Multi-Step Model Predictive Control–Based Design of a Resilient PV–FC–BESS Microgrid for Islanded Electrification

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Abstract:

Achieving reliable and sustainable electrification remains a major challenge for archipelagic countries, where many islands are geographically isolated and disconnected from national transmission networks. In such contexts, microgrids offer a practical solution for local electricity supply, but their performance is strongly affected by renewable energy variability, storage limitations, and dispatch strategy design. This study presents a photovoltaic–fuel cell–battery energy storage (PV–FC–BESS) microgrid framework for autonomous island electrification in the Philippines, with a focus on coordinated system sizing and dispatch control. A differential evolution (DE) algorithm is used to optimize component capacities, while a model predictive control (MPC) based dispatch strategy is implemented to manage real-time operation using solar irradiance forecasts. Solar resource assessment is based on ERA5 reanalysis data, with forecast inputs obtained from the ECMWF Integrated Forecasting System (IFS) and applied within a rolling horizon MPC formulation. The proposed DE–MPC approach is evaluated against conventional rule-based dispatch, the Python Microgrid (Py_M) framework, and the HOMER optimization tool under consistent system assumptions. Results show clear differences among dispatch strategies in terms of excess energy, storage utilization, capacity outage behavior, and unmet demand, highlighting how predictive, multi-step control influences both operational performance and optimal component sizing. By explicitly linking forecast-informed dispatch with design optimization, the proposed framework provides a transparent and adaptable methodology for assessing microgrid performance in isolated island settings, where reliability, efficient energy use, and coordinated storage management are critical.

Keywords:

Microgrid; Photovoltaic; Dispatch Control; Fuel Cell; Energy optimization.

1. Introduction

Renewable energy plays a vital role in addressing the global energy crisis, offering cleaner and more sustainable alternatives to fossil fuels. Sources like solar, wind, biogas, and biomass provide a vast and naturally replenished supply of energy, enabling many countries to gradually shift their energy mix toward greener solutions. From a global contribution of 9.73% in 2014, renewable energy has grown to approximately 14.82% by 2024 [1], reflecting significant progress. However, relying entirely on renewable sources presents certain challenges. One major issue is variability [2][3], solar and wind energy depend on weather and time-of-day conditions, which can cause fluctuations in supply. This can be managed through hybrid systems [4]-[7] and the integration of energy storage technologies [8]-[10] to ensure stable power availability. Another challenge is geographic suitability, as different types of renewables require specific environmental conditions or locations to be efficient, such as strong sunlight for solar or open windy areas for wind turbines [11][12]. Additionally, the high upfront costs of renewable energy installations, including equipment, land, and infrastructure, remain a barrier, especially for developing regions. These factors need to be carefully evaluated when planning for wider adoption of renewable energy.

A microgrid strategy is a localized approach to energy generation and distribution that aims to optimize the use of renewable energy sources while minimizing system losses and improving overall efficiency [13]. It involves integrating various energy resources for example, solar PV, wind turbines, batteries, and backup generators, combined in a network that can operate either independently or in connection with the main grid [14][15]. The success of a microgrid relies heavily on optimal sizing, which ensures that energy resources are appropriately scaled to meet demand without overinvestment or underperformance. In addition, intelligent control systems and precise scheduling are used to manage the flow of electricity, prioritize energy sources, and balance supply and demand in real time [16]. This allows the microgrid to respond efficiently to changes in weather, load patterns, and energy prices, making it especially valuable in remote areas or communities seeking energy independence. Also, a microgrid can function either as part of the main grid or independently in off-grid settings, making it especially suitable for isolated or remote areas such as islands [17][18]. Even in the absence of connection to a national grid, a well-designed microgrid can operate autonomously through internal coordination of its components. Typically, an island microgrid includes renewable energy sources such as solar panels or wind turbines, a controller to manage energy flow, energy storage systems like batteries, and the end-use loads such as homes, schools, or health centers. This configuration, though seemingly simple, enables the supply of electricity at various scales, from individual households to entire communities, thereby playing a critical role in expanding access to electricity in areas where traditional grid extension is difficult or economically unfeasible. Microgrids are increasingly recognized as practical solutions for reliable and sustainable power in underserved regions.

The Philippines has a diverse range of energy resources, including renewable sources such as solar, wind, hydro, and biomass, yet achieving full national electrification remains a persistent challenge. As of 2023 [19], around 91.1 percent of the country’s population has access to electricity, leaving an estimated 2.45 million households still without reliable power. Several factors contribute to this issue, including the country’s complex geography, high dependence on imported fossil fuels, logistical difficulties in reaching rural and remote areas, and limited technical and manpower capacity for large-scale infrastructure development [20]. The Philippines is an archipelago made up of more than 7,100 islands, making it difficult and expensive to build and maintain transmission and distribution networks that connect all regions to a single national grid [21][22]. Currently, the national power system is divided into three major grids: Luzon, Visayas, and Mindanao, each serving specific island groups. However, many smaller and more remote islands remain disconnected from these main grids due to the high costs and technical constraints of undersea cabling and long-distance power transmission. As a result, numerous islands depend on independent or semi-independent microgrids [23][24] to supply electricity to local communities. These microgrids often operate using renewable energy technologies such as solar panels, wind turbines, and small-scale hydro systems, which are well-suited for decentralized energy generation [25][26]. However, their power output can be inconsistent due to variations in weather, solar radiation, and wind speed, which may lead to fluctuations in power quality and supply reliability [27]. In some areas, these renewable systems are supplemented with battery storage [28], diesel backup, or hybrid configurations to stabilize electricity availability and ensure more dependable service to off-grid communities[29].

Most isolated microgrid systems rely primarily on photovoltaic (PV) technology [30][31] as their main source of power generation due to the abundance of solar energy and the decreasing cost of solar panels [32]. However, since solar energy is intermittent and unavailable at night or during cloudy conditions, these systems are often hybridized with energy storage or auxiliary generation technologies to ensure continuous power supply [33]. Common hybrid configurations include PV-Battery Energy Storage System (PV-BESS) [34], PV-Hydro [35], and PV-Pumped Storage [36], each offering distinct operational advantages and limitations depending on site characteristics and resource availability. The selection and optimization of these hybrid systems depend on several factors such as cost, geographic conditions, resource variability, and energy demand profiles [37][38]. In this context, a hybrid configuration combining solar photovoltaic and fuel cell (PV-FC) systems [39] presents a promising alternative for isolated or off-grid communities. The PV-FC system integrates renewable generation with a clean, flexible backup power source that can operate independently of weather or terrain constraints. Unlike diesel generators, fuel cells produce electricity through an electrochemical process, resulting in minimal greenhouse gas emissions, higher efficiency, and reduced mechanical wear [40]. Moreover, fuel cells do not require specific geographic features like elevation differences or water reservoirs needed for pumped storage or hydro systems, making them suitable for diverse environments. As long as a supply of hydrogen [41] or other clean fuels is available, fuel cells can operate continuously, providing a stable and sustainable energy solution. This makes the PV-FC configuration particularly advantageous for remote islands and isolated communities, where reliable, clean, and resilient power generation is essential to complement the variability of solar energy.

Given these advantages, this study proposes the development of a dispatch control strategy based on a photovoltaic–fuel cell (PV–FC) hybrid microgrid designed for autonomous island electrification in the Philippines. The proposed approach employs a model predictive control (MPC) framework that utilizes solar irradiance forecasts to optimize energy management, improve system efficiency, and enhance reliability under varying operating conditions. The objective is to design a flexible and adaptive microgrid control model capable of addressing the intermittency of solar power while minimizing fuel consumption and ensuring continuous energy supply. To evaluate its performance, the MPC-based dispatch strategy will be systematically compared with conventional control methods to assess improvements in energy utilization, operational cost, and overall system resilience.

2. Methods

2.1. Site Selection

Jomalig Island [42], a remote landmass located in the province of Quezon, Philippines, at coordinates 14.7008°N and 122.376°E, spans an area of approximately 56.65 square kilometers and is home to a population exceeding 7,000. Geographically positioned just south of Polillo Island and distant from the Philippine mainland, the island faces significant challenges in accessing reliable electricity. Currently, electrification is limited, and the island relies heavily on imported fossil fuels to operate its local power plant, which contributes to high operational costs and limited supply stability [43]. Figure 1 shows the map of Jomalig Island and the identified location excerpt from the National Solar Radiation Database (NSRDB) [44].

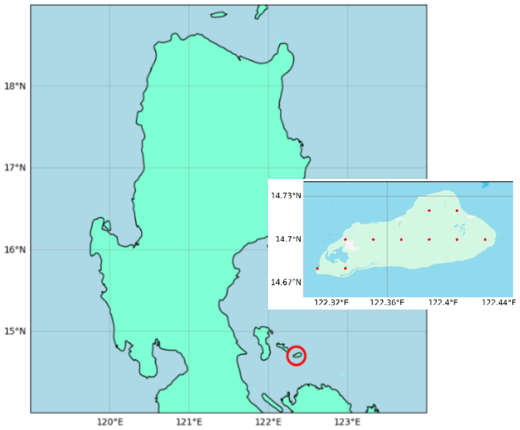

Figure. 1. *Study Area Map – Jomalig Island*

2.2. Data

The solar radiation datasets used in this study were obtained from the ERA5 reanalysis product of the European Centre for Medium-Range Weather Forecasts (ECMWF) [45]. ERA5 provides globally consistent, high-resolution atmospheric and surface variables derived through the assimilation of satellite and in situ observations, and is widely used as a reference dataset for solar energy studies. ERA5 data corresponding to Jomalig Island were extracted for the period January 2023 to December 2024 and treated as the observed baseline for model development and evaluation.

Forecast meteorological data were obtained from the ECMWF Integrated Forecasting System (IFS) [46] using the operational forecast stream. The IFS forecasts were initialized at the 0-hour lead time, representing the start of each daily forecast cycle. The forecast horizon considered in this study spans 31 to 54 hours ahead in Coordinated Universal Time (UTC), corresponding to the next-day prediction window relevant to the study area. The IFS outputs were used at their native temporal resolution and directly compared with the ERA5 reanalysis data to evaluate forecast performance and support the development of the proposed solar-based microgrid control strategy.

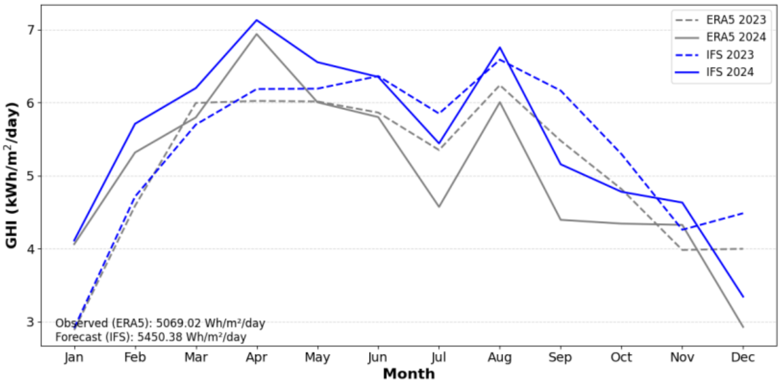

Figure. 2. *Solar irradiance profile in Jomalig Island*

The daily solar irradiance over the study period indicates strong solar resource availability, with the ERA5 reanalysis data showing an average daily Global Horizontal Irradiance (GHI) of 5.07 kWh/m²/day, while the IFS exhibits a slightly higher average of 5.45 kWh/m²/day, as illustrated in Fig. 2. This consistently high level of solar energy highlights its suitability as a dependable resource for the design of isolated microgrid systems, particularly in remote and off-grid locations. Solar resource potential directly influences the optimal sizing of photovoltaic panels and energy storage systems needed to meet local electricity demand. Beyond energy yield considerations, practical system design must also account for capital costs, operation and maintenance requirements, transportation and installation constraints, and applicable taxes to ensure both technical feasibility and economic sustainability.

2.3. Demand Profile

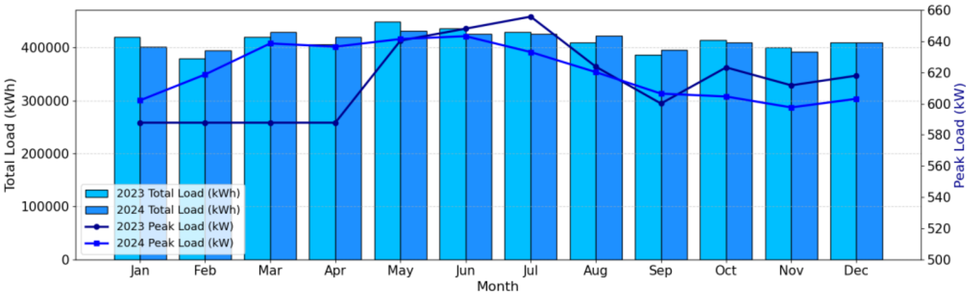

Figure. 3. *Peak power and electricity load profiles per month*

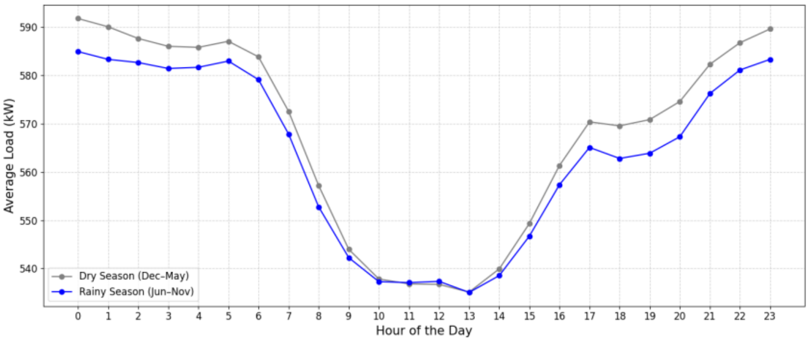

Figure. 4. *Hourly electrical load profile of a microgrid*

Figure 2 and Figure 3 present the annual load profile of a 1 MW isolated microgrid system for the year 2023-2024, derived using publicly available hourly demand data from the National Grid Corporation of the Philippines (NGCP) [47] for the Luzon grid. This approach was taken due to the absence of actual load data for Jomalig Island, which geographically falls within the Luzon region. The synthesized load data shows that peak power demand fluctuated between 655 kW and 444 kW, with the highest total monthly energy consumption reaching approximately 448.7 MWh in May of 2023. When analyzed seasonally, the average hourly load profile during the rainy months (June to November) was around 8% higher than that in the rainy months (December to May), reflecting variations in energy usage patterns possibly influenced by weather conditions. Across both seasons, the daily load behavior followed a consistent structure, with demand peaking during night hours. This night hour’s increase can be attributed to higher electricity use for ventilation and cooling systems, which typically corresponds with elevated ambient temperatures during daylight hours. This load profiling method provides a representative model to support energy system design, particularly for remote island contexts where direct consumption data may not be available.

2.4. Design Configuration and Optimized Designing

Designing an isolated microgrid system requires a comprehensive and accurate modeling process that takes into account the resources and data available for the region [48]. One of the most critical steps in this process is understanding the electricity demand of the area and how much energy is needed, when it is consumed, and how it fluctuates over time. This methodology, often referred to as a demand-driven or load-driven approach, starts from the bottom up [49][50]. It involves analyzing the end-users’ energy consumption patterns and tailoring the generation, storage, and distribution infrastructure to meet those specific needs. This approach is especially vital for fully off-grid systems, where there is no backup from a central grid, and the local demand must be precisely matched by on-site generation and storage capacities to ensure reliability and efficiency. Given the isolated nature of the site, a scientific and data-driven approach is essential to ensure that the development of the microgrid is both efficient and cost-effective. To achieve this, the proponent suggests metaheuristic approach using differential evolution(DE) [51][52] as optimization method that works well for this application due to its computational efficiency and ability to function well with fewer input parameters, a benefit in systems that only use solar energy, where component sizing and resource variability are crucial. The approach centers on evaluating a microgrid configurations that integrates photovoltaic (PV) panels, a fuel cell (FC), and a battery energy storage system (BESS) (see Figure 5). DE will be employed to determine the optimal rated capacities of the system components, ensuring they are appropriately sized to meet the energy demands of the site while maintaining overall system performance.

All relevant parameters utilized in the modelling of microgrid performance are comprehensively detailed in Table 1, along with their corresponding units and values. Derived parameters are noted accordingly, ensuring transparency and traceability of calculations used in the simulation framework.

Table 1. *Input Techno-economic Parameters for PV-FC-BESS Microgrid Simulation.*

Components	Parameters	Values	Unit
PV	Efficiency	21.23	%
	Lifespan	25	Years
	Capital cost	2000	$/kW
	Replacement cost	2000	$/kW
	O&M	15	$/kW
	Derating factor	80	%
BESS	Capital cost	200	$
	Replacement cost	200	$
	O&M	15	$
	Nominal voltage	12	V
	Nominal capacity	1	Ah
	Maximum capacity	83.4	Ah
	Efficiency	80	%
	Lifespan	5	Years
FC	Capital cost	200	$/kW
	Replacement cost	200	$/kW
	O&M	0.03	$/kW
	Lifespan	15	Years
	Efficiency	45	%
Inverter	Capital cost	300	$/kW
	Replacement cost	300	$/kW
	O&M	3	$/kW
	Lifespan	15	Years
	Efficiency	95	%
Electrolyzer	Capital cost	2000	$/kW
	Replacement cost	2000	$/kW
	O&M	20	$/kW
	Lifespan	15	Years
	Efficiency	65	%
Hydrogen tank	Capital cost	300	$/kW
	Replacement cost	300	$/kW

Other parameters	O&M	3	\$/kW
	Lifespan	10	Years
	Project lifetime	25	Years
	Real interest	6.35	%

The objective of the optimization is to identify the appropriate sizes of the microgrid components, including photovoltaic generation, a fuel cell, and a battery energy storage system, in order to minimize the total life cycle cost of the microgrid while maintaining a reliable electricity supply. The objective function accounts for capital investment, component replacement, operation and maintenance expenses, fuel consumption, and penalty costs related to unmet load or violations of operational limits. DE is used as a global optimization technique to explore different combinations of component capacities. At each time step, the operation of the microgrid is determined using a predefined rule based dispatch strategy that gives priority to renewable energy use, controls the BESS SOC within safe operating limits, and supplies the electrical load as required. By incorporating the rule based dispatch directly into the fitness evaluation, the optimization reflects realistic system operation and captures the economic trade-offs associated with different microgrid configurations over the simulation period.

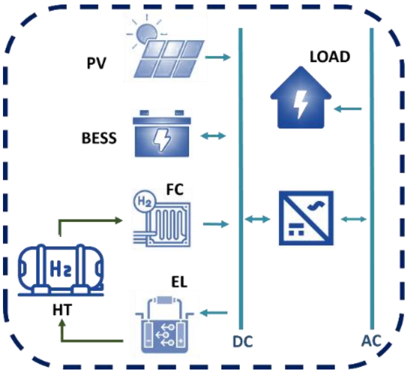

Figure. 5. *Configuration setup of microgrid for PV-FC-BES System*

2.5. Differential Evolution

In order for the system to function at the lowest possible overall cost while still meeting the demand for electricity, the optimization focuses on selecting appropriate sizes for the primary microgrid components, such as solar panels, a fuel cell, and a battery (see configuration setup in Figure 5). The cost calculation includes expenses for installing the equipment, replacing components over time, routine operation and maintenance, fuel use, and additional costs that occur when the system cannot fully supply the load or exceeds its operating limits. Differential Evolution is applied as a search method to test many possible combinations of component sizes [53]. The way the microgrid operates is defined by a simple rule based strategy that decides, at each time step, how power is supplied and stored by giving priority to solar energy, keeping the battery within safe charge levels, and delivering power to the load. This operating logic is included directly in the evaluation of each solution so that system behavior over time is represented in a practical and understandable manner.

$$x = [P_{PV}, P_{FC}, E_{BESS}, P_{EL}, m_{HT}], \quad (1)$$

$$\min C_{sum} = C_{cap} + C_{rep} + C_{O\&M} + C_{penalty}\,, \quad (2)$$

$$C_{rep} = \sum C_r N, \quad (3)$$

$$C_{O\&M} = \sum_{t=1} (C_{OM\cdot PV} + C_{OM\cdot FC} + C_{OM\cdot BESS} + C_{OM\cdot EL} + C_{OM\cdot HT}) \quad (4)$$

$$C_{pen} = C_{pen\cdot rate/kw} \cdot P_{unmet/kw}, \quad (5)$$

$$\begin{cases} 0 \le P_{PV} \le P_{PV\cdot max} \\ 0 \le P_{FC} \le P_{FC\cdot max} \\ 0 \le E_{BESS} \le E_{BESS\cdot max} \\ 0 \le P_{EL} \le P_{EL\cdot max} \\ 0 \le m_{HT} \le m_{HT\cdot max} \end{cases}, \quad (6)$$

The optimization problem defines a set of decision variables that represent the main design parameters of the microgrid, namely the installed capacity of the photovoltaic system (P_{PV}), the rated power of the fuel cell (P_{FC}), the energy capacity of the battery energy storage system (E_{BESS}), the rated power of the electrolyzer (P_{EL}), and the mass capacity of the hydrogen tank (m_{HT}) (see eq. 1). The objective function aims to minimize the total system cost (min C_{sum}), which is expressed as the sum of capital cost (C_{cap}), replacement cost (C_{rep}), operation and maintenance cost ($C_{O\&M}$), and penalty cost ($C_{penalty}$) (see eq.2). The C_{rep} for components that need to be replaced during the project lifetime and is calculated based on the number of replacements (N) and their unit cost (C_r)(see eq.3). The $C_{O\&M}$ is accumulated over the simulation period and includes contributions from each system component, reflecting routine operational expenses (see eq.4). The C_{pen} represents the economic impact of unmet electrical demand and is calculated using a specified penalty rate multiplied by the amount of unmet power (see eq.5). To ensure physically and practically feasible solutions, the optimization is subject to constraints that limit each decision variable within its allowable minimum and maximum values, reflecting technical design limits and operational feasibility of the microgrid components (see eq.6).

2.6. Dispatch Logic

The model predictive control formulation optimizes the operation of the microgrid over a limited future time window using forecasts of photovoltaic generation and load demand. At every time step, the controller looks at how the system will behave over the next few steps in the prediction horizon and decides on a series of control actions that will keep the supply and demand for electricity in balance while taking into account battery operation, hydrogen production and consumption, and the limits of each component's operation [54]. The objective function assigns weights to unmet demand, excess generation, and the use of different devices to guide the dispatch toward realistic operating patterns. Physical system dynamics, including the evolution of BESS state-of-charge (SOC) and hydrogen storage, are explicitly represented as constraints to maintain feasible operation over all predicted steps. Although control decisions are computed for the entire multi step horizon, only the first control action is applied, after which the optimization is repeated at the next time step using updated system states and forecast information.

$$\begin{cases} P_{c\cdot BESS}(t+k) \geq 0 \\ P_{d\cdot BESS}(t+k) \geq 0 \\ P_{FC}(t+k) \geq 0 \\ P_{EL}(t+k) \geq 0 \\ P_{unmet}(t+k) \geq 0' \\ P_{excess}(t+k) \geq 0 \\ SOC(t+k) \\ HT(t+k) \end{cases} \tag{7}$$

At each time step t, the model predictive control framework solves an optimization problem over a finite prediction horizon H, where k=0,1,…,H−1, using forecasted photovoltaic generation and load demand. Although control actions are computed for all future steps within the horizon, only the first control action associated with each decision variable in Eq. 7 is implemented, and the procedure is repeated at the next time step with updated information.

$$P_{f\cdot PV}(t+k) + P_{FC}(t+k) + P_{d\cdot BESS}(t+k) - P_{c\cdot BESS}(t+k) - P_{EL}(t+k) + P_{unmet}(t+k) - P_{excess}(t+k) = L(t+k), \tag{8}$$

$$\begin{cases} SOC(t+k+1) = SOC + \dfrac{\eta_c P_{c\cdot BESS}(t+k) - \frac{P_{d\cdot BESS}(t+k)}{\eta_d}\Delta t}{E_{BESS}} \\ SOC_{min} \leq SOC(t+k) \leq SOC_{max} \end{cases} \tag{9}$$

$$\begin{cases} HT(t+k+1) = HT(t+k) + \dfrac{\eta_{EL} P_{EL}(t+k)\Delta t}{33.33} - \dfrac{P_{FC}(t+k)\Delta t}{3.33\eta_{FC}} \\ HT_{min} \leq HT(t+k) \leq HT_{max} \end{cases} \tag{10}$$

MPC described how power and energy are balanced within the microgrid at each future time step considered by the controller. The power balance constraint in Eq. (8) ensures that the total electrical power supplied by the PV, FC, and BESS is matched with the electrical demand, BESS charging, and EL consumption, while allowing for unmet demand and excess power through dedicated slack terms. Eq. (9) represents the BESS SOC dynamics, where the SOC at the next time step is updated based on the net charging and discharging power, accounting for charging and discharging efficiencies, the length of the time step, and the total battery energy capacity, while remaining within specified minimum and maximum limits. Eq. (10) describes the hydrogen tank dynamics, in which the stored hydrogen level evolves according to hydrogen production from EL and hydrogen consumption by the FC both scaled by their respective efficiencies and energy conversion factors, and constrained within the allowable storage range. Together, these equations capture the physical interactions among electricity generation, storage, and hydrogen conversion in a form that reflects realistic system behavior while remaining interpretable.

The proposed control and optimization framework is evaluated alongside a conventional rule-based dispatch (RBD) strategy and the HOMER optimization tool to provide a consistent point of comparison under similar system assumptions. To ensure a realistic and transparent assessment, multiple objective analysis formulations are considered. These alternative formulations allow the same physical model and operational constraints to be assessed from different economic and operational perspectives, while keeping the comparison grounded in practical performance indicators that are commonly used in microgrid studies.

To maintain methodological uniformity and ensure comparability with industry-standard practices, the optimization framework is aligned with the treatment adopted by HOMER for isolated microgrids. Rather than separating sizing and operation into disjoint steps, the study adopts a combined approach in which optimal sizing and dispatch control are jointly evaluated. In this context, HOMER serves as a benchmark by presenting solutions that inherently reflect the interaction between component sizing and its internal dispatch strategy. This allows the results to be interpreted not only in terms of optimal capacities but also in terms of how those capacities are utilized during operation. Within this framework, Py_M employs MPC as its dispatch strategy, emphasizing forward-looking decision-making based on system states and forecasts. In contrast, the DE-based sizing results are evaluated under two distinct dispatch schemes to highlight the impact of control strategy on system performance. The first uses RBD, representing a simpler and more intuitive control logic, while the second adopts MPC, which enables adaptive and anticipative control. These configurations are referred to as DE-RBD and DE-MPC, respectively.

3. Results

The proposed approach combines system design optimization with dispatch control to develop an efficient model of an isolated microgrid. Rather than focusing only on selecting component sizes, the method integrates dispatch control to reduce unmet demand and excess energy, linking technical performance with economic considerations. The design of a PV–FC–BESS microgrid is first optimized using DE, while the operational feasibility of each candidate design depends on the dispatch strategy applied. In a rule based dispatch scheme, constraints are defined by predefined operating rules such as prioritizing photovoltaic generation, meeting load demand, and managing charging and discharging of storage devices. In contrast, when DE-MPC is used, constraints are introduced through the operational simulation itself. DE generates different combinations of component capacities and power limits, and each combination is evaluated through DE-MPC, which enforces power balance, device limits, BESS SOC boundaries, and hydrogen storage constraints at every time step over the prediction horizon. Designs that cannot operate within these limits naturally result in higher penalty costs or reduced performance, meaning that constraints are effectively applied through the DE-MPC based dispatch during the fitness evaluation rather than being handled directly by the optimization algorithm.

Table 2. *Optimized Component Design for a PV-FC-BES Isolated Microgrid.*

Components	Units	HOMER	Py_M	DE-RBD	DE-MPC
PV	kW	22,713	24,000	80,000	**20,577**
BESS	kWh	36,769	**24,000**	44,447	26,082
FC	kW	**250**	14,000	17,465	7500
EL	kW	**1.8**	2400	11,828	650
HT	kg	1000	2800	1200	**1000**

To further support the development of the optimized microgrid design, the proposed DE–MPC approach is compared with other established models for microgrid sizing and dispatch. In particular, HOMER is considered as a reference tool for component sizing and control dispatch using the same set of microgrid components. HOMER is a freely available software platform that simulates and optimizes hybrid energy systems supplying AC, DC, hydrogen, and thermal loads based on hourly time step operational strategies [55]. In addition, the Python Microgrid (Py_M) framework is included in the comparison, as it is an open source tool designed for the modeling, simulation, and optimization of hybrid microgrid systems within a flexible Python environment [56].

Table 2 shows the summary of the optimized values for an isolated microgrid model. Different approaches are used for optimization with consideration to the components detailed in Figure 5. The results indicate noticeable differences in the selected capacities of photovoltaic generation, battery energy storage, fuel cell, electrolyzer, and hydrogen tank across the four methods. The HOMER and Py_M tools tend to produce relatively moderate and comparable system sizes, reflecting their reliance on predefined dispatch strategies and hourly control logic. In contrast, the DE-based approaches explore a wider design space, leading to larger component sizes in some cases, particularly for PV and storage in the DE–RBD configuration, which reflects the conservative nature of rule-based dispatch in maintaining reliability. The DE–MPC configuration results in more balanced capacities across all components, with comparatively lower PV, electrolyzer, and fuel cell sizes, while maintaining sufficient battery and hydrogen storage. This behavior suggests that the inclusion of predictive, multi-step dispatch control influences the sizing process by allowing more coordinated use of storage and generation resources, thereby reducing the need for oversizing individual components while still meeting system demand.

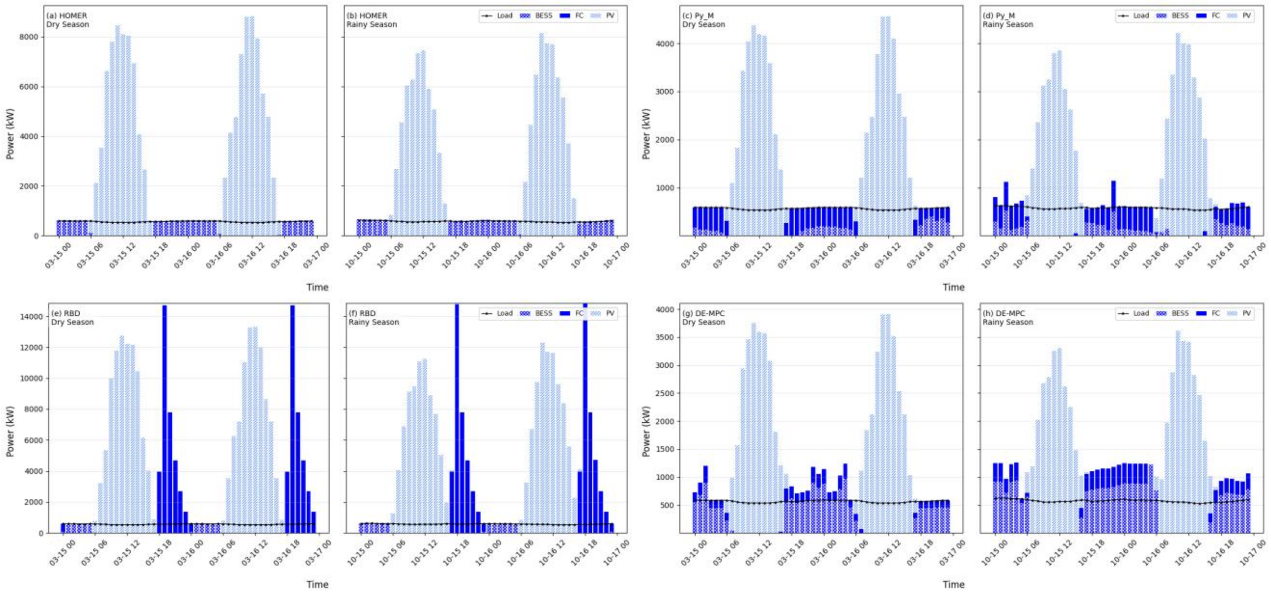

Figure. 6. *Seasonal dispatch behavior of PV-FC-BESS using (a-b)HOMER; (c-d) Py_M; (e-f) DE-RBD (g-h) DE-MPC*

Figure 6 shows the seasonal dispatch behavior of a PV-FC-BESS microgrid. Normally, all dispatch models are consistent with a reduction in the PV production in the rainy season. While this effect involves a reduction in sustainable hydrogen production and battery charging, the optimized result in Table 2 compromises the achievement of objectives in an isolated microgrid model. HOMER displays in Figure 6 (a)-(b) a sustained power distribution in the absence of solar PV production. While this portrays a significant effect in determining the model for control dispatch, the effect in the component prioritization cannot be adjusted. This is shown in the power distribution in the HOMER model; the FC contribution is minimal and concentrated on the BESS contribution in the model. An alternative approach for a PV-FC-BESS model cannot guarantee a HOMER optimization and dispatch to be used in this kind of setup. Py_M (Figure b–c) and DE MPC (Figure g–h) show similar patterns in PV power production, with Py_M exhibiting a slightly higher overall PV output due to the increased PV capacity selected during the design optimization. However, differences become more apparent during non-solar production hours, when storage components play a larger role in meeting demand. In the Py_M dispatch, the fuel cell contributes a substantial share of the supplied power, whereas in the DE MPC strategy the battery energy storage system is more prominently utilized. Although Py_M and DE-MPC follow comparable operational trends, Py_M still shows periods where demand is not fully met, particularly during the rainy season when solar availability is reduced. This contrast reflects differences in how the two strategies manage storage operation and SOC over time, with DE-MPC maintaining a more stable and responsive use of the battery system. In Figure 6 (e–f), the DE-RBD strategy follows a clear and structured dispatch sequence based on predefined component priorities. During daylight hours, power supply is dominated by photovoltaic generation, reflecting the rule that gives priority to direct use of solar energy when available. As solar production declines during non-solar hours, the fuel cell becomes the primary source of electricity, providing a steady contribution in the early night period. Once the fuel cell output is reduced or limited, the battery is then used to support the remaining demand. This results in a largely linear and predictable dispatch pattern, where each component operates in a fixed order rather than adapting dynamically to changing system conditions.

Beyond comparison, excess energy is a significant indication for establishing and refining microgrid objectives especially in an isolated microgrid design, since it directly shows how well generation, storage, and load are coordinated. High excess energy points to inefficiencies in sizing or dispatch and highlights opportunities to improve storage utilization, demand response, or control strategies. Figure 7 illustrates how excess energy (kWh), a key indicator for setting and evaluating operational objectives in a microgrid, is distributed between 08:00 and 17:00 for the four energy management strategies, HOMER, Py_M, DE-RBD, and DE-MPC, a time window chosen because electricity generation is dominated by solar PV during daylight hours, with the fuel cell and battery responding to surplus PV output, so excess energy only arises when the sun is available. The DE-RBD strategy shows the highest median values and the widest interquartile range, with peaks around 12:00 to 14:00, indicating frequent overproduction during peak solar hours. HOMER also displays substantial variability and notable excess energy. In contrast, Py_M exhibits a more compact distribution with comparatively low surplus, particularly during midday, suggesting a closer match between electricity production and consumption. Most notably, DE-MPC maintains excess energy values close to zero across the entire period, reflecting its ability to continuously adjust generation and storage decisions in response to demand. DE-RBD and HOMER often produce more electricity than is needed, especially when the sun is strongest, resulting in unused power, while Py_M manages this imbalance more carefully. DE-MPC behaves like a highly attentive system that keeps energy flows tightly controlled, minimizing waste and maintaining a balanced daily operation.

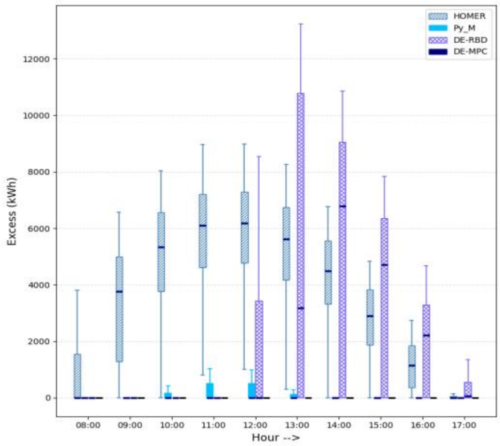

Figure 7. *Excess energy for different dispatch strategies*

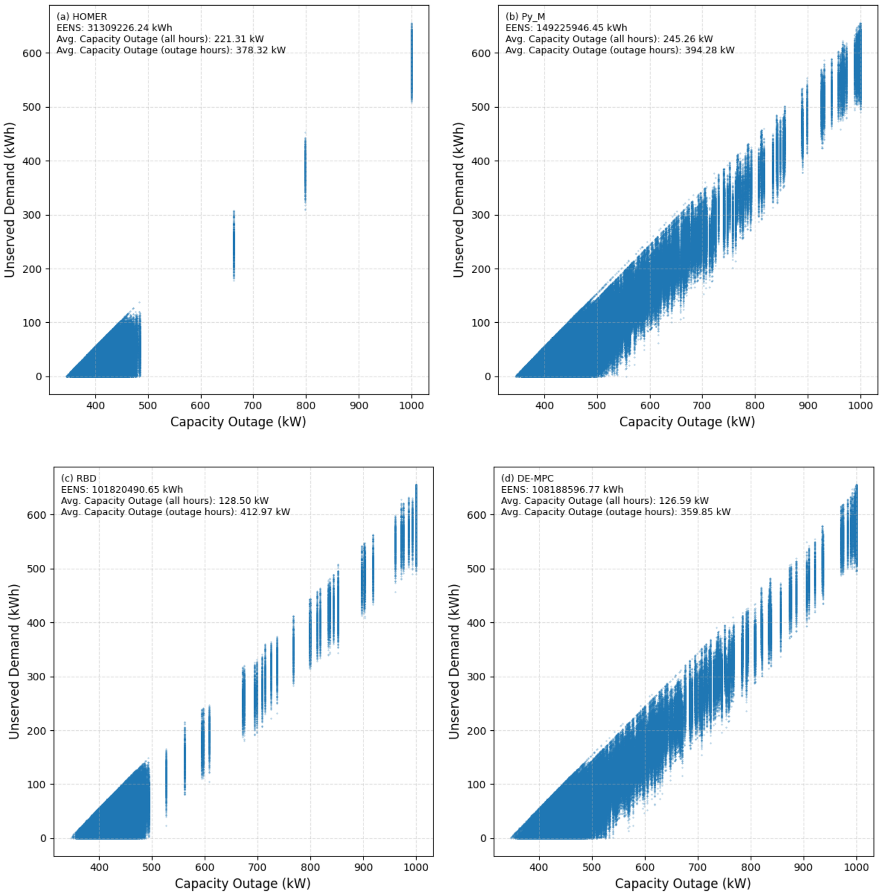

Figure 8. *Relationship between capacity outage and unserved demand under different dispatch strategies, highlighting variations in the frequency and severity of shortage events.*

4. Discussion

The overall performance of a dispatch model cannot be assessed based on a single aspect of its operational behavior. For instance, in Figure 7, most dispatch strategies exhibit substantial levels of excess energy, with the exception of the DE-MPC case, which maintains comparatively lower excess energy as part of its optimization objective. However, the presence of excess energy does not directly indicate whether the system will experience power insufficiency, as it may simply reflect periods of surplus generation. In Figure 8, the HOMER dispatch records the lowest EENS, suggesting strong reliability in terms of energy delivery, yet it also shows one of the higher outage durations. In contrast, DE-MPC demonstrates the lowest outage hours while exhibiting relatively higher EENS compared to other strategies. When considering the BESS SOC behavior in Figure 9, DE-MPC maintains SOC levels more consistently within the defined operating range, while DE-RBD displays a comparable pattern. Additionally, the dispatch behaviors illustrated in Figure 6 highlight distinct operational characteristics across all models, with each strategy emphasizing different priorities in energy allocation and storage usage. Together, these observations show that dispatch model performance varies depending on the metric considered, and each approach presents its own operational strengths and limitations across different performance indicators.

In short, each dispatch model exhibits distinct strengths and weaknesses, which can make the choice of an appropriate strategy challenging for power producers operating an isolated PV–FC–BESS microgrid. When defining operational objectives, a statistical approach grounded in economic performance can provide a clearer basis for comparison. The sizing of the total system extensively employs the weighted sum method, while the quadratic penalty places significant emphasis on reliability and constraint satisfaction. In contrast, the maximum utilization method makes use of high curtailment costs to minimize wasted renewable energy, geometric mean ensures balanced energy handling between system elements, and quadratic weighted sum enhances sensitivity towards essential objectives. By focusing on objective minimization, the dispatch model can be evaluated in terms of how effectively it reduces excess energy and unmet demand while maintaining reliable operation. Given the isolated nature of the microgrid, equal emphasis is placed on extending component lifetime to limit replacement costs and on avoiding energy shortfalls that could compromise system reliability.

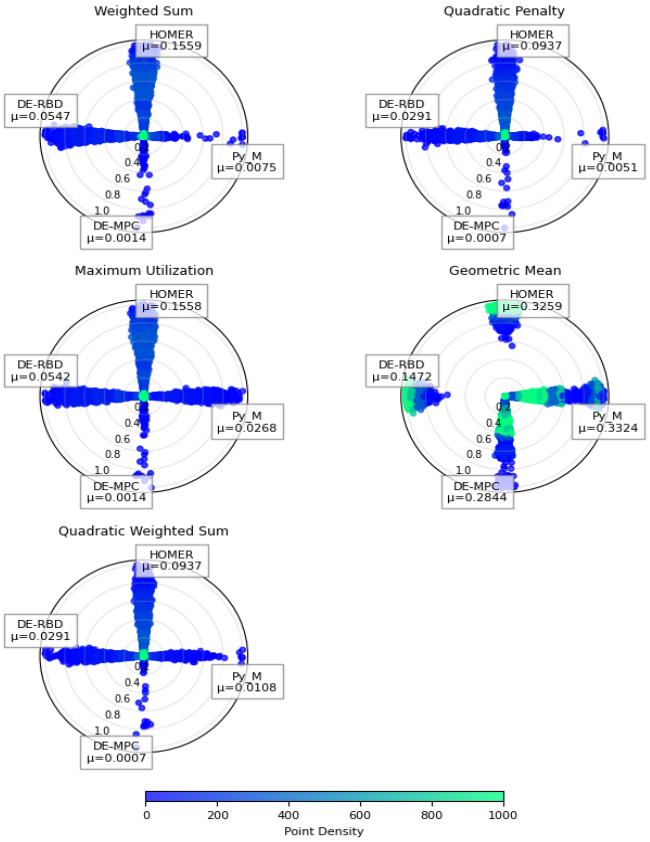

Figure 9. *Density distribution of normalized objective minimization strategies across control dispatch models*

Across all objective minimization methods (Figure 9), the results consistently show that dispatch strategies built on design-stage optimization deliver more reliable and efficient performance than purely rule-based approaches. Under the weighted-sum and quadratic penalty objectives, DE-MPC and Py_M clearly outperform DE-RBD and HOMER, demonstrating that optimized system sizing combined with flexible control leads to better efficiency and stronger compliance with operational constraints. When the focus shifts to maximum utilization, which penalizes excess energy in isolated microgrids, DE-MPC emerges as the strongest performer, highlighting the advantage of predictive, optimization-driven control in reducing curtailment and making better use of available generation. The geometric mean objective, which rewards consistent performance across all criteria, favors the more conservative DE-RBD, reflecting its stable but less flexible rule-based structure, while DE-MPC and Py_M exhibit more adaptive behavior across competing objectives. Finally, when all performance aspects are jointly emphasized through the quadratic weighted sum, DE-MPC clearly dominates, achieving the lowest overall penalty by effectively balancing efficiency, constraint compliance, and energy utilization while avoiding extreme operating conditions. Overall, the findings demonstrate that while different objective formulations highlight different aspects of system behavior, optimization-driven and predictive dispatch strategies in DE-MPC, provide the most robust, adaptable, and practically meaningful performance for isolated microgrid operation, underscoring the importance of objective formulation as a decision-support tool rather than a purely mathematical choice.

5. Conclusion

The proposed DE-MPC demonstrates that an optimized design optimization with dispatch control provides a more effective and realistic approach to operating isolated PV–FC–BESS microgrids. The architecture of the model connects component sizing directly to operational feasibility, leading to fulfilling demand, following operational limits, and managing storage resources when the system is in operation. When compared to traditional tools like HOMER and Py_M, which rely heavily on predefined or hourly dispatch logic, can reach acceptable levels of reliability, but usually at the expense of more excess energy, less flexibility in how components are used, or more stress on storage systems and fewer options for a more realistic approach. DE-RBD, a rule-based techniques work in a stable and predictable way, but their fixed priority structures tend to make systems less adaptable when conditions change and size them conservatively. In contrast, DE–MPC consistently produces more balanced component capacities and more coordinated dispatch behavior by integrating predictive, multi-step control into the optimization process. On the other hand, DE-MPC constantly delivers better balanced component capacities and more coordinated dispatch behavior by using predictive, multi-step control in the optimization process.

In terms of seasonal dispatch patterns, the excess energy dispatch, capacity outages, and the battery SOC, the DE-MPC solution outcomes illustrated the flexibility of adapting the generation/storage output to the variation of the demand. Though none of the dispatch strategies are found optimum for every individual metric of performance, the objective minimization demonstrates that DE-MPC provides the most optimized global performance compared with other strategies under a holistic objective formulation. In this case, for a quadratic weighted sum objective formulation, DE-MPC provides the best results compared with other strategies under the optimization of unmet demand and excess energy with strict adherence to the operation constraints. However, the findings stress that the importance of optimization formulations equally applies to dispatch strategy options. Various objective functions will provide insights into different weaknesses and strengths of systems, and therefore drawing conclusions based on a single aspect could be misleading. By applying multiple objectives to minimization strategies, this research presents a clearer and transparent analysis of the trade-offs between reliability, cost, and resource use within an isolated microgrid system.

In this regard, the results indicate that predictive and optimization-based dispatch approaches like DE-MPC can be most suited for complex microgrid scenarios and resource-constrained conditions. In this regard, the use of DE-MPC can enable better and reliable microgrid functioning, as it avoids critical conditions. In other words, the significance of this study reveals that optimal microgrid functioning does not depend only on properly choosing the microgrid elements and devices, but rather on optimizing and managing them for better performance and functionality.

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Nomenclature

AC	alternating current
BESS	battery energy storage system

DC	direct current
DE	differential evolution
E	energy capacity
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF atmospheric reanalysis version 5 dataset
EENS	expected energy not served (kWh)
EL	electrolyzer
FC	fuel cell
GHI	global horizontal irradiance (W/m^2)
HT	hydrogen tank
IFS	Integrated Forecasting System
m	mass capacity (kg)
MPC	model predictive control
NGCP	National Grid Corporation of the Philippines
NSRDB	National Solar Radiation Database
P	power output (kW)
PV	photovoltaic
Py_M	Python Microgrid
RBD	rule-based dispatch
SOC	state-of-charge
UTC	Coordinated Universal Time

Subscript and Superscript

Cr	per unit replacement cost
OM	operation and maintenance
pen	penalty
rep	replacement
pen·rate	penalty rate

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