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Optimal Dispatch of Diesel-Photovoltaic Hybrid Systems in Isolated Communities with Socioeconomic Prediction of Electricity Demand

Despacho óptimo de sistemas híbridos diésel-fotovoltaico en comunidades aisladas con predicción socioeconómica de la demanda eléctrica

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Abstract

The optimization of economic dispatch in hybrid diesel photovoltaic systems within Non-Interconnected Zones (NIZ) is essential to enhance energy sustainability and reduce operating costs. The variability of renewable generation and the uncertainty of electricity demand hinder efficient planning, underscoring the need for advanced optimization models. The purpose of this research was to develop an economic dispatch model for diesel generators integrated with photovoltaic generation, incorporating electricity demand forecasting. The methodology was based on formulating a quadratic programming problem and applying vector autoregressive models supported by socioeconomic variables. Simulations were carried out in Python using the IPOPT (Interior Point Optimizer) solver. The proposed model aimed to optimize operational efficiency by reducing CO_2 emissions and production costs. The analysis was applied to a modified version of the IEEE 33-bus distribution system. The results showed that the optimal dispatch reduced generation costs by 32.1%, decreasing from USD 15 853.83 in the base scenario to USD 10 769.82 with the inclusion of photovoltaic generation. Likewise, daily fuel consumption decreased by 4 227.4 gallons, while CO_2 emissions were reduced by 41 926.1 kg. In addition, solar generation contributed 4 249.2 kWh per day, equivalent to 5.09% of total demand, directly reducing technical losses from 292 kW to 243 kW. In conclusion, the results demonstrate that the integration of predictive models and optimization techniques improves operational performance and supports sustainable energy planning in isolated communities.

Keywords

Autoregressive vectors, energy forecasting, optimization models, photovoltaic systems.

Resumen

La optimización del despacho económico en sistemas híbridos diésel-fotovoltaico en zonas no interconectadas (ZNI) es clave para potenciar la sostenibilidad energética y reducir costos operativos. La variabilidad de la generación renovable y la incertidumbre en la demanda dificultan una planificación eficiente, lo que resalta la necesidad de modelos avanzados de optimización. El propósito de esta investigación fue crear un modelo de despacho económico de generadores a diésel integrados con generación fotovoltaica, considerando el pronóstico de la demanda eléctrica. La metodología se basó en la formulación de un problema de programación cuadrática y la aplicación de vectores autorregresivos sustentados en variables socioeconómicas. Las simulaciones se realizaron en Python, y el solver IPOPT (Interior Point Optimizer). El modelo buscó optimizar la eficacia operativa, disminuyendo las emisiones de CO_2 y los costos de producción. El análisis se aplicó a una versión modificada del sistema IEEE de 33 nodos. Los resultados mostraron que el despacho óptimo reduce los costos de generación en un 32,1 %, pasando de USD 15 853,83 en el escenario base a USD 10 769,82 con la incorporación de la generación fotovoltaica. De igual forma, se logró una disminución diaria en el consumo de combustible de 4 227,4 galones y una reducción en las emisiones de CO_2 de 41 926,1 kg. Asimismo, la generación solar aportó 4 249,2 kWh por día, equivalente al 5,09 % de la demanda total, contribuyendo directamente a la disminución de las pérdidas técnicas, que pasaron de 292 kW a 243 kW. En conclusión, los resultados demuestran que la integración de modelos predictivos y técnicas de optimización mejora el desempeño operativo y favorece la planificación energética sostenible en comunidades aisladas.

Palabras clave

Vectores autorregresivos, previsión energética, modelos de optimización, sistemas fotovoltaicos.

1. INTRODUCTION

The continuous rise in global energy demand, coupled with the imperative to reduce carbon emissions, has accelerated the transition toward more sustainable and efficient energy systems. Within this framework, isolated communities encounter significant challenges due to their strong dependence on diesel-based generation, which entails high operating costs and considerable environmental impacts [1]. The incorporation of renewable sources, particularly photovoltaic systems, has been extensively examined as a viable alternative to enhance energy performance in such contexts. Nonetheless, the inherent variability of solar power and the uncertainty associated with electricity demand necessitate the application of advanced optimization strategies to ensure efficient and sustainable economic dispatch [2], [3].

Optimization-based approaches have emerged as a crucial tool to address these challenges, demonstrating their effectiveness in improving both the planning and operation of hybrid diesel photovoltaic systems [4]. Furthermore, the inclusion of socioeconomic variables in demand forecasting contributes to energy management strategies that better align with the actual consumption patterns and needs of local populations [5], [6].

Recent developments combining mathematical programming, time-series simulation, and machine learning techniques have significantly improved the utilization of available energy resources, thereby enhancing system reliability and supply continuity [7], [8]. Over the past few years, numerous studies have explored the optimization of economic dispatch in hybrid diesel renewable systems. For instance, the research conducted by [9] proposed a stochastic dynamic programming model to optimize the operation of coal-fired thermal plants, showing that the integration of renewables can substantially reduce operational costs. Similarly, other investigations have applied multi-agent optimization algorithms to economic dispatch problems in distribution networks, concluding that artificial intelligence driven methods can markedly improve energy efficiency [10].

In parallel, recent studies have underscored the relevance of incorporating predictive models into rural grid management. Approaches based on Markov chains and deep learning architectures have been employed to enhance demand forecasting accuracy, achieving notable reductions in estimation errors [11]-[13]. Other works have highlighted the importance of integrating socioeconomic dimensions into demand prediction models to ensure that optimization strategies are adapted to local conditions [14].

Despite these advances, several research gaps remain that justify the development of the present study. First, many existing optimization models overlook variability in demand estimation, which can adversely affect system performance and operational efficiency [15]. Second, limited attention has been paid to the integration of socioeconomic parameters into demand forecasting, a critical factor for tailoring hybrid systems to the specific characteristics of isolated communities [16], [17].

Moreover, few studies have investigated the influence of renewable generation variability on the operational stability of hybrid systems, complicating the design of effective mitigation strategies for intermittency [18]. Another relevant shortcoming involves the scarcity of research combining advanced predictive modeling techniques such as vector autoregression with computational simulations to assess the impact of dispatch strategies on cost reduction and emission control [19], [20]. Finally, the optimization of energy storage remains marginal in most current models, constraining its potential to improve the operational efficiency of diesel renewable hybrid systems in non-interconnected regions [21].

In response to these gaps, the present research aims to develop and assess an optimization model for the optimal dispatch of diesel photovoltaic generation in isolated communities. The model integrates socioeconomic variables into electricity demand forecasting through the use of vector autoregressive models and computational simulations. The ultimate objective is to formulate an economic dispatch framework that combines diesel generation and photovoltaic inputs while accounting for demand dynamics.

The contribution of this study lies in the design of a comprehensive mathematical model for optimal dispatch in diesel photovoltaic hybrid systems, intended to enhance energy planning and management processes. The proposed methodology incorporates demand forecasting techniques based on socioeconomic indicators, thereby improving the accuracy and applicability of decision making in hybrid microgrids. Unlike conventional approaches that treat demand as a static input or rely exclusively on historical data, this research introduces a dynamic analysis tailored to the real conditions of Non-Interconnected Zones (NIZ) using vector autoregression and computational simulations. This methodological integration enables more efficient energy planning, quantifiable reductions in operational costs and CO_2 emissions, and strengthens the sustainability and feasibility of the energy transition in isolated territories.

The remainder of this article is structured as follows. Section 2 outlines the adopted methodology, detailing the simulation design, computational tools, and mathematical models used in demand forecasting and economic dispatch. Section 3 presents the results and discussion, evaluating the model's performance. Finally, Section 4 provides conclusions on the model's applicability to energy planning.

2. METHODOLOGY

The proposed methodology seeks to enhance the economic dispatch process through the precise management of short-term power forecasts. The analysis integrates photovoltaic distributed generation (PV-DG) into a modified IEEE 33-node test system, enabling the evaluation of thermal generation dispatch under realistic operating conditions. The entire implementation was carried out in Python using the IPOPT solver to ensure computational efficiency and robustness.

The assessment focuses on key performance indicators such as reductions in generation costs, energy losses, fuel consumption, and CO_2 emissions, as well as improvements in voltage stability and overall system reliability. The methodological framework is structured into several key stages: data acquisition and preprocessing, load simulation and demand forecasting for the IEEE 33-bus system, economic dispatch optimization, and the subsequent analysis and validation of performance metrics. A detailed description of the algorithm developed to address the optimization problem is presented below.

Step 1: Start
Step 2: Data collection and processing
- Power demand, and generation (monthly and hourly profile)
- Environmental variables (temperature, radiation)
- Characterize the distribution network (topology, R, X, Z, length, load, voltage)
- GPV sizing (selection of the photovoltaic panel (Icc, Voc, Pmax, energy to be supplied)
- Calculation and efficiency (temperature losses)
- Levelized Cost of Energy (LCOE)

Step 3: Load Simulation and Electrical Demand Forecasting (IEEE 33 System)
- VAR model (medium-term power forecasting)
- Load flow simulation with Matpower (Voltage profile, power losses, system demand)

Step 4: Economic dispatch
- Objective function (Min. generation costs)
- Decision variables (power generated by diesel and photovoltaic)
- Restrictions (power balance, voltage limits, generation capacity)
- Running simulations without DG (baseline System Performance)
- Optimal location of DG (criticality index based on power losses and voltage profiles)
- Simulations (integration of DG into the distribution system)
- Solving the optimization problem (continuous quadratic programming, Python, and the IPOPT solver)

Step 5: Results analysis
- Reduction in network losses, improvement in voltage profiles, reduction in CO_2 emissions, and reduction in operating costs
- Comparison of scenarios, validation of system efficiency and sustainability

Step 6: End

2.1 Problem formulation

Isolated communities largely depend on diesel-based generation systems, which are characterized by high operational costs and significant CO_2 emissions, thus compromising their long-term sustainability and economic feasibility. The incorporation of renewable energy sources, particularly solar generation, emerges as a promising alternative; nevertheless, the inherent variability of these resources, coupled with fluctuations in electricity demand, complicates efficient energy dispatch planning. Traditional approaches often treat demand as a static parameter or rely solely on historical consumption patterns, disregarding the socioeconomic dynamics that influence energy use and growth. Such simplifications may result in suboptimal allocation of resources and partial exploitation of the renewable generation potential already installed.

In response to these limitations, the present study proposes an optimization framework that integrates demand forecasting with socioeconomic indicators to deliver a more comprehensive and context-sensitive modeling approach for isolated systems. by employing vector autoregression techniques and computational simulations, the model enhances operational efficiency while enabling measurable reductions in both costs and CO_2 emissions. Ultimately, this approach supports more resilient and sustainable energy planning, contributing to the gradual transition toward cleaner and more reliable distributed generation schemes.

2.1.1 VAR model (Vector Auto Regressive)

A VAR model is a model constructed from reduced form simultaneous equations without constraints. The procedure is applied to examine the behavior of a variable, Y, through a group of variables X. This model produces a correlation with more than one variable, and they are related linearly [22], [23]. In a VAR model, all variables are considered equally and are explained by their own past values and those of each other. The model consists of as many equations as variables and includes the lagged values of all of them as explanatory factors in each equation. Once estimated, it is possible to exclude certain explanatory variables depending on their statistical significance. The general formulation of the model is expressed in (1), (2) and (3).

$$y(x_1, x_2 \dots x_n) = b_0 + b_1 x_{11} + b_2 x_{21} + \cdots + b_n x_{n1} \quad (1)$$

$$y_1 = b_0 + b_1 x_{11} + b_2 x_{21} + b_3 x_{31} + b_n x_{n1} \quad (2)$$

$$y_2 = b_0 + b_1 x_{12} + b_2 x_{22} + b_3 x_{32} + b_n x_{n1} \quad (3)$$

2.1.2 Active and reactive power losses

The sum of the active and reactive losses in each branch, as explained in (4) and (5), can be used to calculate the total active and reactive energy loss in distribution networks.

$$Ploss = \sum_{br=1}^{nbr} I_{br}^2 * R_{br} \quad (4)$$

$$Qloss = \sum_{br=1}^{nbr} I_{br}^2 * X_{br} \quad (5)$$

Where Ploss is the total active power loss, b_r is the branch location, n_{br} represents the number of branches, I_{br} is the series current flowing through the branch, and R_{br} is the resistance of the branch, Qloss refers to the total reactive power loss, X_{br} is the reactance of that branch.

2.1.3 Solar cell power losses

The power losses of the solar generator due to the effect of the surrounding temperature on the solar cell surface are explained by (6). As explained in (7), a solar cell's efficiency tends to decline with increasing temperature. This is because heat has a detrimental effect on the cell's ability to produce energy [24].

$$\Delta P_{cel} = P_{cel_{stc}} * (1 + \frac{\Upsilon}{100}(T_{cel} - 25)) \quad (6)$$

$$T_{cel} = T_a + G(\frac{NOCT - 20}{800}) \quad (7)$$

Where, ΔP_{cel} is the variation of the power output, $P_{cel_{stc}}$ is the nominal power of the cell, Υ is the thermal coefficient of power of the cell, The solar cell's temperature is denoted by T_{cel}, the ambient temperature by T_a, G is the solar radiation, and the thermal coefficient under non-standard conditions by $NOCT$.

2.1.4 Associated costs of thermal generation

The cost function of the diesel generator is modeled using a quadratic equation (8) [25]. Where C_{G_T} is the cost of diesel thermal generation, P_{g_T} is the active power, $a_{g_T}, b_{g_T}, c_{g_T}$ are defined as the cost coefficients of the thermal generator.

$$C_{G_T} = a_{gT} * P^2{}_{g_T} + b_{g_T} * P_{g_T} + c_{g_T} \tag{8}$$

2.1.5 Costs associated with PV generation

The costs of implementation, operation, and maintenance of photovoltaic generation are detailed in (9) [26]. Where $C_{G_{pv}}$ are the renewable generation costs, c_{pv} is the cost coefficients, P_{pv} is the power of the photovoltaic module.

$$C_{G_{pv}} = C_{pv} * P_{pv} \tag{9}$$

2.2 Mathematical model

2.2.1 Objective function – minimize total generation costs

The mathematical model consists of an objective function and a set of constraints that ensure compliance with the system's operational requirements. It also ensures that electricity demand is met over a 24-hour horizon, taking into account load variability, technical losses, and fluctuations in environmental conditions. The key elements that make up the model are detailed in (10).

$$\text{Min } C_{tot_G} = \sum_{g_T=1}^{n_{g_T}} \sum_{t=1}^{T} \left(a_{g_{T,t}} * P^2{}_{g_{T,t}} + b_{g_{T,t}} * P_{g_{T,t}} + c_{g_{T,t}} \right) - \sum_{pv=1}^{n_{p_V}} \sum_{t=1}^{T} \left(C_{pv,t} * P_{pv,t} \right) \tag{10}$$

2.2.2 Restriction: power balance

They refer to the balance of production of each thermal unit equation (11), taking into account that total production is adequate to cover the needs of the electrical system for over 24 hours.

$$P_{g_{T,t}} + P_{pv,t}.(\Upsilon_i) - P_{Load,t} - P_{Loss_{i,j,t}} = 0, \ \ \forall \text{ t} \in \{ 1,..\text{T} \}, \forall \text{ pv} \in \{ 1,..n_{pv} \}, \forall \, g_T\{ 1,..n_{g_T} \}, \Upsilon_i \in \{ 0,1 \} \tag{11}$$

2.2.3 Restriction: power limits in thermal generation

Equations (12) and (13) refer to the upper and lower limits of the power of each thermal generator, ensuring that the capacities and operating requirements are respected.

$$P_{g_{T,t}}{}^{min} \leq P_{g_{T,t}} \leq P_{g_{T,t}}{}^{max} \quad \forall \text{ t} \in \{ 1,..\text{T} \}, \forall \, g_T \in \{ 1,..,n_{g_T} \} \tag{12}$$

$$Q_{g_{T,t}}{}^{min} \leq Q_{g_{T,t}} \leq Q_{g_{T,t}}{}^{max} \quad \forall \text{ t} \in \{ 1,..\text{T} \}, \forall \, g_T \in \{ 1,..,n_{g_T} \} \tag{13}$$

2.2.4 Restriction: voltage limit

The acceptable voltage limits within the requirement are established by standards and engineering criteria as detailed in (14).

$$V_i{}^{min} \leq V_i \leq V_i{}^{max} \qquad \forall \text{ i} \in \{ 1,2..,\text{nbus} \} \tag{14}$$

2.3 Test and simulation system

To carry out the simulations, the 33-node IEEE models, widely used in power flow studies and optimization in distribution networks, were used. However, these systems were modified to incorporate four diesel generators, three of 2000 kW and one of 1250 kW, all connected to node 1 (slack), to replicate the conditions of the generation system of the municipality of Inírida, in the department of Guainía, Colombia. This region is classified as a Non-Interconnected Zone [27]. This configuration facilitated the evaluation of the impact of the incorporation of renewable generation on economic dispatch. Through computer simulations, the performance of the system was examined with voltage stability, loss reduction, and operating cost optimization. The general information on the test systems is detailed in Table 1.

Table 1. Test system – IEEE 33. Source: own elaboration.

Variable	Value
Nodes	33
Branches	32
Generator	4
Load	32
Voltage (kV)	12.66
Gen set (kW)	7250

Figure 1 shows the modified diagram of the IEEE 33-bus test system. The total system load is 3715 kW and 2300 kVAr. Four diesel generator sets were incorporated for the generation system, achieving a total capacity of 7250 kW. The total power losses are 203 kW and 143 kVAr.

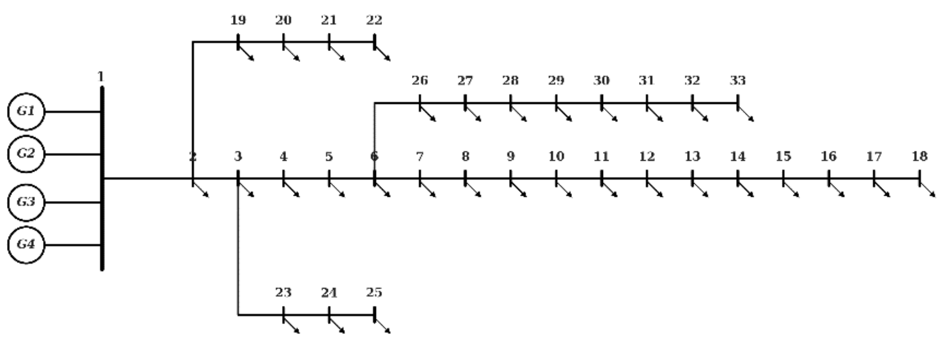

Figure 1. Modified IEEE 33-Node test system. Source: own elaboration.

2.3.1 Simulation scenarios

This study analyzes the medium-term power projection and economic dispatch of thermal plants. The proposed scenarios seek to evaluate technical losses, voltage profile, CO_2 emissions, and operating costs. Six scenarios are developed, starting with the baseline scenario without DG, and then progressively integrating PV generation. The scenarios are described in Table 2.

Table 2. Simulation scenarios. Source: own elaboration.

Case 1	Scenario	Source PV	Power capacity PV (kWp)
Demand	0	Without PV	0
Forecast 2029	1	1(PV)	100
IEEE bus	2	2(PV)	200
System	3	3(PV)	300
	4	4(PV)	400
	5	5(PV)	500

2.3.2 Solar module selection and levelized cost of energy (LCOE)

The selected solar panel is the Hiku6 model, which belongs to the Canadian Solar brand, characterized by its monocrystalline structure and a maximum power of 550 Wp. The solar generator capacity is set at 100.2 kWp, based on a daily demand of 405.94 kWh.

This calculation considers an operating period between 6:00 a.m., and 6:00 p.m., ensuring sufficient generation to meet the system's energy needs. One important metric for assessing a generating system's economic feasibility is the levelized cost of energy (LCOE), as it integrates the initial investment, operating, administrative, and maintenance costs, as well as the energy produced over its lifetime [28]. For a 100.2 kWp photovoltaic generator, an LCOE of 0.068 USD/kWh was obtained, making it a key factor for optimizing economic dispatch. Technical details are presented in Table 3.

Table 3. Solar module technical data - LCOE. Source: own elaboration.

Solar module selection	Electrical data	Photovoltaic Generation Sizing	Electrical data
Reference - Canadian Solar HiKu6 Mono PERC		Peak Solar Hour (PSH) - Inírida Region	4.05
Maximum rated power (Pmax) - W	550	Energy available per day (kWh/d)	405.94
Operating voltage (Vmp) - V	41.7	Maximum power of the PV generation system (kWp)	100.2
Operating current (Imp) - A	13.2	Module power (Wp)	550
Open circuit voltage STC- (Voc) - V	49.6	Number of photovoltaic modules (un)	182.2
Short circuit current- (Isc) - A	14	*LCOE (Levelized Cost of Energy)* LCOE= CAPEX+OPEX/Energy Life Cycle (USD/kWh)	0.068
Module efficiency - %	21.5		
Temperature STC - °C	25		
Nominal temperature of the operation module °C +-3	42.0		
Temperature coefficient (Pmax) %/°C	-0.34		
Temperature coefficient (Voc) %/°C	-0.26		
Temperature coefficient (Isc) %/°C	0.05		
Minimum temperature recorded in the areas °C	20		

2.3.3 Solar cell temperature

As shown in Figure 2, when the ambient temperature rises above 38.2°C, the solar cell can reach a temperature of approximately 67.9°C. This observation highlights the strong dependency of panel efficiency on thermal conditions. As the cell temperature increases, the overall system performance declines, with efficiency levels stabilizing around 85%, thereby confirming the notable impact of temperature on photovoltaic operation.

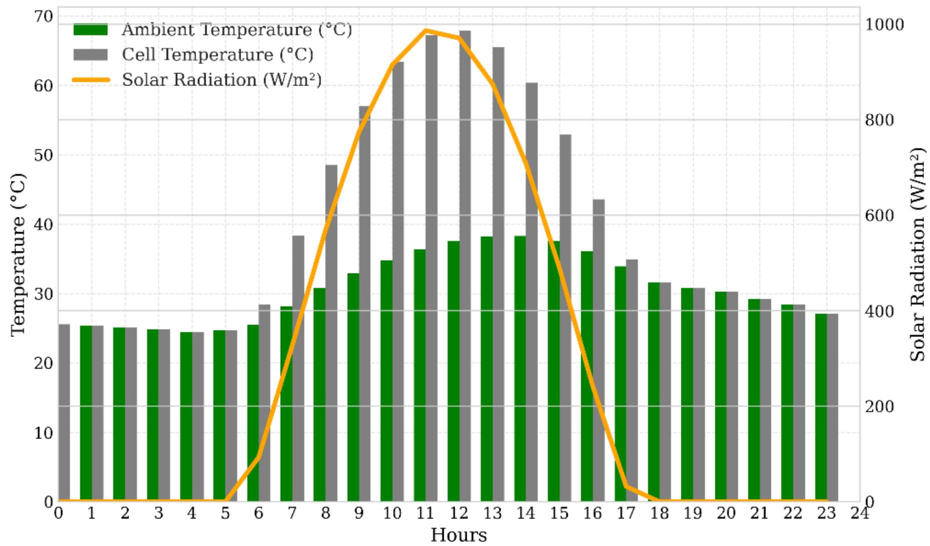

Figure 2. Solar panel efficiency curve. Source: own elaboration.

2.3.4 Energy demand forecast

This section presents the electric power demand forecasting technique based on the Vector Autoregression (VAR) method. The database used includes monthly records from January 2010 to December 2023, as detailed in Figure 3.

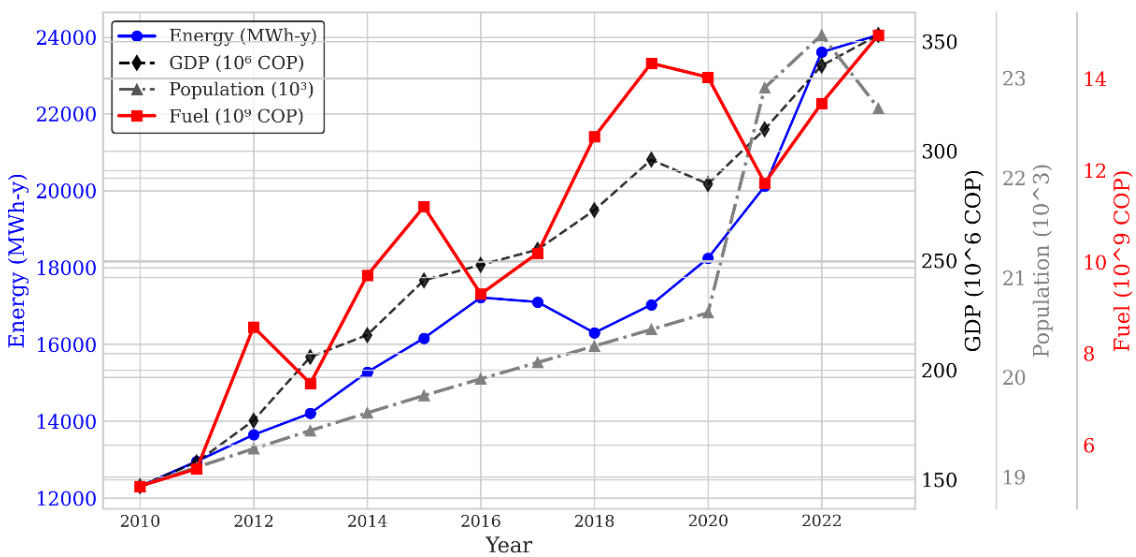

Figure 3. Time series: GDP, Energy, Population and $_ fuel. Source: own elaboration.

For the analysis of electricity demand forecasts, key econometric variables were used, such as the region's GDP, population, and fuel costs. The database used corresponds to the municipality of Inírida, located in the department of Guainía, Colombia. The purpose of the multicriteria model developed is to identify the most efficient technique for selecting the most relevant variables. To this end, statistical variable selection methods were applied, including backward, forward, and stepwise approaches. Table 4 shows the results of the VAR model.

Table 4. Results and interpretation of the VAR model. Source: own elaboration.

Indicator	Value	Interpretation
Multiple correlation coefficient	0.975	It indicates a very strong relationship between the explanatory variables and the dependent variable.
Coefficient of determination (R^2)	0.951	Explains 95.1% of the variability in electricity demand through GDP, population, and fuel price variables.
Adjusted R^2	0.935	Adjusts for the number of variables in the model, maintaining high explanatory power.
Standard error	785.02	The model shows a moderate average deviation in the predictions.
F-statistic	58.15	It indicates that the overall model is statistically significant ($p < 0,001$).
Significant variable	Population ($p = 0.034$)	Population has a positive and statistically significant effect on electricity demand.
Variables with low significance	GDP and fuel price ($p > 0.05$)	Their effect is less decisive within the 95% confidence interval.

The VAR model demonstrates strong statistical performance, with a multiple correlation coefficient of 0.975 and an R^2 of 0.95, indicating that 95% of the variability in energy demand is explained by the selected variables. The adjusted R^2 value of 0.93 indicates that the model exhibits strong explanatory capacity relative to the sample size. The ANOVA results ($F = 58.15$; $p < 0.001$) further confirm the overall statistical validity of the model. Among the explanatory variables, population emerges as a positive and statistically significant determinant ($p = 0.034$), underscoring its direct impact on energy demand. In contrast, GDP and fuel price, although not statistically significant ($p > 0.05$), display coherent and stable relationships with the dependent variable. The sensitivity analysis reinforces these findings by identifying population as the primary driver influencing future demand projections. Taken together, these results demonstrate that the VAR model is both statistically robust and theoretically coherent, making it an appropriate tool for examining energy demand dynamics in NIZ.

The VAR model was implemented to estimate the evolution of electricity demand over a 60-month period. The results show that, by 2029, demand will increase by 18.2%, as detailed in Figure 4.

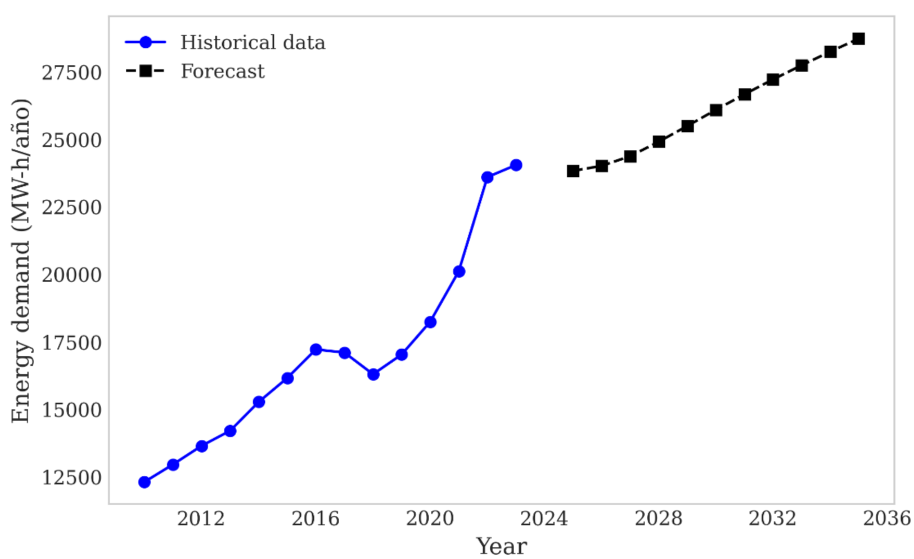

Figure 4. Energy demand forecast – VAR model. Source: own elaboration.

With this projection, we evaluate the hourly power demand of the test system, considering its maximum power. Figure 5 shows the projection for the IEEE 33-node test model, highlighting a peak demand of 4397 kW. This information allows us to analyze the system's performance throughout the study period.

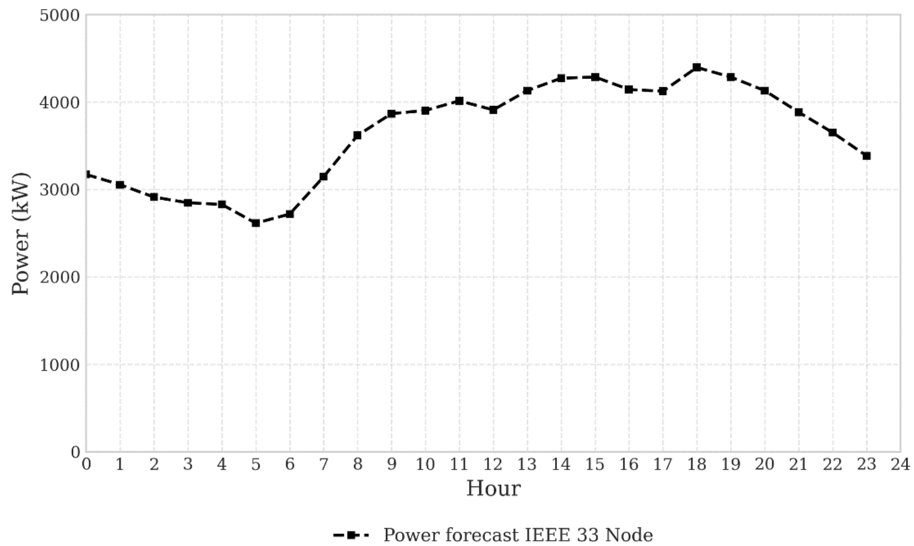

Figure 5. Power forecast 2033 - IEEE 33-node test system. Source: own elaboration.

2.3.5 Location criteria for distributed generation

The selection of nodes for the DG installation was based on a criticality index (CI) that considers the highest power losses and the lowest voltage profile value recorded in the IEEE 33 test model. The power losses and voltage profiles were evaluated with Matpower version 7.1. Table 5 shows the location of the DG, indicating the selected nodes and the values associated with the power losses, voltage levels, and the criticality index.

Table 5. Criticality index - DG node location. Source: own elaboration.

DG node location	Ploss IEEE33	Voltage p.u.	Critical Index (CI)
6	55	0.940	3.30
3	74	0.980	1.48
28	16	0.920	1.28
5	27	0.962	1.02
29	11	0.911	0.97

2.3.6 Fuel input and output cost function

In this study, the QSK60-G6 and KTA50-G3 diesel generators, with nominal powers of 2500 kVA and 1578 kVA, are used as references. They are part of the generation system of the municipality of Inírida, Colombia. The fuel input and output cost functions of these machines are analyzed to determine their impact on operational efficiency and cost reduction in power generation. The cost functions of each machine are detailed in Table 6.

Table 6. Cost function. Source: own elaboration.

Reference	Gen. Set	Cost function
QSK60-G6	2500 kVA	Y=6E-6X^2 + 0.1398X + 28.012
KTA50-G3	1578 kVA	Y=1E-6X^2 + 0.1478X + 15.004

3. RESULTS AND DISCUSSION

This analysis includes the incorporation of photovoltaic DG into the modified IEEE 33-node model. The results are evaluated in terms of generation cost reduction, technical power losses, fuel consumption, voltage profiles, and CO_2 emissions, among other aspects.

3.1 Scenario evaluation - IEEE 33-node test system

In Table 7, the results of the performance of the optimization model applied to the economic dispatch of generation are analyzed and evaluated.

Table 7. Results of simulated scenarios – IEEE 33 system. Source: own elaboration.

Scenario	Source PV	Power capacity (kWp)	Generation cost (USD)	Ploss (kW)	Energy Gen set (kW)	DG contribution to grid (kWh)	Fuel consumption (gal)	CO_2 emissions (kg)	Nodes locate DG
0	Without GD	0	$ 15853.82	292	92027.3	0	6222.9	61717.8	0
1	1 (PV)	100	$ 14842.48	282	91128.7	849.84	5826.0	57780.7	6
2	2 (PV)	200	$ 13811.68	278	90100.0	1699.68	5421.4	53767.9	6, 3
3	3 (PV)	300	$ 12790.96	264	89136.3	2549.52	5020.7	49794.3	6, 3, 28
4	4 (PV)	400	$ 11775.37	257	88205.2	3399.36	4622.1	45840.7	6, 3, 28, 5
5	5 (PV)	500	$ 10769.82	243	87339.1	4249.20	4227.4	41926.1	6, 3, 28, 5, 29

3.1.1 Base scenario without integrating DG

The baseline scenario represents grid operation without distributed generation integration. In this case, all energy is supplied by diesel generators, with CO_2 emissions of 61 717.8 kg and a daily fuel consumption of 6 223.0 gallons. Generation costs reach USD 15 853.83 per day, while power losses amount to 292 kW.

3.1.2 Scenario with DG integration

Fuel consumption and CO_2 emissions: The incorporation of PV generation demonstrates a significant decrease in diesel power generation. As shown in Figure 6, a reduction in fuel consumption and CO_2 emissions is detailed. In Scenario 1, the energy supplied by the diesel generators is 91 128.7 kWh, implying a daily consumption of 5 826.0 gallons of fuel and a reduction in CO_2 emissions to 57 780.7 kg, achieving a contribution of 6.4 % in the reduction of emissions. In scenario 3, CO_2 emissions are reduced to 49 794.3 kg, while fuel consumption decreases to 5 020.8 gallons per day. The energy supplied by the diesel generators is 89 136.4 kWh per day. In scenario 5, CO_2 emissions are reduced to 41 926.1 kg and fuel consumption to 4 227.4 gallons per day. Daily generation from the generator sets decreases to 87 339.1 kWh.

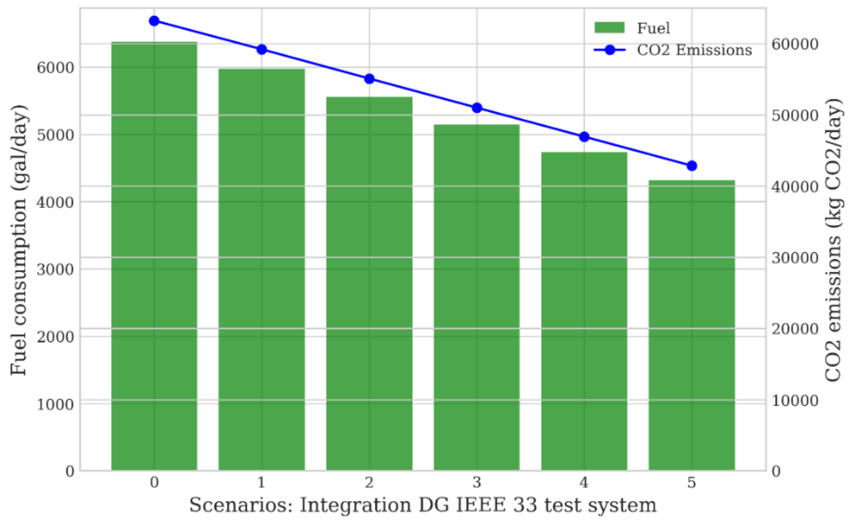

Figure 6. Fuel consumption and CO_2 emissions IEEE 33-node test system. Source: own elaboration.

Voltage profile with DG integration: DG plays a fundamental role in electrical distribution networks. It positively impacts voltage profiles, minimizing them and improving the quality of the electricity supply. Figure 7 shows the voltage profiles in the IEEE 33-node test system. It is evident that the progressive incorporation of DG significantly improves voltage levels, increasing from 11 390 V to 11 533.3 V at some points, ensuring compliance with regulatory standards.

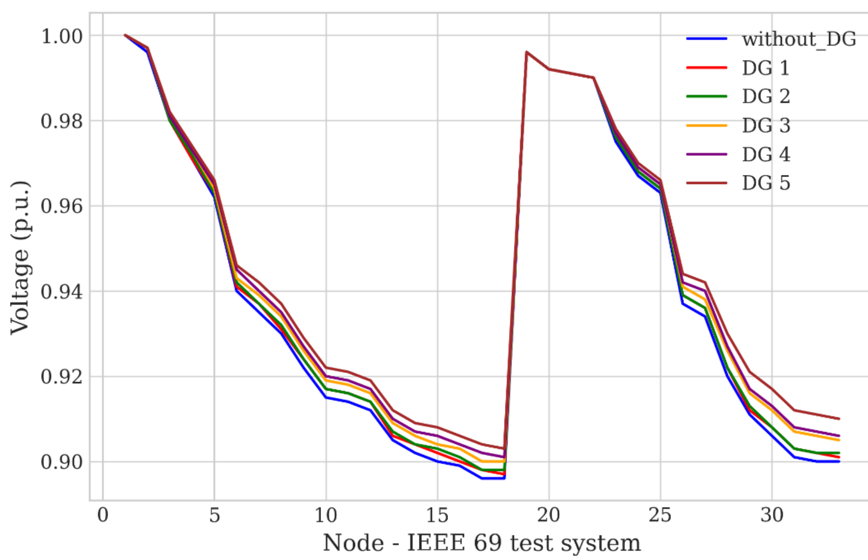

Figure 7. Voltage profile – IEEE 33-node test system. Source: own elaboration.

Generation costs and power losses: The results of scenarios 1, 3, and 5 are shown to illustrate this behavior. Figure 8 shows that, as distributed generation is gradually integrated at the selected nodes, generation costs decrease steadily. Figure 9 also reveals that power losses in the test system have decreased.

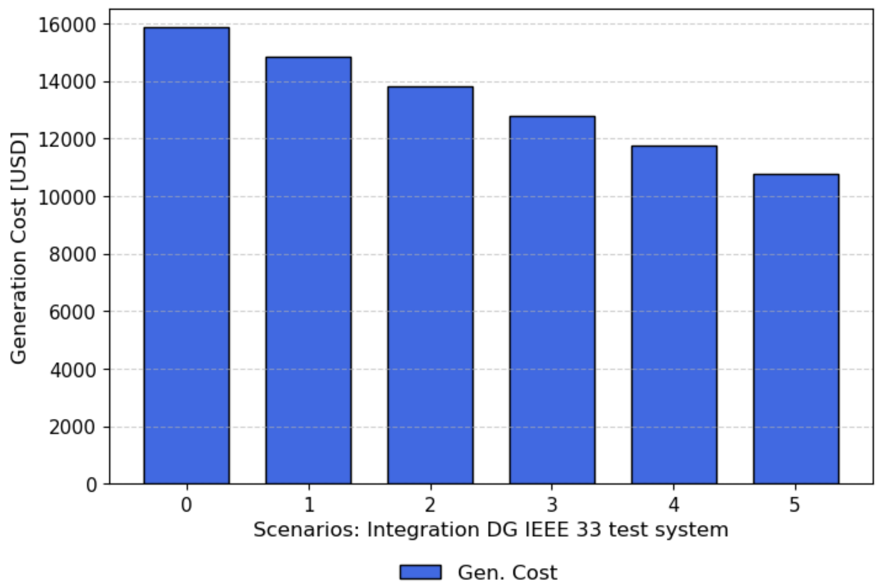

Figure 8. Generation cost – IEEE 33 node test system. Source: own elaboration.

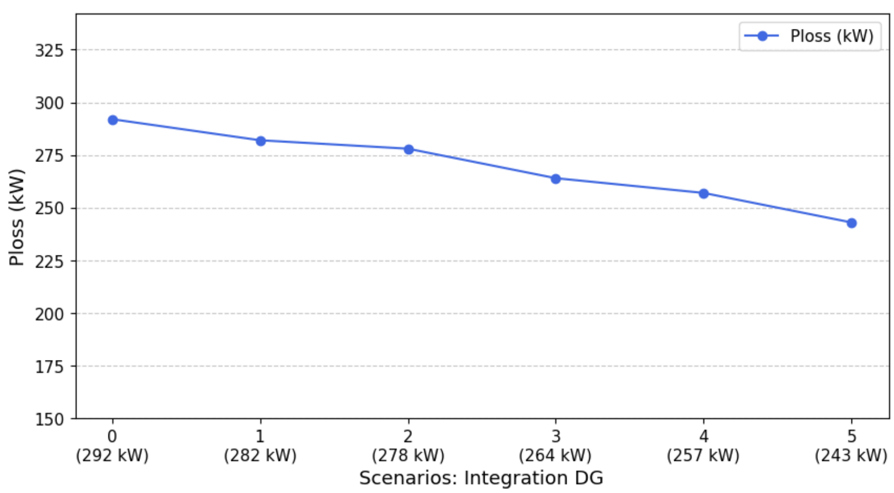

Figure 9. Ploss – IEEE 33-node test system. Source: own elaboration.

In Scenario 1, with an installed capacity of 100 kW of photovoltaic (PV) generation, generation costs are reduced to USD 14 842.48, while power losses decrease to 282 kW. In scenario 3, with 300 kW of photovoltaic generation, generation costs decrease to USD 12 790.96, with power losses of 264 kW. This scenario represents a 19.3% contribution to generation costs. In scenario 5, where the photovoltaic capacity is 500 kW, generation costs drop to USD 10 769.82 and power losses decrease to 243 kW. This helps reduce energy production costs by 32.1%.

Contribution of photovoltaic generation to distribution networks: Integrating distributed photovoltaic energy generation into distribution networks represents a significant energy contribution. In Scenario 1, distributed photovoltaic generation delivers 849.8 kWh of energy to the distribution network, as illustrated in Figure 10. This contribution represents a small decrease in the use of diesel, with a decrease of 0.98% in thermal generation.

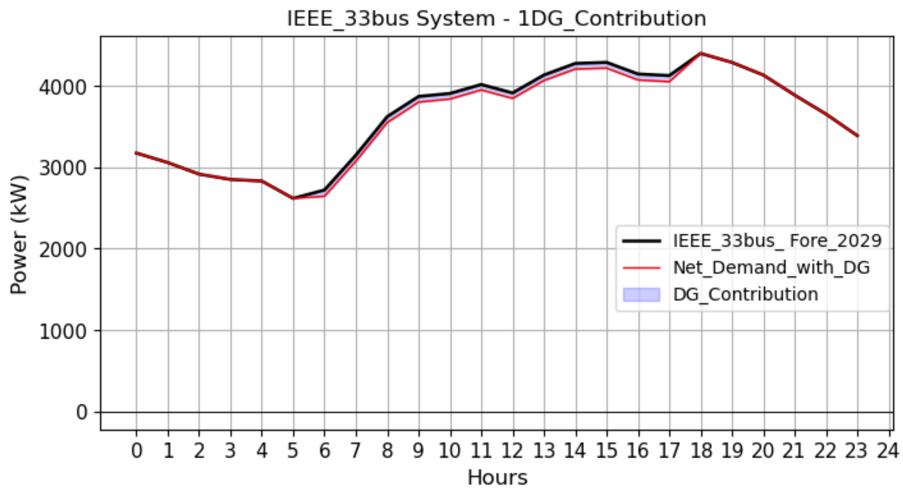

Figure 10. 1DG Contribution IEEE 33-node test system. Source: own elaboration.

In Scenario 2, the distribution grid receives 1 699.7 kWh of energy from distributed photovoltaic generation. As shown in Figure 11, this integration enables a 2.09% reduction in diesel thermal generation, indicating a moderate amount of distributed generation in the energy mix.

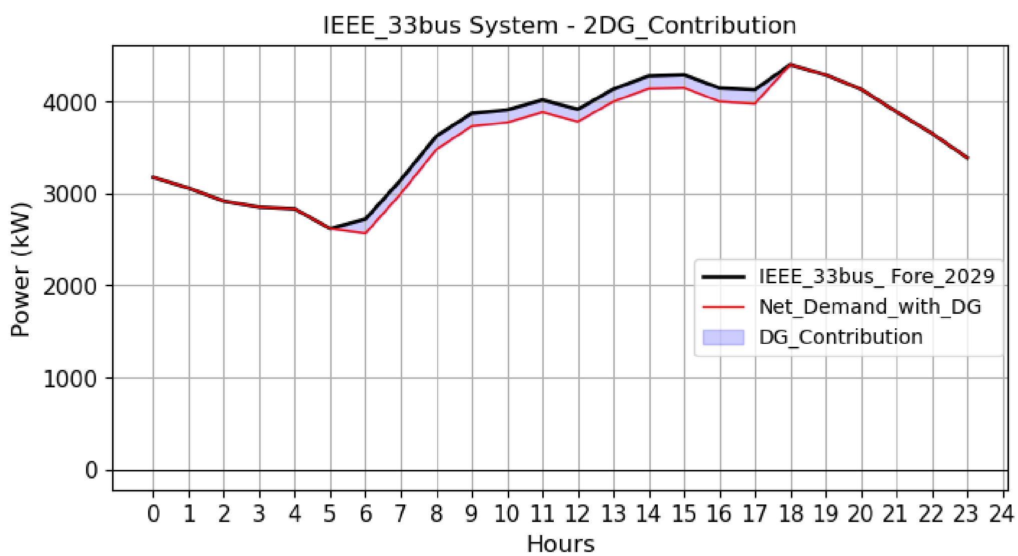

Figure 11. 2DG Contribution IEEE 33-node test system. Source: own elaboration.

In Scenario 3, as shown in Figure 12, 2 549.5 kWh of energy are injected into the distribution system by photovoltaic distributed generation. In this instance, DG's involvement enables a 3.14% reduction in thermal generation, demonstrating a moderate contribution to the decrease in fossil fuel consumption. In Scenario 4, Figure 13 illustrates how 3 399.2 kWh of energy are contributed to the electrical grid by distributed photovoltaic generation. By reducing thermal generation by 4.15 %, this contribution amounts to a negligible decrease in diesel fuel consumption. In Scenario 5, the distribution grid receives 4 249.2 kWh of energy from distributed photovoltaic generation. As seen in Figure 14, this integration enables a 5.09% decrease in diesel thermal generation, indicating a moderate amount of distributed generation in the energy mix.

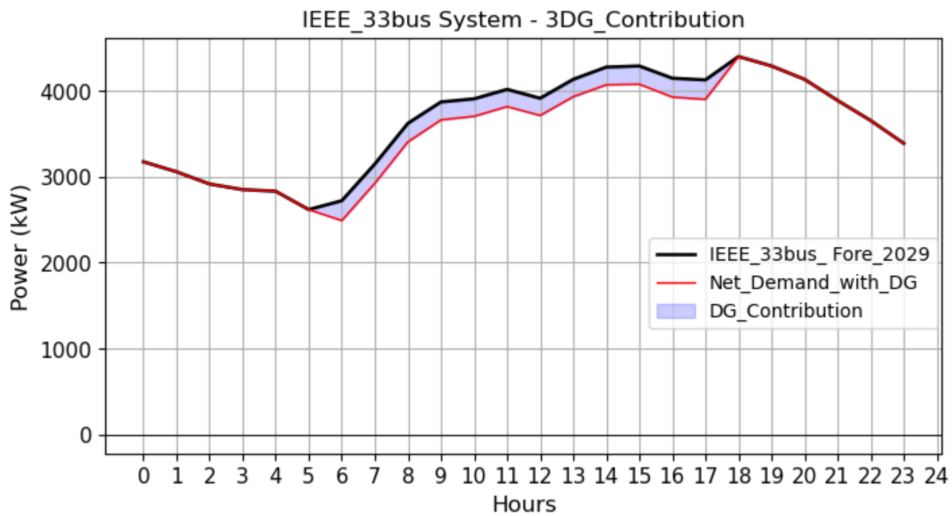

Figure 12. 3DG Contribution IEEE 33-node test system. Source: own elaboration.

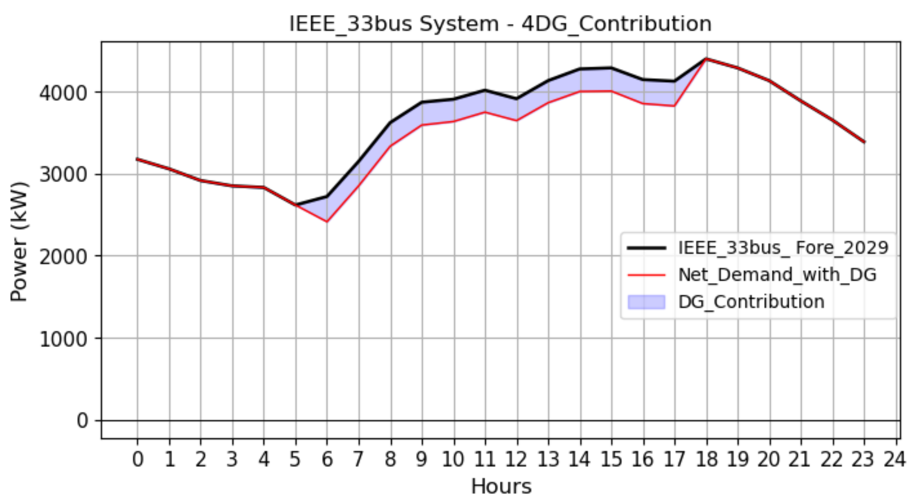

Figure 13. 4DG Contribution IEEE 33-node test system. Source: own elaboration.

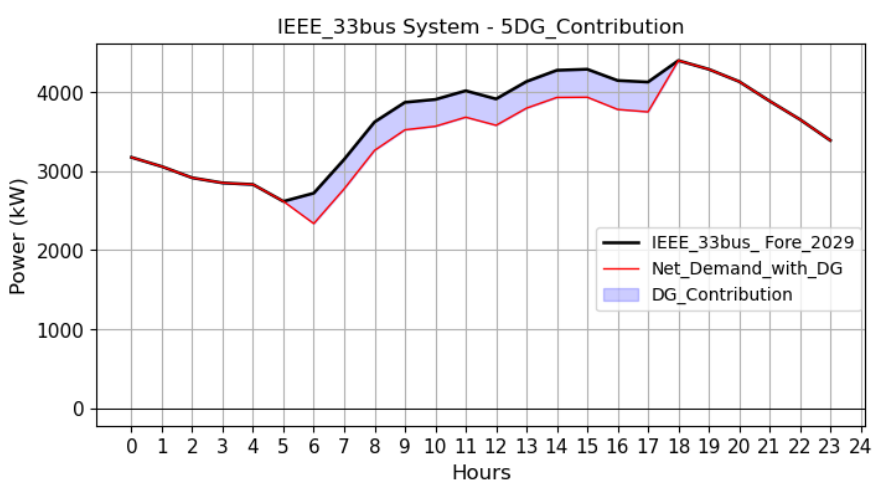

Figure 14. 5DG Contribution IEEE 33-node test system. Source: own elaboration.

Hybrid generation cost curve: Figure 15 illustrates how the generation cost curve gradually drops as the DG share rises, culminating in a reduction of 32.1% in the final scenario. These findings show the financial advantages of DG integration when compared to the base diesel generation curve.

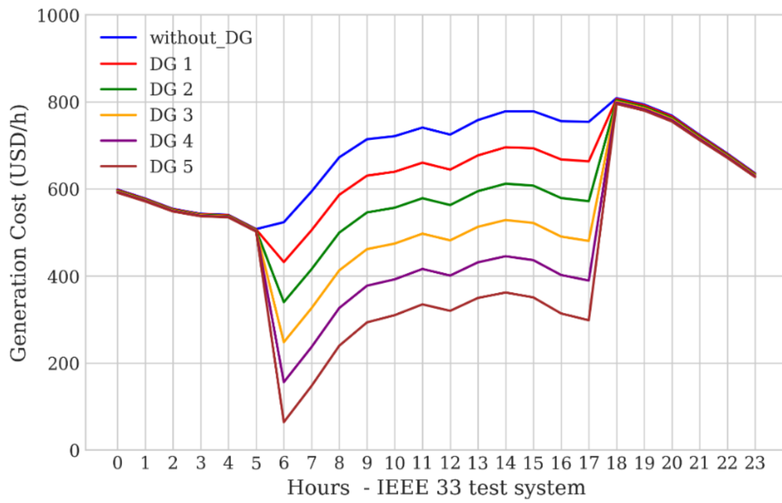

Figure 15. Duck cost curve. Source: own elaboration.

The results of this research indicate that optimizing the economic dispatch of diesel photovoltaic hybrid systems leads to significant reductions in both operating costs and CO_2 emissions in non-interconnected regions. These findings align with previous studies, such as [29], which employed a stochastic dynamic programming model and reported substantial cost reductions compared to conventional deterministic approaches. The present work not only corroborates those results but also extends the analysis by incorporating socioeconomic variables into the demand forecasting process, enabling more accurate and context specific planning.

Furthermore, compared with the study in [30], which used heuristic algorithms to optimize dispatch in hybrid systems, the results obtained here highlight that demand forecasting accuracy plays a decisive role in overall dispatch efficiency. As demand uncertainty decreases, dependence on diesel generation is reduced, and renewable penetration improves, consistent with recent conclusions emphasizing the need for robust predictive strategies to manage energy variability [31], [32].

While the multi-agent framework and stochastic dynamic programming proposed in [33] demonstrate benefits for autonomous microgrid coordination, this study introduces an integrated modeling approach that combines socioeconomic forecasting with deterministic optimization, providing a more accessible tool for regions with technological constraints. This contribution supports more informed decision making for local system operators, an aspect often overlooked in advanced methodologies such as those in [34] and [35].

Additionally, the inclusion of socioeconomic variables such as population growth, consumption behavior, and economic activity indicators aligns with evidence presented in [36], which shows that these factors significantly improve load forecasting accuracy. This study confirms that energy demand in isolated communities is shaped not only by technical dynamics but also by social and economic conditions, reinforcing the relevance of comprehensive approaches such as those suggested in [37].

Moreover, the results show that integrating photovoltaic generation helps reduce technical losses and emissions, consistent with recent research on hybrid systems for decarbonizing remote regions [38], [39]. However, the present work provides a distinct contribution by jointly incorporating demand forecasting, socioeconomic characterization, and an optimization model, offering a methodology that is more flexible and better suited to real operating conditions.

Overall, this research helps bridge an important gap in the literature, as many previous studies have addressed economic dispatch from a purely technical perspective, often overlooking the influence of socioeconomic variables on energy planning. This study demonstrates that incorporating such variables not only enhances forecasting accuracy but also supports more equitable and sustainable strategies for isolated communities. In doing so, it provides a methodological foundation to strengthen public policy development focused on sustainable energy supply planning.

3.1.3 Limitations

Although this research has achieved significant progress, certain limitations must be acknowledged to provide a realistic perspective on its scope. One of the main challenges lies in the availability and reliability of data, since information on energy consumption and local economic dynamics in isolated communities is often scarce or inconsistently recorded. To address this issue, historical datasets were employed; however, the precision of the model may still be influenced by the quality and completeness of the available information.

Another relevant aspect concerns the need for pilot implementations and context-specific calibration prior to the application of the optimization model in real environments. The model's performance largely depends on its capacity to adapt to the unique characteristics of each community, which may require additional methodological refinement.

Moreover, this study did not explore in depth the influence of human factors, such as community acceptance of the proposed model or the level of technical expertise within local populations elements that could considerably affect the success of future implementations. In addition, while the model integrates photovoltaic generation, it provides only a limited examination of energy storage management. Previous research has shown that incorporating battery systems can substantially enhance network stability and decrease operational costs in hybrid diesel renewable configurations, highlighting an area that warrants further investigation [40].

Finally, future developments could benefit from the integration of advanced machine learning algorithms to improve forecasting precision, as well as multi-objective optimization strategies capable of simultaneously addressing economic, environmental, and reliability considerations.

4. CONCLUSIONS

The results of this research reveal that optimizing the economic dispatch of hybrid diesel photovoltaic systems in isolated communities leads to notable reductions in both operating costs and CO_2 emissions, while simultaneously enhancing the overall efficiency and sustainability of the energy supply. The incorporation of vector autoregressive models for demand forecasting, combined with computational simulations, made it possible to design a more precise and context-specific model that reflects real consumption dynamics in remote areas.

Depending on the degree of renewable energy penetration, the optimization process can reduce generation costs by up to 32.2%. Likewise, when fuel consumption reaches 4 320.4 gal/day, CO_2 emissions decrease by approximately 42 848.9 kg. Improvements were also observed in voltage quality as distributed generation was gradually integrated, increasing voltage levels from 11 390 V to 11 533.3 V in certain nodes. This enhancement reduces the unnecessary operation of diesel generators and promotes greater use of renewable sources.

The study successfully fulfilled its main objective: to develop and assess an optimal dispatch model for hybrid diesel–photovoltaic generation that increases system efficiency while minimizing operational costs and emissions in non-interconnected regions. The proposed methodology not only optimizes energy generation but also incorporates socioeconomic considerations into dispatch planning. Unlike earlier approaches that concentrated solely on technical parameters, this research emphasizes the relevance of including economic and social variables in the management of energy demand, thus providing a more comprehensive framework applicable to real-world scenarios.

Furthermore, implementing the optimization model under different simulated conditions allowed an evaluation of thermal generation behavior and projected demand patterns, generating valuable insights for strategic decision-making in energy planning and system operation. Future research may build upon this framework by integrating advanced machine learning algorithms, such as recurrent neural networks, to further refine demand forecasting accuracy.

Finally, pilot applications in real communities are encouraged to assess the practical viability of the model and to explore funding mechanisms that support its implementation in vulnerable regions. Overall, this work advances efficient energy planning and management in isolated communities, offering an innovative and adaptable pathway for sustainable energy optimization in future studies.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHORSHIP CONTRIBUTION

Carlos Arturo Páez: Conceptualization, Methodology, Research, Formal Analysis, Validation, Document Writing, Document Editing, and Supervision.