Optimization and Technical-Economic Evaluation of DC Microgrids with Integrated Renewable Energy Sources

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Abstract. The growing use of renewable energy sources has made the development of efficient and sustainable microgrids increasingly important. In this context, direct current (DC) microgrids have emerged as a suitable solution, as they are more efficient and compatible with renewable energy generation and storage systems.

A mixed-integer linear programming (MILP) model is proposed to optimize the design of DC microgrids comprising photovoltaic modules, wind turbines and energy storage systems. The model determines the optimal number of energy storage systems and generation components. Furthermore, energy exchanges with the main grid are also determined over a long-term planning horizon.

The proposed model is evaluated using five case studies corresponding to different storage configurations and grid interaction scenarios. These case studies are based on seasonal load profiles derived from actual consumption data and solar irradiance data collected between 2019 and 2023. Technical and financial metrics, such as net present value (NPV), levelized cost of electricity (LCOE), internal rate of return (IRR), and payback period (PBP), are used to evaluate the system's performance.

Results show that photovoltaic-based configurations provide the most cost-effective solutions under current market conditions, while the inclusion of storage systems improves long-term profitability despite higher initial investment. Sensitivity analysis highlights the strong influence of energy prices and equipment costs on the optimal configuration.

Keywords: Direct Current Microgrids · Mixed Integer Linear Programming · Renewable Energy

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1 Introduction

With increasing ecological and economic concerns, several countries are providing incentives for the production of clean and sustainable energy. Renewable energy plays an important role in reducing greenhouse gas emissions while contributing to electricity production [21]. This is in line with the Paris Agreement [18], established in 2015, which represents an important milestone in the fight against climate change. The main objective of this agreement is to limit the rise in global temperatures and promote sustainable practices, such as the use of renewable resources.

The growing use of renewable energy sources (RES) leads to considerable challenges for the planning and operation of modern electricity systems. The variability and intermittency of sources such as solar and wind power require flexible and efficient solutions to ensure system reliability and economic viability.

Microgrids (MG) have emerged as an essential component in the development of smart grids. These are small-scale energy systems designed to maximize energy efficiency. They capitalize on production potential, enabling more efficient resource management and contributing to greater system flexibility and resilience. The importance of microgrids in promoting energy efficiency is highlighted by Directive 2018/2002 [5]. These decentralized systems for energy production and distribution facilitate the efficient integration of renewable sources. Flexible operational strategies and optimization algorithms provide microgrids with versatile and effective solutions to contemporary energy demands [20].

This paper presents an MILP model to determine the optimal size and operation of DC microgrids. The system includes photovoltaic and wind generation and considers long-term planning based on seasonal representative days. Different system configurations are analyzed, including the evaluation of techno-economic indicators such as Net Present Value (NPV), Levelized Cost of Energy (LCOE), Internal Rate of Return (IRR), and Payback Period (PBP). In addition, a sensitivity analysis is used to see how changes in energy prices and equipment costs affect system performance.

The paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 presents the optimization model and describes techno-economic indicators. Section 4 describes the case study and Sect. 5 discusses the results. Finally, Sect. 6 presents the main conclusions of the work.

2 Microgrid Optimization: Literature Review

Microgrids represent an innovative advancement in the field of energy distribution, characterized by low-voltage networks that efficiently integrate diverse energy sources, loads, and storage systems [6,9]. Several works in the field of microgrids are referenced below. The article [1] provides a detailed analysis of microgrid architectures and their applications, exploring how MG, composed of both renewable and conventional energy sources, can improve the efficiency and sustainability of electrical systems. The study in [7] examines the transition between grid-connected and islanded operation modes of microgrids. The

main focus is to ensure a smooth transition between these modes without interruptions in energy supply. The work presented in [4] provides an overview of microgrids and practical guidelines for their implementation and operation, highlighting their numerous benefits, including increased resilience and reliability of the energy supply, particularly during main grid failures.

The integration of energy storage systems (ESS) is a promising solution to overcome some limitations and facilitate grid stability. The combination of ESS with renewable energies in microgrids can reduce reliance on conventional energy sources, enhance system resilience and reliability, and contribute to grid decarbonization [19]. Many countries are advancing toward the adoption of smart grids to achieve goals such as environmental sustainability, adequate energy supply, and the integration of electric vehicles, where RES and ESS play a crucial role [2]

To ensure the effective and sustainable operation of renewable energy systems, it is crucial to employ optimization techniques that capture their complexity. Among the widely used methods, Mixed-Integer Linear Programming (MILP) stands out for its ability to model both discrete and continuous variables, providing a powerful framework for addressing the complex decisions involved in integrating, managing, and optimizing renewable energy sources and storage systems. This versatility and effectiveness have made MILP a widely adopted approach in the literature for optimizing renewable energy systems.

In [12,17], the authors employed an MILP model to optimize hybrid renewable energy systems to meet winery demand, accounting for equipment installation costs and environmental constraints related to sustainability.

The article [13] uses a MILP model to optimize the management of an isolated microgrid with storage, accounting for uncertainties in load and renewable energy production. The main objective is to minimize operating costs while ensuring the reliability and continuity of the energy supply.

Although much work has been done in this field, significant challenges remain. It is important to undertake long-term planning, account for component deterioration, and combine optimization techniques with the assessment of technical and economic indicators.

In this context, this paper proposes a MILP-based optimization model for the design and operation of a DC microgrid integrating renewable energy sources and storage systems. The proposed approach incorporates long-term planning, seasonal variability, and a comprehensive techno-economic assessment, providing a more integrated framework for microgrid analysis and decision-making.

3 Optimization Model and Techno-Economic Indicators

This section presents the optimization model and techno-economic indicators.

3.1 Optimization Model

The aim of this work is to design microgrids with renewable energy sources in order to maximize overall benefits. The grid integrates solar and wind power

generation and is supported by energy storage systems to efficiently manage charging and discharging operations, thereby minimizing energy purchases over a 20-year horizon. The problem is formulated as a MILP model to optimize energy production, storage, and distribution, whilst simultaneously respecting technical and economic constraints. The model formulation considers four typical days for each season, with each day divided into 24 h periods, enabling a detailed analysis of the system behavior throughout the year.

Sets and Parameters.

- $D = \{1, \ldots, nd\}$, set of $nd = 4$ periods of a day, one for each season of the year;
- $H = \{1, \ldots, nh\}$, set of $nh = 24$ hourly periods, corresponding to one day;
- $A = \{1, \ldots, na\}$, set of $na = 20$ periods of a year, which is the project lifespan;
- k^{bat}, battery capacity, in kWh;
- pc_{ij}, energy purchase price, in €/kWh, in hour $i \in H$ and day $j \in D$;
- pv_{ij}, energy sale price, in €/kWh, in hour $i \in H$ and day $j \in D$;
- dc_{ij}, energy consumption, in kWh, in hour $i \in H$ and day $j \in D$;
- epv_{ij}, solar energy, in kWh, produced by a solar panel in hour $i \in H$ and day $j \in D$;
- et_{ij}, wind energy, in kWh, produced by a wind turbine in hour $i \in H$ and day $j \in D$;
- cm^{pv}, annual maintenance cost, in €, for the solar panel;
- cm^{t}, annual maintenance cost, in €, for the wind turbine;
- cm^{bat}, annual maintenance cost, in €, for the battery;
- cm^{inv}, annual maintenance cost, in €, for the inverter;
- ca^{pv}, acquisition cost, in €, of a solar panel;
- ca^{t}, acquisition cost, in €, of a wind turbine;
- ca^{inv}, acquisition cost, in €, of an inverter;
- ca^{bat}, acquisition cost, in €, of a battery;

Decision Variables.

- x^{pv}, integer variable representing the number of solar panels to be installed;
- x^{t}, integer variable representing the number of wind turbines to be installed;
- yc_{ija}, energy, in kWh, bought from the grid during hour $i \in H$, day $j \in D$, and year $a \in A$;
- yv_{ija}, energy, in kWh, sold to the grid during the hour $i \in H$, day $j \in D$, and year $a \in A$;
- z^{bat} binary variable that takes the value 1 if batteries are used;
- soc_{ija}, battery state of charge at the beginning of hour $i \in H$ (with $i = 1$ representing the initial state), day $j \in D$, and year $a \in A$;
- yib_{ija}, energy, in kWh, injected into the battery in hour $i \in H$, day $j \in D$, and year $a \in A$;
- ydb_{ija}, energy, in kWh, discharged from the battery in hour $i \in H$, day $j \in D$, and year $a \in A$;

- wib_{ija}, binary variable that takes the value 1 if there is energy injection into the battery and 0 otherwise, in hour $i \in H$, day $j \in D$, and year $a \in A$;
- wdb_{ija}, binary variable that takes the value 1 if the battery is discharging and 0 otherwise, in hour $i \in H$, day $j \in D$, and year $a \in A$;
- wc_{ija}, binary variable that takes the value 1 if energy is bought and 0 otherwise, in hour $i \in H$, day $j \in D$, and year $a \in A$;
- wv_{ija}, binary variable that takes the value 1 if energy is sold and 0 otherwise, in hour $i \in H$, day $j \in D$, and year $a \in A$;
- wb_{ija}, binary variable that takes the value 1 if batteries are used and 0 otherwise, in hour $i \in H$, day $j \in D$, and year $a \in A$;

Objective Function. The objective function (1) corresponds to the maximization of the total profit, TP, over the 20-year planning horizon. This profit is obtained by subtracting the total costs, which include energy purchase costs, equipment purchase costs, and maintenance expenses, from the revenue generated by energy sales. Additionally, an inflation rate of 1.39% is considered over the 20 years.

$$\begin{aligned} \max \quad TP = 91.25 \cdot \sum_{i \in H} \sum_{j \in D} \sum_{a \in A} \left(yv_{ija} \cdot pv_{ij} - yc_{ija} \cdot pc_{ij} \right) \cdot (1.0139)^{(a-1)} \\ - x^{pv} \cdot ca^{pv} - x^{t} \cdot ca^{t} - z^{bat} \cdot ca^{bat} - z^{bat} \cdot ca^{bat} \cdot (1.0139)^{10} - ca^{inv} \\ - \sum_{a \in A} \left(x^{pv} \cdot cm^{pv} + x^{t} \cdot cm^{t} + z^{bat} \cdot cm^{bat} + cm^{inv} \right) \cdot (1.0139)^{(a-1)} \end{aligned} \tag{1}$$

As mentioned earlier, a representative day was selected for each season of the year. To extrapolate the results to the entire year, the corresponding value was multiplied by 91.25, which represents the average number of days per season. Battery investment is modeled considering a unit lifetime of 10 years. Therefore, when battery storage is selected, an initial investment is incurred in the first year and a replacement cost is considered in year 11 of the project horizon.

Constraints. Constraint (2) enforces the energy balance for each hour $i \in H$, day $j \in D$, and year $a \in A$:

$$\begin{aligned} \forall i \in H, j \in D, a \in A, \quad x^{pv} \cdot epv_{ij} \cdot (1 - 0.0055)^{(a-1)} + x^{t} \cdot et_{ij} \cdot (1 - 0.015)^{(a-1)} \\ + ydb_{ija} + yc_{ija} = dc_{ij} + yib_{ija} + yv_{ija} \end{aligned} \tag{2}$$

The left-hand side represents the available energy (generation, battery discharge, and grid import), while the right-hand side accounts for demand and energy allocation (battery charge and energy sold). The parameters 0.0055 (0.55%) and 0.015 (1.5%) represent the annual degradation rates of photovoltaic panels and wind turbines, respectively.

The state of charge (SOC) of the batteries at the beginning and at the end of each day is defined by constraints (3) and (4):

$$\forall j \in D, a \in A, \quad soc_{1ja} = 0.0 \tag{3}$$

$$\forall j \in D, a \in A, \quad soc_{25,ja} = 0.0 \tag{4}$$

Here, $soc_{25,ja}$ represents the state of charge at the end of the representative day (start of hour 25), which corresponds to the end of hour 24, ensuring that battery operation can be consistently replicated across days of the same season.

The SOC of the batteries must also satisfy the following limits:

$$\forall i \in H, j \in D, a \in A, \quad soc_{ija} \geq 0.0 \tag{5}$$

$$\forall i \in H, j \in D, a \in A, \quad soc_{ija} \leq 0.9 \cdot k^{bat} \cdot z^{bat} \tag{6}$$

The dynamics of the SOC between consecutive hours is given by:

$$\forall i \in H, j \in D, a \in A, \quad soc_{i+1,ja} - soc_{ija} = yib_{ija} - ydb_{ija} \tag{7}$$

The energy injected into and discharged from the battery is constrained by the binary variables and the battery capacity:

$$\forall i \in H, j \in D, a \in A, \quad \begin{cases} yib_{ija} \leq 0.9 \cdot k^{bat} \cdot wib_{ija} \\ yib_{ija} \leq 0.9 \cdot k^{bat} \cdot z^{bat} \\ ydb_{ija} \leq 0.9 \cdot k^{bat} \cdot wdb_{ija} \\ ydb_{ija} \leq 0.9 \cdot k^{bat} \cdot z^{bat} \end{cases} \tag{8}$$

The binary variables ensure that charging and discharging cannot occur simultaneously:

$$\forall i \in H, j \in D, a \in A, \quad wib_{ija} + wdb_{ija} \leq 1 \tag{9}$$

Finally, an upper limit on the energy charged or discharged per hour is imposed, according to the battery's rated power.

$$\forall i \in H, j \in D, a \in A, \quad yib_{ija} \leq 5.0, \quad ydb_{ija} \leq 5.0 \tag{10}$$

These constraints ensure that the battery, when installed, operates physically consistently and within its technical limits, while avoiding simultaneous charging and discharging.

The quantities of energy purchased (yc_{ija}) and sold (yv_{ija}) are continuous decision variables representing, respectively, the amount of energy bought from and sold to the grid during hour $i \in H$, day $j \in D$, and year $a \in A$. Their operation is controlled by the binary variables wc_{ija} and wv_{ija}, which indicate whether a purchase or sale occurs in a given period.

The following linear constraints then ensure a proper logical relationship between the continuous energy variables and the corresponding binary variables:

$$\forall i \in H, j \in D, a \in A, \quad yv_{ija} \leq wv_{ija} \cdot M, \quad yc_{ija} \leq wc_{ija} \cdot M \tag{11}$$

where M is a large constant, representing an upper bound on the energy that could be purchased or sold in a single period.

In each period, the purchase and sale of energy cannot occur simultaneously,

$$\forall i \in H, j \in D, a \in A, \quad wv_{ija} + wc_{ija} \leq 1 \tag{12}$$

The constraint (13) represents the limitation on the number of photovoltaic modules that can be installed, due to the physical space available on the roof.

$$x^{pv} \leq 48 \tag{13}$$

Constraint (14) imposes non-negativity on the injected and discharged energy from the battery.

$$\forall i \in H, j \in D, a \in A, \quad yib_{ija} \geq 0, ydb_{ija} \geq 0 \tag{14}$$

Constraint (15) imposes non-negativity on the number of installed turbines.

$$x^{t} \geq 0 \tag{15}$$

Constraints (16) specify the binary nature of a subset of the decision variables.

$$\forall i \in H, j \in D, a \in A, \quad wib_{ija}, wdb_{ija}, wc_{ija}, wv_{ija}, wb_{ija}, z^{bat} \in \{0, 1\} \tag{16}$$

Changes in parameters, such as the cost of the components, renewable energy production, and load profiles, have a substantial impact on the results. They alter the cost-benefit dynamics and modify the microgrid's operational strategies. These parameters can vary significantly between regions (such as solar radiation, temperature, and wind speed), affecting the technical and economic performance and the viability of the microgrid. The model presented is easily adaptable to other data, facilitating its application in different locations without requiring major structural modifications.

3.2 Techno-Economic Indicators

To evaluate the economic performance of the proposed microgrid configurations, several standard indicators are considered, including LCOE, NPV, IRR, and PBP [3].

The LCOE (17) represents the average cost of energy production over the system lifetime, accounting for investment, operation, and maintenance costs. The NPV (18) evaluates the profitability of the investment by comparing discounted cash inflows and outflows. The IRR indicates the expected return rate

of the project, while the PBP measures the time required to recover the initial investment, (19) and (20).

$$\text{LCOE} = \frac{\sum_{n=1}^{N} \frac{C_n + O_n + M_n}{(1+i)^n}}{\sum_{n=1}^{N} \frac{Q_n}{(1+i)^n}} \tag{17}$$

$$NPV = \sum_{n=1}^{N} \frac{R_{ln}}{(1+i)^n} - I_t \tag{18}$$

$$\sum_{n=1}^{N} \frac{R_{ln}}{(1+IRR)^n} - I_t = 0 \tag{19}$$

$$PBP = \frac{\sum_{n=1}^{N} \frac{R_{ln}}{(1+i)^n}}{I_t} \tag{20}$$

where C_n represents the capital costs or initial investment, O_n denotes the operational costs, M_n refers to the maintenance costs, Q_n is the energy produced in year n, i is the discount rate, N represents the project lifetime, in years, where R_{ln} represents the net revenue of year n, and I_t represents the total investment updated to year 0.

These indicators are computed based on the optimized system configuration and are used to compare the economic viability of the different case studies.

4 Case Study: Microgrid Description

This section presents the case study used to validate the proposed optimization model. The analyzed system is a grid-connected microgrid integrating renewable energy sources, storage, and a consumer load, enabling the assessment of operational and economic performance under realistic conditions.

The microgrid consists of a photovoltaic (PV) system, a wind turbine, an energy storage system (ESS), a consumer load, and a bidirectional DC/AC inverter, as illustrated in Fig. 1. The system is connected to the main grid, allowing both energy import and export.

The PV generation is modeled using a JAM66S30-505/MR/1500V module [16], considering typical performance parameters. Solar irradiance and temperature data were obtained from the Photovoltaic Geographical Information System (PVGIS) platform, using average daily profiles for representative months (January, April, July, and November) over the period 20192023, for the Porto region, with a tilt angle of 35°.

Wind generation is obtained using a Aeolos-V 10 kW turbine model [15]. Wind speed data were obtained from the Portuguese Institute for Sea and Atmosphere (IPMA), based on historical measurements from a meteorological station in Porto.

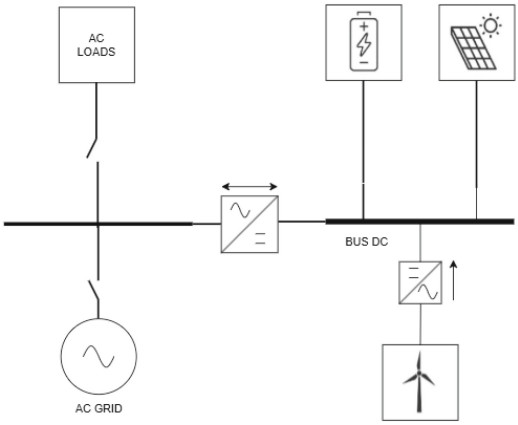


Fig. 1. DC Microgrid block diagram

The storage system is modeled as a lithium-ion battery, Huawei LUNA2000-10-SO [11], with typical operational characteristics, including charging/discharging limits and efficiency. A nominal capacity of 10 kWh is considered, with constraints on maximum charging and discharging power.

DC/AC inverters play a crucial role in renewable energy production systems. They are responsible for converting the energy produced by photovoltaic modules and wind turbines, which is in direct current (DC), into alternating current (AC), which is used by electrical equipment and the power grid. The FoxESS 25kW inverter [10] stands out as a modern and reliable solution for medium- and large-scale applications. This model is bidirectional, enabling operation in two energy flow directions. It converts renewable energy or energy discharged from the battery to power the electrical grid or local consumption. Additionally, when energy prices are low, the system can acquire energy from the grid, converting the alternating current from the grid into direct current to recharge the batteries for later use. This bidirectional flow optimizes the use of renewable energy and reduces energy costs.

The data for the load profiles were obtained from the E-REDES Open Data platform. Four representative days, each corresponding to a different season of the year, for consumers from the Porto region were considered, allowing the analysis of seasonal variability in demand.

The energy purchase and sale prices were obtained from the Iberian Electricity Market Operator [14], based on the average of 24 h of each day in the months of January, April, July, and November over the last five years.

The values considered for the cost of purchasing and maintaining energy production and storage components are based on market data.

5 Results and Discussion

This study analyzes the feasibility and operational efficiency of different microgrid configurations and compares their performance across various operational scenarios. Five main case studies were developed, Case Study I, II, III, IV and V. Each one represents a distinct combination of renewable energy generation, energy storage systems, and grid interactions, providing a solid basis for technical and economic comparisons. The proposed optimization model determines the optimal number of PV modules and wind turbines, as well as the number of batteries, and manages energy exchange. Hourly load profiles, solar irradiance, and wind speed data were incorporated to capture on-site operating conditions. The model aims to balance production with consumption while minimizing costs, accounting for constraints such as physical installation limits, production capacity, and the operational requirements of the energy storage system (ESS).

Case Study I serves as a baseline for calculating savings in other cases. In this case, the system relies entirely on the electrical grid, with no PV panels, wind turbines, or batteries. The total energy acquisition cost to meet the load is 119,472.59 €. Therefore, in the other cases, we can compute the savings by comparing with this value.

Case Study II does not include the use of storage systems and considers the possibility of installing photovoltaic panels and wind turbines. In the optimal solution, 24 PV modules are installed and no wind turbines, resulting in equipment and maintenance costs of 3,767.18 € and 1,292.61 €, respectively. These amounts represent a total savings of 20,244.62 € when compared to the baseline scenario.

Case Study III still does not consider the use of storage systems, but, in order to obtain a hybrid system, at least one wind turbine is required. The model selects 22 PV modules and 1 wind turbine, resulting in equipment cost of 23,388.68 € and maintenance cost of 8,025.20 €. Comparing with the baseline scenario, this system yields a negative net benefit of 545.46 €, indicating that this configuration is not economically viable.

In Case Study IV, two 10-kWh battery systems are installed, enabling energy storage to optimize system operation and grid interaction. In the optimal solution, 48 PV modules are installed, with no wind turbines. Equipment and maintenance costs are 16,684.38 € and 5,724.80 €, respectively. In this case, there is a savings of 30,589.75 € compared to the baseline, highlighting the storage system's significant impact on its long-term profitability. An additional case study (Case V) was also considered, which includes the use of batteries and requires the installation of at least one wind turbine. This case did not demonstrate economic advantages compared to the previous cases.

Techno-Economic Analysis

In Fig. 2 the LCOE for each case study is presented. This indicator is used to evaluate the average energy production cost over the system's lifetime. A discount rate of 4% was used, obtained from [8]. Case II exhibits the lowest LCOE

due to the adoption of low-cost renewable technology, whereas configurations incorporating batteries or wind turbines incur higher LCOE values.

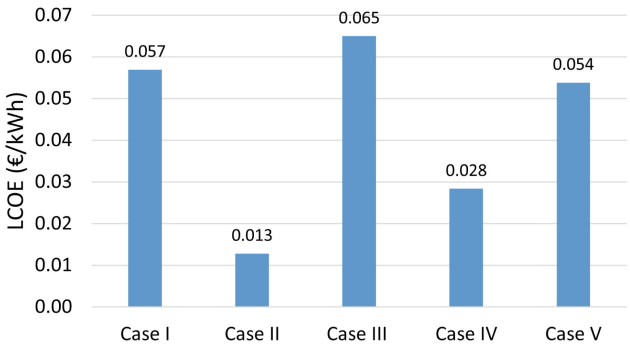


Fig. 2. Levelized Cost of Energy for all the cases studies

Figure 3 presents the NPV for all cases. The obtained values indicate that Cases II and IV are profitable, while Cases III and V are economically unattractive.

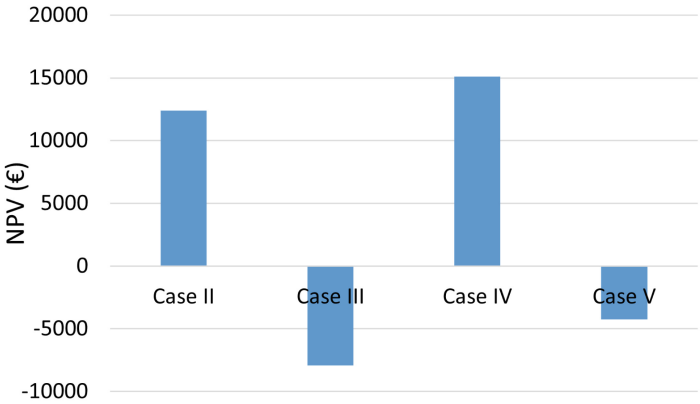


Fig. 3. Net Present Value for different cases studies

The IRR and PBP assessments are presented in Table 1. It can be concluded that Case II achieves the highest IRR (30.13%) and the shortest PBP (3.14 years), while Case IV provides moderate returns (IRR 12.43%, PBP 7.07 years) with substantial cumulative profit. Cases III and V exhibit low or negative IRR and a prolonged PBP, which underscores the limited financial viability of hybrid systems that include wind turbines at the chosen site for the system installation.

Table 1. Internal Rate of Return and Payback Period for each case

Case	IRR (%)	PBP (years)
Case II	30.13%	3.14
Case III	-0.22%	20.48
Case IV	12.43%	7.07
Case V	2.67%	15.27

Fig. 4 illustrates the amortization over the project's lifetime, showing how the invested value is progressively recovered throughout the system's lifespan.

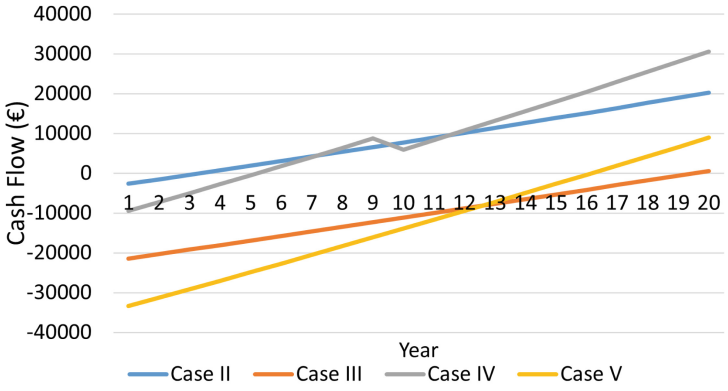


Fig. 4. Cash Flow during project life time for different cases studies

Sensitivity Analysis

To assess the robustness of the system under market fluctuations, Case IV was re-evaluated under variations in energy prices and equipment costs. The analysis included a ±20% change in purchase and sale prices, a 20% reduction in PV and wind turbine costs, and a 40% reduction in wind turbine costs. Results indicate that higher energy prices (Case VI) increase profitability, achieving the highest IRR (15.84%) and shortest PBP (5.77 years). Reductions in equipment costs (Cases VIII and IX) moderately improve economic performance, with Case IX (40% reduction in wind turbine cost) yielding the lowest LCOE and enhanced cost-effectiveness (Tables 2 and 3, Figs. 5 and 6).

Discussion

Overall, the results demonstrate that PV-based configurations are the most cost-effective and reliable solution in the short-to-medium term, while storage integration enhances long-term profitability and operational flexibility. Wind turbines,

Table 2. Summary of sensitivity analysis results

Case	Optimal configuration	Savings (€)
Case VI (+20% purchase & sale price)	48 PV + 2 Bat	41188.39
Case VII (-20% purchase & sale price)	48 PV + 2 Bat	19989.39
Case VIII (-20% PV & Turbine cost)	48 PV + 2 Bat	32050.68
Case IX (-40% Turbine cost)	48 PV + 2 Bat + 4 Turb	34031.32

Table 3. Internal Rate of Return and Payback Period for the new case studies

Case	IRR (%)	PBP (years)
Case VI	15.84%	5.77
Case VII	8.74%	9.10
Case VIII	13.64%	6.55
Case IX	4.42%	13.08

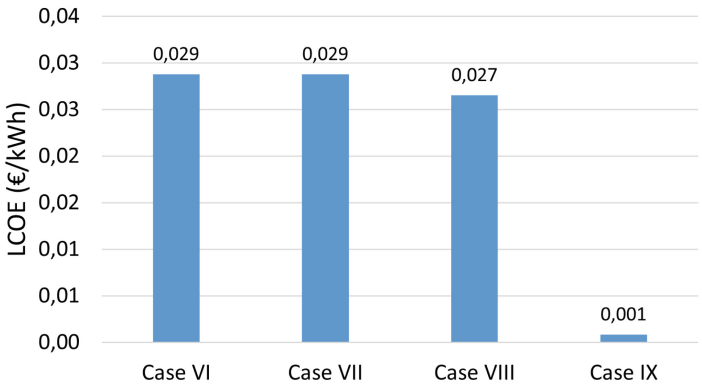


Fig. 5. Net Present Value for different cases studies

despite offering energy diversification, contribute less to economic feasibility due to higher initial costs and suboptimal performance in the studied context. Sensitivity analysis confirms the strong dependence of microgrid profitability on energy market prices and, to a lesser extent, on equipment cost reductions. The proposed model is adaptable for future integration of alternative storage technologies, such as thermal or hydrogen systems, which could further enhance flexibility and sustainability in hybrid microgrid designs.

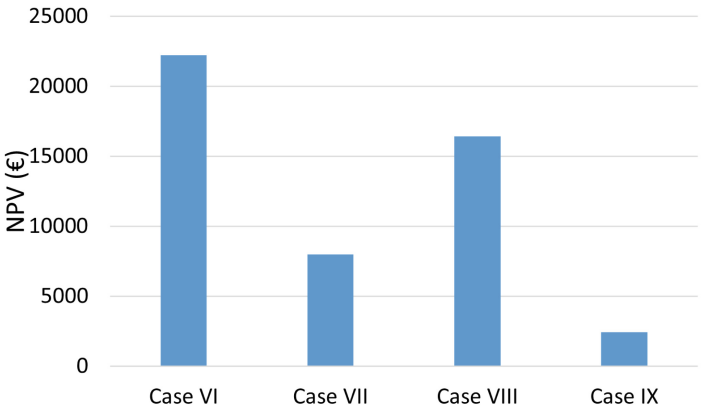


Fig. 6. Net Present Value for sensitivity analysis case studies (VIIX)

6 Conclusions

This study analyzed five microgrid configurations to evaluate the impact of renewable energy integration and energy storage systems on operational efficiency and economic performance. The main objective was to identify the most effective system configuration to maximize operational profit, reduce dependence on the electrical grid, and improve sustainability.

Case II, with the installation of 24 photovoltaic modules without storage, achieved the best performance in terms of cost-effectiveness, Internal Rate of Return (30.13%), and shortest Payback Period (3.14 years). So, the PV-based solutions are highly efficient and economically viable for the analyzed scenario. In contrast, Case IV, which incorporates 48 PV modules and two batteries, provided the highest cumulative profit over a 20-year horizon (30,589.75€), highlighting the long-term advantages of combining PV energy production with storage capacity.

The inclusion of batteries in Case IV enabled energy storage during periods of high solar production for later use during periods of low production, or to meet demand or sell it to the grid, thereby increasing the system's autonomy and operational flexibility. However, the higher initial investment associated with the batteries limited short-term economic performance. The integration of wind turbines did not prove beneficial in the context studied. Although it contributes to production diversification, the high installation cost of wind turbines and their lower-than-expected performance reduced economic viability compared to configurations dominated by photovoltaic energy.

The sensitivity analysis performed demonstrated the strong dependence of microgrid profitability on energy market prices. A 20% increase in purchase and sale prices (Case VI) significantly enhanced economic performance, achieving the highest IRR and shortest Payback Period, while a 20% decrease (Case VII) resulted in negative returns. Reductions in equipment costs (Cases VIII and

IX) provided moderate improvements, particularly through wind turbine cost reductions, which led to lower LCOE and improved techno-economic performance. Nevertheless, the effect of PV cost reductions is limited by the available installation area, which caps the number of panels at 48 and restricts additional benefits. These results indicate that, once spatial constraints are reached, further reductions in PV costs have diminishing returns, shifting the optimization focus toward other system components or design strategies.

The proposed optimization model is flexible and can accommodate alternative storage technologies, such as thermal or hydrogen systems, which could improve system flexibility and resilience in hybrid microgrid designs. Future research may explore these options to fully assess their long-term techno-economic benefits.

Overall, the results indicate that PV-based systems are the most attractive solution for short- to medium-term projects, while storage integration offers substantial advantages in long-term profitability and operational management, providing valuable guidance for microgrid design and investment decisions.

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