeconomic analysis of a hybrid power system based on the cost-effective hydrogen production method for rural electrification, a case study in Iran. Energy, 190: 116421

[21] Samy, M. M., Elkhouly, H. I., and Barakat, S. (2020) Multi-objective optimization of hybrid renewable energy system based on biomass and fuel cells. International Journal of Energy Research, 2020: 1-17

[22] Turkdogan, S. (2021) Design and optimization of a solely renewable-based hybrid energy system for residential electrical load and fuel cell electric vehicle. Engineering Science and Technology, an International Journal, 24(2): 397-404

[23] Naderipour, A., Abdul-Malek, Z., Nowdeh, S. A., Kamyab, H., Ramtin, A. R., Shahrokhi, S., and Klemeš, J. J. (2021) Comparative evaluation of hybrid photovoltaic, wind, tidal, and fuel cell clean system design for different regions with remote application considering cost. Journal of Cleaner Production, 283: 124207

[24] Jahangiri, M., Mostafaeipour, A., Rahman Habib, H.U., Saghaei, H., and Waqar, A. (2021) Effect of Emission Penalty and Annual Interest Rate on Cogeneration of Electricity, Heat, and Hydrogen in Karachi: 3E Assessment and Sensitivity Analysis. Journal of Engineering, 2021: 6679358

[25] Zhang, H., & Li, Y. (2018) "Fuzzy Decision-Making in Off-Grid Power Systems." IEEE Transactions on Sustainable Energy, 10(4), 789-802

[26] Wang, L., & Chen, X. (2020) "Optimizing Multisource Power Generation Systems with Fuzzy Logic." In Proceedings of the International Conference on Renewable Energy (pp. 112-125) Springer

[27] Afolabi, T., & Farzaneh, H. (2023) Optimal design and operation of an off-grid hybrid renewable energy system in Nigeria's rural residential area, using fuzzy logic and optimization techniques. Sustainability, 15(4), 3862

[28] Gupta, S., & Singh, R. (2016) "A Comprehensive Review of Fuzzy Decision-Making in Renewable Energy Systems." Renewable and Sustainable Energy Reviews, 28, 23-36

[29] O. H. Mohammed, Y. Amirat, and M. Benbouzid, "Particle Swarm Optimization Of a Hybrid Wind/Tidal/PV/Battery Energy System. Application To a Remote Area In Bretagne, France," *Energy Procedia*, vol. 162, pp. 87-96, Apr. 2019, doi: 10.1016/J.EGYPRO.2019.04.010

[30] Y. Yoshida and H. Farzaneh, "Optimal design of a stand-alone residential hybrid microgridsystem for enhancing renewable energy deployment in Japan," *Energies*, Vol. 13, No. 7, Apr. 2020, doi: 10.3390/EN13071737

[31] Techno Economic Analysis of Stand-Alone Hybrid Renewable Energy System. Hanieh Borhanazad Research Project Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Engineering, Faculty of Engineering, University of Malaysia. Semantic Scholar."https://www.semanticscholar.org/paper/TECHNO-ECONOMIC-ANALYSIS-OFSTAND-ALONE-HYBRID-IN

Lumpur./d9965017849575104ddde7ee4adbe8ef8dd31f7d (accessed Aug. 5, 2024)

[32] W. M. Amutha and V. Rajini, "Cost benefit and technical analysis of rural electrificationalternatives in southern India using HOMER," *Renew. Sustain. Energy Rev.*, Vol. 62, pp. 236-246, Sep. 2016, doi: 10.1016/J.RSER.2016.04.042

[33] M. A. Mohamed, A. M. Eltamaly, and A. I. Alolah, "Sizing and techno-economic analysis of stand-alone hybrid photovoltaic/wind/diesel/battery power generation systems," *J. Renew. Sustain. Energy*, Vol. 7, No. 6, p. 063128, Dec. 2015, doi: 10.1063/1.4938154

[34] L. Xu, Z. Wang, Y. Liu, and L. Xing, "Energy allocation strategy based on fuzzy control considering optimal decision boundaries of standalone hybrid energy systems," *J. Clean. Prod.*, Vol. 279, Jan. 2021, doi: 10.1016/J.JCLEPRO.2020.123810

[35] Abdul, D., & Wenqi, J. (2022) Evaluating appropriate communication technology for smart grid by using a comprehensive decision-making approach fuzzy TOPSIS. *Soft Computing*, *26*(17), 8521-8536