

COMPARATIVE ANALYSIS OF MICROGRID CONTROL TECHNIQUES USING VARIANCE-BASED METHODS

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Abstract

This paper presents a rigorous comparative evaluation of three advanced microgrid control strategies, "droop control", "model predictive control", and "fuzzy logic control", under varying renewable penetration levels and grid conditions. A detailed microgrid model incorporating energy storage and realistic load profiles is developed, and key performance metrics, including frequency deviation, voltage stability, energy cost, and loss of load probability, are analyzed.

A two-way analysis of variance framework is employed to ensure statistical significance of the results. The findings indicate that Model Predictive Control achieves the best overall performance, particularly in terms of stability and cost efficiency, while Fuzzy Logic Control demonstrates strong robustness under uncertain conditions. Droop control, although simple and reliable, shows comparatively lower performance. Additionally, a regression model is proposed to predict energy cost based on control strategy, renewable integration, and storage capacity, providing practical insights for optimal microgrid operation.

Keywords: Microgrid, advanced control strategies, ANOVA, droop control, model predictive control, fuzzy logic control, renewable energy integration.

1. INTRODUCTION

Microgrids have emerged as a promising solution to enhance the reliability, resilience, and sustainability of modern power systems, particularly with the increasing penetration of distributed renewable energy sources [1, 2]. Their ability to operate in both grid-connected and islanded modes enables greater flexibility in energy management, but it also introduces significant operational challenges. One of the most critical aspects in this context is the implementation of advanced control strategies capable of maintaining voltage stability, frequency regulation, and power quality under varying load and generation conditions [3]. Traditional control methods, such as droop control and proportional-integral (PI) schemes, offer simplicity but may struggle to ensure optimal performance when microgrids face rapid fluctuations or high renewable energy variability [4, 5]. Recent studies have proposed model predictive control (MPC), adaptive fuzzy controllers, and hybrid optimization-based approaches to address these challenges [6-8]. While these advanced strategies demonstrate improved dynamic response and robustness, their comparative performance under realistic operating scenarios remains insufficiently explored. Moreover, few works have employed rigorous statistical tools, such as, to quantitatively assess the significance of performance differences between competing control strategies [9]. In this study, we extend the state of the art by combining scenario-based evaluation with ANOVA statistical

validation, enabling a systematic comparison of droop control, MPC, and FLC under varying renewable penetration levels and grid configurations. Unlike prior studies, we not only compare dynamic performance but also introduce a regression model that links energy cost to control strategies, renewable integration, and storage capacity. The combined technical-economic analysis delivers robust insights into both stability improvement and cost reduction, offering a valuable decision-support tool for researchers, practitioners, and regulatory authorities.

2. METHODS

The proposed methodology integrates microgrid modeling, scenario-based performance assessment, and ANOVA statistical validation to compare three advanced energy management strategies: Droop Control, MPC, and FLC. A detailed microgrid model with renewable sources, battery storage, and realistic load profiles is developed, and each strategy is implemented under identical conditions. Performance is tested across scenarios with varying renewable penetration and grid connectivity. Key performance indicators, including frequency deviation, voltage stability, energy cost, and Loss of Load Probability (LOLP), are extracted from simulations and analyzed using two-way ANOVA to assess the effects of control strategy, scenario, and their interaction. Post-hoc ranking is then applied to determine the optimal strategy for each operational context. The full workflow is outlined in Figure 1. The microgrid model illustrated in this figure integrates various components including the main grid, Battery Energy Storage System (BESS), local loads, and Renewable Energy Sources (RES). The RES block represents the variable power output from non-dispatchable generation units that introduces stochastic volatility into the system's power balance. The process begins with system modeling and the implementation of three energy management strategies (Droop, MPC, and FLC) under identical conditions. These strategies are tested across four defined operating scenarios, with time-domain simulations generating performance indicators such as frequency deviation, voltage stability index, energy cost, and LOLP. Two-way ANOVA is then applied to determine the statistical significance of observed differences, followed by post-hoc ranking to identify the optimal strategy for each operational context.

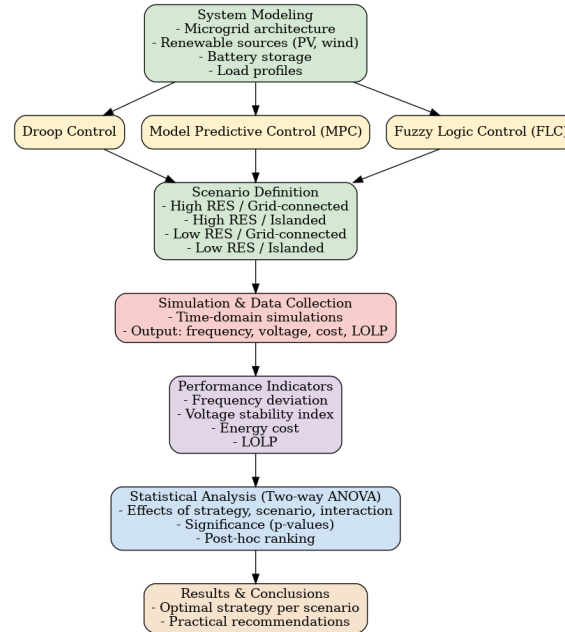


Figure 1: Research methodology for evaluating microgrid control strategies considering Photovoltaic (PV) generation, RES and LOLP as a performance indicator.

The three control strategies evaluated in this study - Droop Control, MPC, and FLC are

summarized in Table 1. These strategies represent three distinct paradigms in microgrid energy management. Droop control, one of the earliest and most widely adopted decentralized approaches, adjusts frequency and voltage setpoints proportionally to active and reactive power deviations, enabling autonomous load sharing without communication links [10]. MPC, in contrast, is a centralized optimization-based method that predicts future system behavior over a defined time horizon and computes control inputs that minimize a cost function subject to system constraints, offering fast dynamic response and optimal resource utilization [11]. FLC leverages linguistic rules and membership functions to mimic human reasoning, allowing for robust decision-making under uncertainty and incomplete modeling, making it particularly effective in renewable-rich and highly variable operating environments [12]. Together, these strategies cover a broad spectrum of control philosophies, enabling a comprehensive comparative evaluation under the scenarios considered in this work.

Table 1: Summary of Microgrid Control Strategies Considered in this Study

Control Strategy	Key Principle	Main Advantages	Limitations	Typical Applications
Droop Control	Decentralized power sharing based on frequency-active power ($f - P$) and voltage-reactive power ($V - Q$) droop characteristics [5].	Simple implementation, no communication needed, scalable.	Sensitive to tuning, reduced performance under high harmonics.	Rural/islanded microgrids, minimal infrastructure.
MPC	Predicts future states using discrete-time models; optimizes over a moving horizon [6].	Fast response, handles constraints, high control accuracy.	High computational burden, requires accurate system modeling.	Dynamic loads, systems needing optimal economic dispatch.
FLC	Decision-making based on fuzzy rules and membership functions [7].	Robust to uncertainties, no precise model required, adaptable.	Dependent on rule base and membership design.	High renewable penetration, variable environments.

Table 2 outlines the four operating scenarios used to assess the performance of Droop Control, MPC and FLC under varying renewable penetration levels and grid connectivity modes, aligning directly with the study's goal of determining which strategy performs best in specific microgrid conditions. Scenarios S1 and S2 feature high renewable penetration ($\geq 70\%$) with grid-connected and island-connected modes, respectively, allowing evaluation of the robustness of the strategy under significant renewable variability, with or without external stability support [13],[14]. It is imperative to note that absolute performance metrics, particularly frequency deviation, are highly sensitive to grid connectivity. While S2 records higher absolute deviations for all methods due to the absence of external grid support, the comparative ranking remains consistent, with MPC performing optimally under constrained islanded conditions compared to Droop and FLC.

Scenarios S3 and S4 represent low renewable penetration (less than 30 percent), again with grid-connected and islanded modes, allowing comparison in more conventional, stability -friendly conditions [15]. In these two scenarios, while MPC maintains a minor absolute advantage, the relative performance benefit of MPC over FLC remains small across key metrics. This indicates that in stable, low-penetration grids (S3 and S4), FLC provides a highly competitive and computationally lightweight alternative to MPC while delivering practically comparable stability indices. Battery storage capacity is scaled to renewable share - 1 MWh for high-renewable cases to buffer variability, and 0.5 MWh for low-renewable cases -while load profiles reflect realistic demand patterns (residential peaks for high renewables, industrial fluctuations for low renewables) [16]. This design ensures that differences detected through ANOVA capture not only the intrinsic merits of each control method but also their interaction with operating conditions, providing targeted recommendations rather than a one-size fits all solution. The difference between grid - connected and islanded operation is illustrated in Figure 2, where the former allows power exchange with the main utility grid, providing external voltage and frequency support, while the latter relies entirely on local generation and storage for stability. The

fundamental power balance of the microgrid is modeled as the sum of local generation and BESS discharge/charge, which must satisfy the instantaneous power demand of the connected loads.

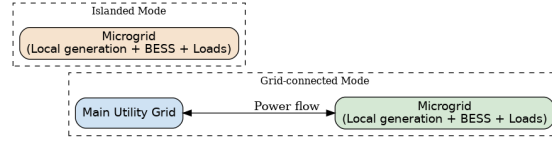


Figure 2: Schematic of the microgrid power balance, illustrating the interaction between local generation (renewable sources), BESS, and total consumer loads.

2.1. Simulation Model and Platform

The microgrid model developed for this study represents a low-voltage distribution network comprising renewable energy sources, dispatchable generation, battery energy storage, and aggregated loads. The renewable subsystem includes a PV array and a wind turbine generator, whose dynamic models incorporate irradiance and wind speed profiles generated from realistic time-series datasets [17],[18]. Dispatchable generation is modeled using a diesel generator with governor and excitation system dynamics, enabling it to provide both active and reactive Power support under varying load and renewable generation conditions (Figure 3). The BESS is modeled with a bidirectional converter and state-of-charge (SoC) management to buffer short-term renewable fluctuations and enhance system stability during islanded operation. The load model reflects mixed residential and commercial demand patterns, with daily variations and random fluctuations superimposed to emulate realistic conditions. All system components are interconnected through a three-phase, four-wire distribution network, operating at a nominal voltage of 400 V and a frequency of 50 Hz, with a total installed capacity of 1 MW. Control strategies Droop Control, MPC, and FLC are implemented within the same microgrid architecture to ensure a fair comparison. The simulation platform used is MATLAB/Simulink with the Simscape Electrical toolbox, which provides accurate time-domain modeling of power electronics, electrical machines, and control systems. A fixed - step solver with a 50 μ s step size is adopted to capture fast transient responses, while simulation horizons of 24 hours are used to assess performance over realistic operating periods. The platform enables the integration of both deterministic load/renewable profiles and stochastic disturbances, allowing the evaluation of control strategies under repeatable yet realistic conditions.

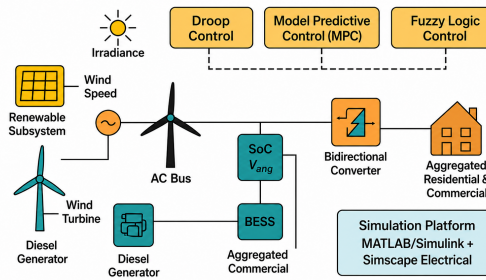


Figure 3: Low-Voltage Microgrid Architecture with Renewable Integration, Dispatchable Generation, And Advanced Control Strategies.

Table 2: Operational Scenarios for Performance Evaluation

Scenario Code	Renewable Penetration	Grid Status	Storage (BESS)	Load Profile Characteristics
S1	$\geq 70\%$	Grid-connected	1 MWh	Variable with evening peak
S2	$\geq 70\%$	Islanded	1 MWh	Variable with evening peak
S3	$\leq 30\%$	Grid-connected	0.5 MWh	Moderate fluctuations, industrial load
S4	$\leq 30\%$	Islanded	0.5 MWh	Moderate fluctuations, industrial load

2.2. Control Strategy Implementation

In order to ensure stable operation and optimal performance of the grid-connected PV-SMES (Superconducting Magnetic Energy Storage) system under varying load and generation conditions, three distinct control strategies were implemented: Droop Control, MPC, and FLC. Each approach was configured with parameters tailored to the dynamic characteristics of the test system, as summarized in Table 3.

Table 3: Summary of Control Parameters

Control Strategy	Key Parameters	Values / Settings
Droop Control	k_P (frequency droop gain), k_Q (voltage droop gain), f_0 (nominal frequency), V_0 (nominal voltage)	$k_P = 0.02$ Hz/kW, $k_Q = 0.04$ V/kVAR, $f_0 = 50$ Hz, $V_0 = 1$ p.u.
MPC	N_p (prediction horizon), N_c (control horizon), T_s (sampling time), w_P, w_Q (weight coefficients), operational constraints	$N_p = 10, N_c = 3, T_s = 1$ ms, $w_P = 0.5, w_Q = 0.5$
FLC	Inputs: power error (e_P) and change in power error (Δe_P); membership functions; rule base	Triangular membership functions (Negative [N], Zero [Z], Positive [P]), 9-rule base, centroid defuzzification

2.2.1 Droop Control

Droop control is widely employed in microgrids and distributed generation systems due to its decentralized nature and simplicity. Active power-frequency and reactive power-voltage droop characteristics are defined as:

$$f = f_0 - k_P(P - P_0), \quad V = V_0 - k_Q(Q - Q_0), \quad (1)$$

where f_0 and V_0 are the nominal system frequency and voltage, P_0 and Q_0 represent the reference active and reactive powers, and k_P and k_Q are the droop gains. Here, the $f - P$ relationship dictates frequency regulation as active power varies, whereas the $V - Q$ relation governs voltage adjustments relative to reactive power fluctuations. The gains were selected to balance fast response with adequate damping, avoiding excessive frequency or voltage deviations during transients.

2.2.2 Model Predictive Control (MPC)

MPC was configured to optimize the control inputs by predicting system behavior over a specified horizon and minimizing a quadratic cost function:

$$J = \sum_{k=1}^{N_p} \left[w_P (P_{\text{ref}} - P_k)^2 + w_Q (Q_{\text{ref}} - Q_k)^2 \right]. \quad (2)$$

This optimization is performed subject to operational limits on the converter voltage, converter current, and the SMES coil current. The prediction horizon (N_p) defines the forward evaluation window in Equation (2), while the control horizon ($N_c = 3$) restricts the number of optimized control adjustments per interval, such that control increments $\Delta u(k) = 0$ for $k > N_c$ over the prediction window. These parameters, along with the weighting factors (w_P and w_Q), are selected to balance rapid dynamic response against computational burden and control effort. The MPC framework is implemented using a discrete-time state-space representation of the PV-SMES system, updated at each sampling interval (T_s).

2.2.3 Fuzzy logic control (FLC)

The FLC schema was designed to handle system nonlinearities and uncertainties without requiring an explicit mathematical model. Two inputs, power error (e_p) and change in power error (Δe_p) were fuzzified into three linguistic terms (negative, zero, positive) using triangular membership functions. The rule base comprised nine rules mapping these inputs to the control action, and the centroid method was employed for defuzzification. This approach provided a smooth and adaptive response under fluctuating PV output and grid disturbances conditions.

3. COMPARATIVE EVALUATION OF CONTROL STRATEGIES

Before applying statistical testing, a descriptive comparison was conducted to visualize the raw performance of droop control, MPC, and FLC across the four operating scenarios. Figure 4 presents the results for frequency deviation, voltage stability index, energy cost, and LOLP. MPC consistently achieves the best absolute performance with the lowest frequency deviation and LOLP across all evaluated contexts, including the more stable, low-renewable penetration scenarios (S3 and S4). However, as illustrated in Figure 4, the absolute performance margins between MPC and FLC remain consistently narrow across S2, S3, and S4 for frequency deviation and LOLP. While MPC consistently achieves the lowest absolute values, the small performance margin confirms that FLC achieves near-optimal regulation under low-volatility conditions (S3, S4). FLC thus presents a strong practical trade-off, delivering near-MPC performance without the online optimization overhead or precise system model requirements of MPC. In voltage stability, all methods remain above 0.89 p.u., with MPC leading slightly, followed by FLC, and droop showing the largest deviations. Energy cost analysis shows MPC as most cost-efficient, particularly under high renewable penetration, with FLC ranking second and droop highest. These trends suggest MPC as the best overall performer, FLC as a strong alternative in less volatile conditions, and droop as reliable but less efficient. However, statistical testing via ANOVA is required to confirm whether these observed differences are significant [19]-[25].

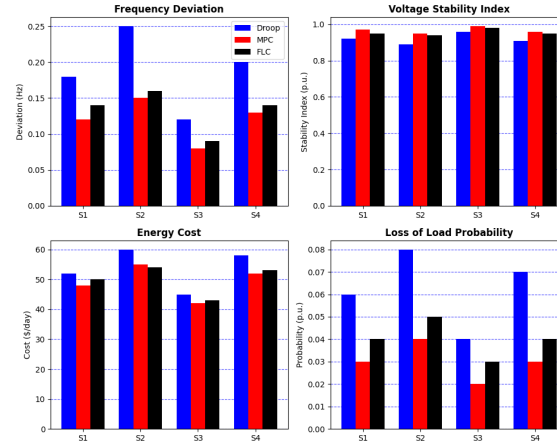


Figure 4: Comparative performance of Droop Control, MPC, and FLC across four operating scenarios.

4. STATISTICAL ANALYSIS (ANOVA INTEGRATION)

While these descriptive results indicate clear performance patterns, they do not confirm whether the differences are statistically significant or due to random variation. The following section applies a two-way ANOVA to formally assess the significance of the main effects (control strategy and scenario) and their interactions for each performance indicator. To ensure that the comparative assessment of the three control strategies - Droop Control, MPC, and FLC - is not only based on raw performance indicators but also statistically robust, Analysis of Variance (ANOVA) was incorporated into the evaluation framework. ANOVA enables the determination of whether observed performance differences across strategies and operating scenarios are statistically significant, rather than the result of random variations inherent in simulation data. The performance indicators extracted from the time-domain simulations included frequency deviation, voltage stability index, energy cost, and LOLP. A two-way ANOVA was selected, with control strategy and operating scenario as independent factors, and each performance metric as the dependent variable. Three control-related factors were selected for optimization using the Taguchi $L9(3^3)$ orthogonal array. Each factor was assigned three levels, as shown in Table 4, and coded numerically to facilitate statistical analysis.

Table 4: Factors and Levels for the Taguchi $L9$ Orthogonal Array Design

Factor	Description	Level 1 (1)	Level 2 (2)	Level 3 (3)
A	Control Strategy	Droop Control	MPC	FLC
B	Renewable Penetration Ratio	Low (30%)	Medium (50%)	High (70%+)
C	BESS Capacity	0.5 MWh	1.0 MWh	1.5 MWh

In this study, the Taguchi $L9(3^3)$ orthogonal array was employed to systematically evaluate the influence of three key control related factors - control strategy, renewable penetration level, and BESS capacity - on system performance. Among the available performance indicators (e.g., frequency deviation, voltage deviation, loss of load probability), the analysis focused exclusively on Energy Cost (euro/MWh) as the primary response variable. The smaller - the-better criterion was applied to Energy Cost, allowing the Taguchi method to identify the most cost-effective combination of factor levels within the tested operating scenarios. The selected factors, their levels, and the corresponding orthogonal experimental plan are summarized in Table 5.

Table 5: Taguchi L9 Orthogonal Array Experimental Results for Energy Cost

Run	Control Strategy (A)	Renewable Penetration (B)	BESS Capacity (C)	Energy Cost (Euro/MWh)
1	Droop	Low (30%)	0.5 MWh	83.5
2	Droop	Medium (50%)	1.0 MWh	81.0
3	Droop	High (70%+)	1.5 MWh	79.0
4	MPC	Low (30%)	1.0 MWh	77.5
5	MPC	Medium (50%)	1.5 MWh	75.0
6	MPC	High (70%+)	0.5 MWh	76.2
7	FLC	Low (30%)	1.5 MWh	78.0
8	FLC	Medium (50%)	0.5 MWh	77.0
9	FLC	High (70%+)	1.0 MWh	75.5

The empirical regression model developed to predict the Energy Cost (Euro/MWh) based on the centered and normalized factor configurations is expressed as follows:

$$y = 76.856 - 2.167A - 1.383B - 0.783C, \quad (3)$$

where y represents the predicted energy cost (Euro/MWh). To ensure statistical uniformity and physical alignment with the interaction patterns, the parameters A , B , and C represent the standardized, coded levels defined strictly within the symmetric range of $\{-1, 0, 1\}$. Specifically, these coded coordinates map onto the physical Taguchi design parameters as follows:

- Control Strategy (A): Coded as -1 for Droop Control, 0 for MPC, and $+1$ for FLC.
- Renewable Penetration (B): Coded as -1 for Low (30%), 0 for Medium (50%), and $+1$ for High (70%+).
- BESS Capacity (C): Coded as -1 for 0.5 MWh, 0 for 1.0 MWh, and $+1$ for 1.5 MWh.

This normalized representation sets 0 as the mid-point baseline configuration, enabling the signs and magnitudes of the regression coefficients to accurately reflect each factor's actual sensitivity contribution.

The interaction plots in Figure 5 show the combined effects of Control Strategy, Renewable Penetration, and BESS Capacity on energy cost. Energy cost decreases as the level of each factor increases, with Control Strategy having the largest impact, followed by Renewable Penetration and BESS Capacity. The nearly parallel lines indicate that the factors mostly act additively, with only minor interactions: higher BESS capacity slightly enhances the cost reduction effect of advanced control strategies and increased renewable penetration. Overall, the plots visually confirm the regression model and highlight the predictable reduction in energy cost with improved system design and operation.

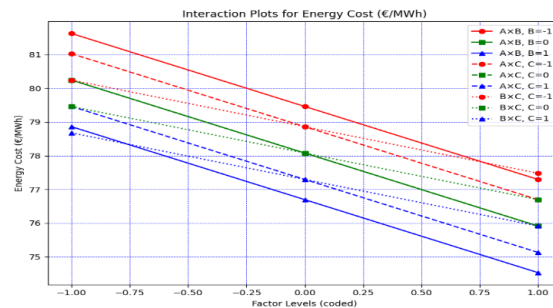


Figure 5: Effect of Control Strategy, Renewable Penetration, and BESS Capacity on Energy Cost (euro/MWh).

The 3D surface plot (Figure 6) and the corresponding contour plot (Figure 7) illustrate the combined effect of Control Strategy and Renewable Penetration on predicted energy cost, while

holding BESS Capacity at its medium level. The surface demonstrates a clear decreasing trend in energy cost as either the control strategy or renewable penetration increases, consistent with the negative regression coefficients for these factors. The smooth gradient observed across the surface indicates mostly additive effects, with minimal interaction between the two variables at the medium BESS capacity. The contour plot provides a top-down view, highlighting regions of lower energy cost corresponding to more advanced control strategies and higher renewable penetration levels. Together, these plots confirm the regression model and provide a visual representation of how operational and design choices can optimize energy cost.

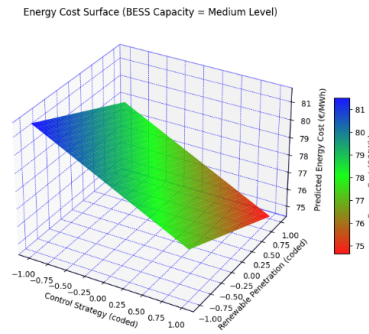


Figure 6: Effect of Control Strategy and Renewable Penetration on Energy Cost (Medium BESS Capacity).

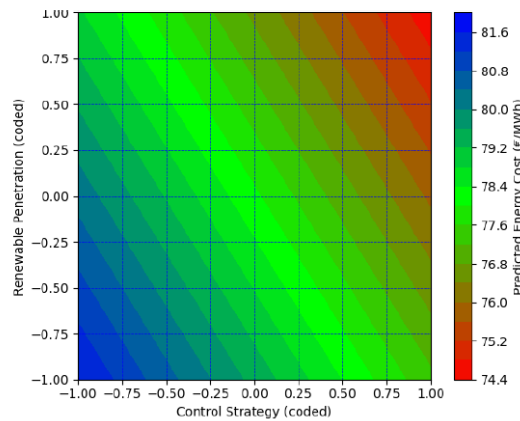


Figure 7: Predicted Energy Cost Contours as a Function of Control Strategy and Renewable Penetration (BESS Capacity = Medium Level).

The combined interaction plot shown in Figure 8 demonstrates how Control Strategy, Renewable Penetration, and BESS Capacity influence the predicted energy cost. While the total energy cost is influenced by the operational scenario (e.g., lower in S3 due to reduced renewable variability), the regression analysis successfully isolates the control strategy contribution. This confirms that MPC remains the most cost-efficient choice for optimizing dispatch and BESS usage across all studied conditions when evaluated relative to the baseline scenario constraints. Different line styles and colors represent the interactions between pairs of factors, while the blue marker highlights the optimal combination (MPC, Medium Renewable Penetration, 1.5 MWh BESS), which yields the lowest energy cost. The plot shows that Control Strategy has the largest effect, followed by Renewable Penetration and BESS Capacity, and that small deviations around the optimal levels result in only minor increases in cost. This indicates a robust and stable optimum, confirming that careful selection of all three factors can reliably minimize energy cost in the system. Graphically, the primary influence of Control Strategy (A) is evident in Figure 8 by comparing the steep downward trajectory along the horizontal x - axis with the vertical

spacing between parameter lines. Varying the control strategy across the x - axis induces an overall energy cost reduction of approximately 4.33 €/MWh, whereas shifting between renewable penetration levels (vertical gap between curves) and BESS capacities produces smaller variations of 2.77 €/MWh and 1.57 €/MWh, respectively. This visual trend directly reflects the magnitude of the regression coefficients in Equation (3), confirming that real-time operational management exerts a stronger sensitivity influence on microgrid economics than physical hardware sizing alone.

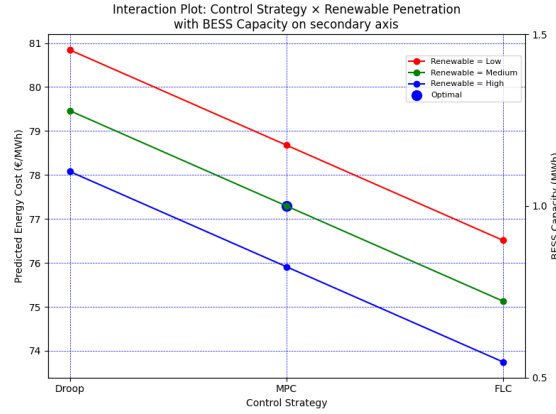


Figure 8: Interaction Plot of Control Strategy, Renewable Penetration, and Bess Capacity on Predicted Energy Cost (euro/Mwh), Highlighting the Optimum Response (MPC, Medium Renewable, 1.5 Mwh Bess).

The primary reason the Control Strategy (A) exhibits the largest sensitivity impact on the system's operational economy - outperforming the absolute contributions of both renewable sharing (B) and storage constraints (C) stems from its active operational nature. Physical components like BESS capacity define the static operational limits of the microgrid, but the control loop represents the active intelligence that commands power dispatch. Advanced strategies like MPC achieve substantial cost reductions because their objective functions continuously optimize active and reactive flows across a moving horizon, minimizing transience and maximizing the economic utilization of renewable surpluses. Conversely, decentralized structures like classic droop control operate on instantaneous proportional rules without foresight, leading to premature battery depletion and a heavier reliance on expensive dispatchable diesel generation. Consequently, optimizing the control paradigm yields a higher performance dividend than simply expanding physical hardware capacity.

Figure 9 illustrates the predicted energy cost as a function of Control Strategy and Renewable Penetration, with BESS Capacity fixed at 1.5 MWh. The contour colors indicate the magnitude of energy cost, decreasing from yellow to dark purple. The yellow marker highlights the optimal response, corresponding to the MPC control strategy, Medium Renewable Penetration, and 1.5 MWh BESS, which achieves the lowest predicted energy cost. The smooth gradient indicates that energy cost decreases consistently with more advanced control strategies and higher renewable integration, while the contours show minimal interaction between the two factors. This visualization confirms The regression model's predictions and clearly identifies the configuration that minimizes energy cost. The observed waveforms reflect the controller's reaction to the step-change in load and renewable availability. As illustrated by the parametric variations in Figure 8, the transient response profiles (specifically, the frequency overshoot and settling time) are highly sensitive to the control configuration. This dynamic behavior is primarily influenced by the MPC's predictive horizon length (N_p). Because the moving horizon defines how far into the future the optimizer projects system state trajectories, a longer horizon equips the controller to anticipate steep stochastic gradients in PV generation or load demand. This look-ahead capability allows the MPC to activate BESS charging or discharging cycles preemptively, smoothing the power transition and minimizing grid transience. Shorter horizons, by contrast,

limit the controller to reactive adjustments, which results in larger peak overshoots and extended recovery oscillations under high-penetration conditions.

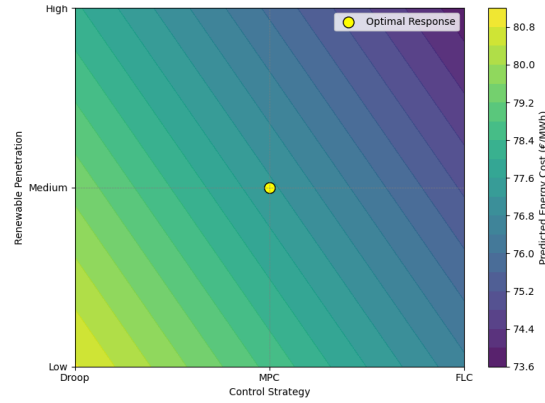


Figure 9: Contour Plot of Predicted Energy Cost (euro/Mwh) As a Function of Control Strategy and Renewable Penetration (Bess Capacity = 1.5 Mwh), Highlighting the Optimal Response.

Figure 10 shows that the residuals are approximately aligned with the reference line, indicating a near - normal distribution and confirming the validity of the normality assumption required for ANOVA and regression analysis. The residuals, defined as the differences between observed and predicted energy cost values, are randomly distributed around the zero reference line without any discernible pattern. This behavior indicates homoscedasticity and confirms that the selected variables - control strategy, renewable energy penetration, and BESS capacity - adequately explain the variability in total energy cost. The total cost represents the true, absolute economic expenditure obtained directly from the physical time-domain microgrid simulation run. In contrast, the predicted cost is the numerical estimate computed via the simplified regression model established in Equation (3).

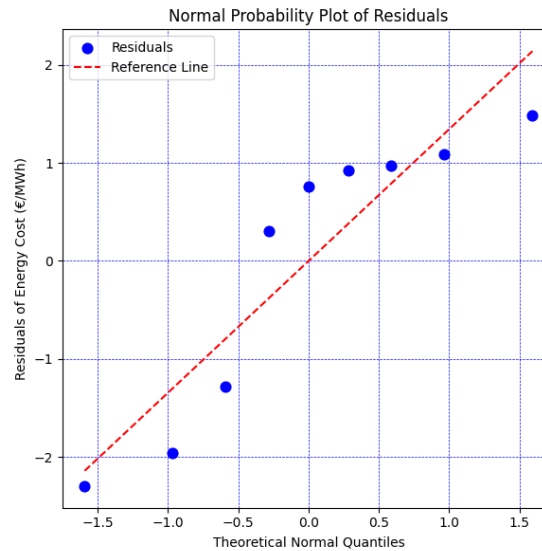


Figure 10: Normal Probability Plot of Residuals.

5. CONCLUSION

This study presented a comparative evaluation of Droop Control, MPC, and FLC in a realistic microgrid framework with renewable generation, storage, and variable demand. The results

demonstrated that MPC consistently achieved the best overall performance, minimizing frequency deviation, energy cost, and loss of load probability, particularly in high-renewable islanded scenarios. FLC provided robust and adaptive behavior in moderately variable conditions, while droop control, though simple and communication-free, showed reduced efficiency and higher costs. The application of two-way ANOVA confirmed that these performance differences are statistically significant, and the regression model revealed that control strategy has the greatest influence on energy cost, followed by renewable penetration and storage capacity. Together, these findings offer both technical and economic insights, guiding operators in selecting control strategies that balance stability, cost, and robustness.

DECLARATION OF GENERATIVE AI IN SCIENTIFIC WRITING:

During the preparation of this work, the authors used Google Gemini in order to improve language, readability, and formatting. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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