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Optimizing Wind Turbine Deployment: A Cost Analysis of Centralized Aggregation versus Decentralized Dispersion for Enhanced Financial Viability

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ABSTRACT

This study provides a complete cost analysis of two different wind turbine deployment strategies: centralized aggregation in a single location and decentralized dispersion across three locations. The main goal is to analyze the internal rate of return (IRR), a fundamental financial indicator for determining the economic sustainability of each deployment strategy. This research also identifies the most financially advantageous investment opportunity among various competing strategies. The analysis includes a comprehensive computation of annual cash flow forecasts. Furthermore, the analysis involves a detailed calculation of annual cash flow projections, providing a robust foundation for a thorough examination of the financial implications associated with each deployment method. Beyond a mere numerical comparison, this study goes deeper to illuminate the disparities in costs, revenues, and overall economic feasibility that emerge between the centralized and decentralized deployment scenarios. The analysis results underscore the imperative of thoughtful deployment strategies in enhancing the overall profitability of renewable energy projects, recognizing that financial considerations must be carefully weighed alongside technical and environmental factors for a holistic decision-making process in the renewable energy sector.

Keywords: Cash Flow, Feed-in Tarif, Financial Viability, Renewable Energy Investment, Power Fluctuation.

1. Introduction

The escalating global adoption of wind power signifies a transformative era in sustainable energy, underscored by significant achievements in recent years. In 2022 alone, wind power accounted for an impressive 22% of new electricity capacity installed in the United States, amounting to a substantial $12 billion in capital investment[1]. This growth is mirrored on a global scale, as wind electricity generation witnessed an unprecedented surge of 265 TWh in 2022, culminating in a total of over 2,100 TWh[2]. Amidst this soaring momentum, the imperative for sustainable energy development has gained prominence, prompting a strategic shift towards renewable energy sources, decentralized energy systems, and innovations in energy storage technologies. This shift is not merely a response to climate change; it is a proactive measure aimed at mitigating environmental degradation[3].

The integration of cutting-edge information and communication technologies, such as artificial intelligence, blockchain, and advanced communication systems, represents a paradigm shift in the realm of renewable energy. These technologies hold the promise of streamlining the planning and functioning of smart energy systems characterized by extensive integration of renewable energy sources[4]. As the backbone of the transition towards a clean energy future, renewable energy resources establish a clear link between energy, the environment, the economy, and society[5]. Against the backdrop of varied energy needs, fossil fuel availability, and the gradual phasing out of coal and crude oil reliance by nations[6], innovative solutions like wind-solar hybrid projects have been proposed to accelerate installation, enhance grid stability, and optimize transmission efficiency and cost-effectiveness[7].

In the intricate landscape of wind energy research, the deployment strategy of wind turbines emerges as a pivotal factor, wielding substantial implications for the overall efficiency and economic viability of wind energy projects. Artificial intelligence techniques, including unsupervised machine learning methods like Principal Component Analysis (PCA), have been proposed to develop asset management strategies, ensuring the safe and cost-effective operation of wind turbines[8]. Moreover, the analysis of extensive databases containing information on wind turbine locations and Geographic Information System (GIS) data

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has become crucial. These empirical data challenge assumptions made in energy system models and contribute to more accurate assessments of wind power potential. Furthermore, the optimization of offshore wind turbine substructures is gaining prominence, as it promises increased competitiveness through considerations of both engineering models and economic effects, ultimately leading to more cost-efficient offshore wind farms[9].

In[10], the authors explore the expenses and inefficiencies linked to various network configurations for collection systems in offshore wind farms that consolidate the power electronic converters of the turbines. Two main network topologies are evaluated: star topology and cluster topology. In the star topology, each turbine is linked individually to its dedicated converter on a platform containing multiple converters. Conversely, the cluster topology connects several turbines through a single large converter. Both AC and DC configurations are considered, alongside standard string topologies for reference purposes. It is observed that star and cluster topologies exhibit elevated costs and losses compared to the string topology. Generally, DC configurations demonstrate lower costs and losses than AC, although the certainty of commercially available converters remains uncertain. Another study in[11] explores the spatial dependence structure of wind power and its influence on electricity spot prices. Using a stochastic simulation model with copulas, it analyzes the full spatial dependence of wind power using German data. The research emphasizes the significance of the specific location of a wind turbine in relation to the aggregated wind power in the system, indicating that a linear dependence structure would often overestimate the market value, particularly with higher wind power penetration. Possible challenges in the large-scale integration of wind power into markets arise due to the adverse impact of upper tail dependence on market value.

Aggregating wind turbines in a single location and dispersing them across multiple locations have different cost implications. The comprehensive examination of the valuation of distributed wind turbines offering ancillary services is lacking; however, a particular paper introduces an optimal approach for market participation by distributed wind turbines and assesses various strategies within the context of California[12]. Another paper analyzes the wind energy potential of three locations in Poland and finds that the most favorable location for a small wind turbine is the coastal site, in comparison the other two locations have significantly longer payback periods[13]. Additionally, a case study in Delaware, US, considers various factors such as wind resources, site geology, transmission constraints, and operation costs to assess the economic feasibility of wind turbines, with a base case levelized cost of energy of approximately $70/MWh[11]. Therefore, the cost analysis of aggregating wind turbines in a single location and dispersing them across multiple locations depends on factors such as market participation, location-specific characteristics, and project feasibility.

Research on the cost analysis of aggregating wind turbines in a single location versus dispersing them across multiple locations has yielded mixed results. Research in[14] found that a mix of dispersed wind sites can optimize system reliability, while authors in[15] identified specific sites with excellent wind resources and economic viability for grid integration. However, research in[16] highlighted the need for an optimization method for the installation capacity of dispersed wind farms, and authors in[17] suggested that a dispersed array of wind turbines can reduce the variability of total wind power output. These studies collectively suggest that while dispersed wind sites can offer reliability and economic benefits, careful planning and optimization are necessary to maximize these advantages.

This research offers a distinct perspective on the financial viability of renewable energy projects, particularly in wind turbine deployment. Unlike prior studies focusing on specific cost metrics, our work takes a holistic approach, considering a diverse set of analysis metrics. Going beyond traditional centralized versus decentralized deployment discussions, we recognize the financial aspect as pivotal in decision-making.

Our investigation delves into the economic intricacies of wind turbine deployment, centering on an annual cash flow projection. What sets our work apart is the inclusion of a multifaceted set of cost analysis metrics, extending beyond conventional considerations. By incorporating factors like market participation, location-specific characteristics, and project feasibility, our research provides decision-makers in the renewable energy sector with a nuanced understanding. To facilitate this comprehensive analysis, we explore the impact of power fluctuations on the economic feasibility of wind farm projects.

The study not only informs stakeholders about the economic dynamics of deployment but significantly contributes to the broader discourse on enhancing renewable energy project efficiency. Our research emphasizes the pivotal role of thoughtful deployment strategies in maximizing project profitability, marking a departure from conventional paradigms and presenting a pioneering contribution to renewable energy literature. We specifically introduce the concept of a penalty factor as a regulatory mechanism, providing a tangible strategy for minimizing output power fluctuations. This innovative approach aligns economic interests with environmental objectives, fostering a win-win situation for grid stability and wind farm profitability.

This paper is structured as follows: Section 2 presents the employed methodology, offering insights into the research approach. Section 3 delves into the analysis and presents the results obtained. Finally, Section 4 and Section 5 provide a discussion and a concluding summary of the work, accompanied by noteworthy suggestions for future research endeavors.

2. Methodology

This study is an integral and progressive extension of our ongoing research in the realm of mitigating the impact of uncertainties related to wind turbines[18]. The primary focus of this study is to explore strategies for achieving a consistent annual output power generation of 200MW from wind turbines. The analysis involves aggregating all turbines at a single site and distributing them across three distinct locations. Wind data for Tarifa, Spain, a recognized optimal location for wind farming, was collected over a one-year period, with wind speed measurements taken at 10 meters height within the city. Tarifa was chosen for its publicly accessible and unrestricted wind data. Subsequently, the same methodology was applied to wind turbines distributed across Barbate and Algeciras sites, utilizing meteorological wind data measured at an elevated height of 80-meter.

The study centers around a relatively large wind farm comprising V90-3.0MW Vestas wind turbines[19]. The analysis considers wind power variability concerning the specific target output power of 200MW. Due to the intermittent nature of wind, the wind power plant operates at a 30% load factor, resulting in significant variations in power generation output throughout the year. This aligns with the 30% load factor commonly seen in wind power plants[20]. The integration of wind power into the Spanish grid at a 30% share has been found to be technically feasible and economically reasonable[21]. For broader relevance, the study employs V90-3.0MW Vestas wind turbines, known for their 80-meter tower height and capability to generate a maximum power of 3MW at a wind speed of 15 m/s. The turbines have designated wind speeds at which they start operating (cut-in) and cease operation (cut-out), which are 3.5 m/s and 25 m/s, respectively. The analysis framework encompasses the entire one-year wind dataset for each location, evaluating the variability in power output concerning the 200MW target. Emphasis is placed on the 30% load factor and its influence on the farm's operational continuity.

Furthermore, to comprehensively evaluate the financial viability of centralized and decentralized wind turbine deployment strategies, we employed a set of key financial metrics. These metrics were strategically chosen to provide a holistic understanding of the economic dynamics associated with each deployment scenario. The following subsection outlines the specific financial metrics utilized in our study:

1. Internal Rate of Return (IRR): This metric served as a primary indicator of the profitability of each deployment strategy. We calculated the IRR for both centralized (Tarifa) and decentralized (Tarifa, Algeciras, and Barbate) scenarios.

2. Cash Flow Projection: An annual cash flow projection was meticulously calculated to capture the financial dynamics associated with each deployment strategy. This projection considered factors such as initial capital investment, operational costs, revenue from power sales, and applicable tax incentives or subsidies.

3. Depreciation Deduction: The annual depreciation value of the wind turbines was calculated using the Sinking Fund Method, considering various financial factors and cash flows to determine the reduction in the value of the turbines over their operational lifespan.

4. Penalty Factor Analysis: In response to the fluctuating nature of wind power output, we introduced a penalty factor as a regulatory mechanism. This factor, calculated based on the percentage of root mean square error (ePMRSE), played a crucial role in assessing the economic impact of power fluctuations on wind farm projects.

By employing this set of key financial metrics, we aimed to offer a comprehensive comparison between centralized and decentralized wind turbine deployment strategies, considered various economic considerations.

3. Analysis and Results

The analysis results are split into two primary sections. In the initial segment, the output power of both aggregated and distributed wind turbines is assessed. Subsequently, the second section delves into the economic analysis of the proposed scenarios, providing a comprehensive examination of their financial implications.

3.1. Analysis and Results

3.1.1. Scenario one

In accordance with Vestas turbine specifications, wind speed calculations at an elevation of 80 m are derived from data initially gathered at a 10 meters height. This essential transformation is executed through the application of a conversion factor of 1.1927 using equation (1), as prescribed by the wind speed calculator developed by the Danish Wind Industry Association—a crucial reference depicted in Figure 1 within our research[22].

$$ws_{80} = ws_{10} \times 1.1927 \quad (1)$$

Where: ws_{80}: refers to the speed of wind at 80 m elevation in meters per second, ws_{10}: wind speed at 10 m denotes the speed of wind at a 10 m elevation in meters per second.

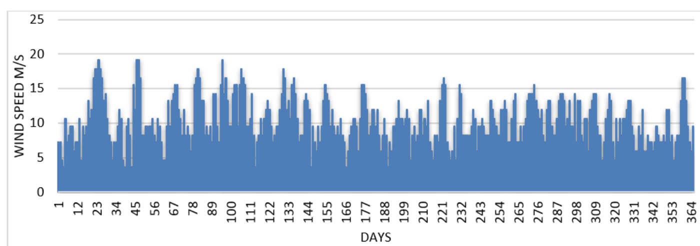

Figure 1: displays meteorological wind data at an elevation of 80 meters in Tarifa throughout the year.

The computation of power output from turbines at varying wind speeds is conducted based on the manufacturer's power curve, as elucidated in Figure 2, ensuring precision and reliability in our analyses for publication in high-impact journals.

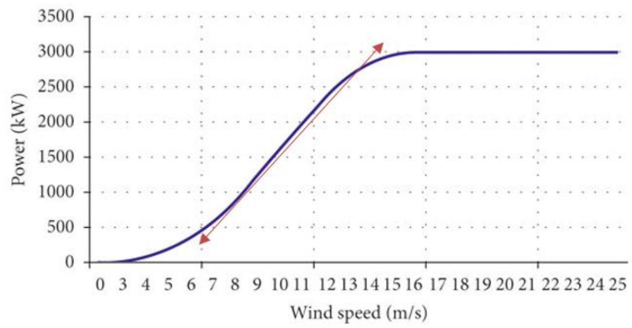

Figure 2: illustrates the standard power curve for the Vestas V90-3.0MW turbine type.

In the absence of a dedicated power curve equation for precise output calculations at individual wind speeds, we resort to a straightforward method of linear interpolation between 5.5 m/s and 15 m/s. The resulting linear equation is expressed as follows:

Determining slope:

$$\frac{y - y1}{x - x1} = \frac{y2 - y1}{x2 - x1} \qquad (2)$$

$$\frac{\mathrm{y} - 0}{\mathrm{x} - 5.5} = \frac{3 - 0}{15 - 5.5}$$

Equation of a straight line:

$$y = 0.316x - 1.74 \qquad (3)$$

In this context, "y" represents a function of "x" measured in meters per second (m/s).

Equation (3) holds validity within the data points ranging from 5.5 m/s to 15 m/s. This range is determined by the constant turbine output power of 3 MW above 15 m/s and the output power registering as zero below 5.5 m/s, as demonstrated earlier. While acknowledging that Equation (3) may not be the most precise, its application yields satisfactory results. Employing this equation in conjunction with the power curve depicted in Figure 2 enables the calculation of the annual output power per turbine.

$$P_{out}(ws_{80}) = (ws_{80} \times 0.316) - 1.74 \qquad (4)$$

$$P_{out} = (7.288 \times 0.316) - 1.74 = 0.5630 \frac{MW}{Turbine} \qquad \text{given } \mathrm{P_{out}} \text{ at } 7.288\mathrm{m/s}$$

$$P_{Total} = P_{out} \times N \qquad (5)$$

$$P_{Total}(130\ turbines) = 0.5630 \times 130 = 73.48\ in\ MW \qquad \text{given total power of 130 turbines.}$$

The daily electricity generated from the wind farm is determined through the application of equations (4 and 5) in a manner consistent with the methodology employed for yearly calculations.

$$P_{out} = 547.296\ in\ MW$$

$$P_{max} = 3 \times 365 = 1095\ MW \qquad \text{given 3 in MW and 365 days in a year.}$$

In the given context:

- $P_{out(WS80)}$ represents the actual output power per turbine at the standard wind speed in a day.
- P_{Total} signifies the wind farm's power output in a day.
- N stands for the number of turbines.
- P_{out} denotes the actual output power per turbine in a year.
- P_{max} corresponds to the maximum output power per turbine annually.

$$L.F = \frac{P_{out}\ MW}{P_{max} MW} \qquad (6)$$

$$L.F = \frac{547.296}{1095} \rightarrow L.F = 49\%$$

In this context, L.F. represents the Load Factor for the city of Tarifa. Evidently, Tarifa exhibits an exceptionally high load factor, underscoring its suitability as an ideal location for the implementation of a wind farm.

The main goal of this investigation was to ensure the consistent generation of 200 MW of power by the wind farm throughout 292 days each year, with a planned downtime of 73 days allocated for maintenance. To achieve this goal, a configuration of 130 turbines was determined. Given the fixed number of turbines, the wind farm's power output can be easily determined using equation (5).

The generated electrical energy, illustrated in Figure 3, reveals that the accumulated power is the daily power generation of the farm minus the target of 200 MW. This accumulation pattern is evident on both daily and annual scales, showcasing significant fluctuations. Remarkably, these fluctuations persist even within a single day. Mitigating such variations necessitates the consideration of energy storage solutions, wherein surplus power generated during high wind speeds can be stored and subsequently utilized during periods of low wind speeds. Despite this strategy, it is observed that the accumulated power reaches 72 GWh, surpassing the total of 96 GWh if the farm were to be turned off for 73 days for maintenance. This discrepancy poses a challenge, as accommodating such substantial energy storage demands becomes impractical, pointing towards the need for further exploration of viable solutions.

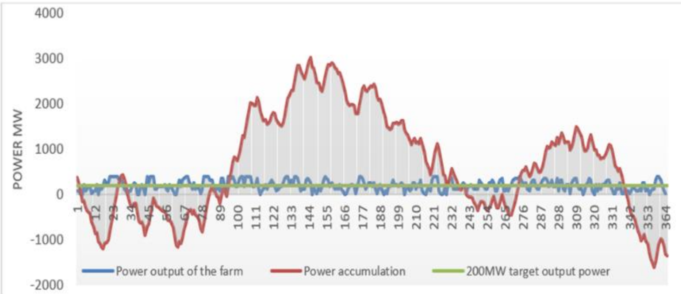

Figure 3: Power output from a configuration of 130 turbines, power accumulation, and the objective power throughout a year.

3.1.2. Scenario two

An innovative approach proposed in this paper to mitigate the power fluctuations of the plant involves the dispersion of wind turbines across multiple locations instead of consolidating them in a single area. This strategy extends the total duration of wind availability, diminishing instances of zero power generation while moderating the peak instantaneous power output. Further, the computations described earlier are duplicated to evaluate wind information at an 80 m elevation for two extra sites, namely Algeciras and Barbate in Spain, as illustrated in Figure 4.

These three prospective locations, Tarifa, Algeciras, and Barbate, are positioned in relative proximity, making the idea of connecting them into a unified power plant plausible. However, they are sufficiently distant to exhibit distinct meteorological data (Figure 4). To be more precise, Algeciras is situated 11.26 Km northeast of Tarifa, while Barbate is located 35 km northwest of Tarifa. The proposed plant's turbine distribution is divided among three locations as follows: 40 turbines at Algeciras city site, 40 turbines at Barbate city site, and 50 turbines at Tarifa city site. Significantly, Tarifa, with the highest load factor among these locations, has been assigned a greater number of turbines, aligning strategically with its substantial wind power potential.

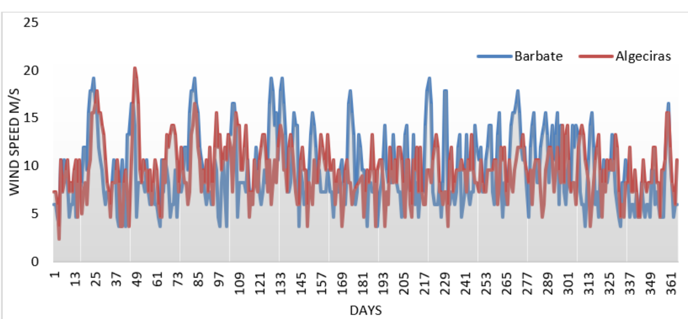

Figure 4: Meteorological wind speed data at 80 m height for Barbate and Algeciras sites.

Calculations above are reiterated to ascertain the daily power generation at each location. Subsequently, the output power from Tarifa, Algeciras, and Barbate is harmoniously aggregated, treating the three sub-farms as integral components feeding into the network collectively as a single extensive farm. A direct comparison is made by visually representing the output power of both scenarios in Figure 5.

Evidently, the results illustrate a substantial reduction in the number of days when the plant is not generating power. Moreover, the Excel interpolation data lines depict a noticeably smoother output power curve compared to the scenario where all turbines are concentrated in a single location. This outcome signifies the enhanced stability and reduced volatility achieved by the distributed arrangement of wind turbines across multiple locations.

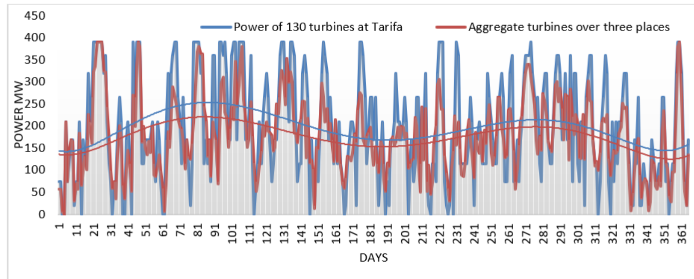

Figure 5: Enhancing the stability of power output in the proposed scenario as contrasted with the initial scenario.

3.2. Economic Analysis of the Proposed Scenario

The recent surge in the integration of renewable energy sources into the electrical grid, with a particular emphasis on wind power, has significantly impacted network stability[23]. This growth in renewable energy adoption is driven by a global commitment to reduce greenhouse gas emissions and transition toward cleaner energy sources[24]. However, the intermittent and variable nature of wind power generation poses considerable challenges to the stable operation of power systems. These fluctuations in wind power output create multiple obstacles for transmission companies, which are tasked with the complex responsibility of incorporating and delivering power generated by wind farms to consumers.

One of the critical issues at hand is that the current framework for integrating wind farms into the grid often overlooks the economic implications of power fluctuations. The focus has primarily been on increasing the capacity of renewable energy generation, with less attention given to the challenges of maintaining the grid's reliability in the face of intermittent wind power. As a result, these fluctuations have the potential to disrupt grid stability, leading to issues like voltage fluctuations and grid imbalances.

In response to these challenges, there is a growing recognition of the need for new pricing regulations that incentivize wind power developers to address power fluctuations. These regulations are designed to ensure that the power output from wind farms is consistent and predictable, making it easier for the grid to absorb this renewable energy source. This strategy aims to strike a balance between environmental sustainability and grid reliability.

The proposed technique for smoothing wind farm power output becomes pivotal in this context. By implementing measures to reduce power output variability, wind farm owners can enhance the predictability and reliability of their generation, aligning it more closely with grid demand patterns. However, the critical question that arises is whether this technique is financially viable for wind farm owners. It is essential to assess the economic feasibility of these measures to determine if they are a win-win solution, benefiting both the stability of the grid and the profitability of wind farm operations.

3.2.1. The Economic Modelling of Wind Farm

A cost analysis has been conducted to evaluate the disparities between two distinct approaches to wind turbine deployment: aggregating turbines in a single location versus dispersing them across three separate locations. The internal rate of return (IRR) serves as the key financial metric for this comparative assessment[25]. This analysis aims to determine which approach offers a more financially advantageous investment opportunity.

An annual cash flow projection has been meticulously calculated to accomplish this. The primary objective of this cash flow assessment is to ascertain whether the proposed technique, whether it involves centralized aggregation or decentralized distribution of wind turbines, ultimately translates into profitability for the farm owners. The cash flow projections are based on a set of equations that capture the financial dynamics associated with each deployment strategy.

These equations encompass a range of financial parameters, such as initial capital investment, ongoing operational costs, revenue generated from power sales, and any applicable tax incentives or subsidies. By applying these equations, it becomes possible to quantify the financial implications of the proposed techniques and discern whether they represent a sound economic investment for the wind farm owners. In doing so, it aids in guiding strategic decision-making and identifying the approach that aligns most favorably with the overarching financial goals of the project.

$$G = P \times n \times \tau \quad (7)$$

$$T_C = P \times n \times s \quad (8)$$

$$CF_0 = -I \quad (9)$$

$$CF_{1-10} = G - C_m - I_N - L_{in} - L_p + D - I_T \quad (10)$$

$$CF_{11-20} = G - C_m - I_N + D - I_T \quad (11)$$

$$\sum_{I=0}^{n} CF_I (1 + IRR)^{-i} = 0 \quad (12)$$

Where: In the equation provided, the variables are defined as follows: T: Represents the retail tariff, which is the rate at which electricity generated by the wind turbines is sold to consumers or the grid. G stands for gross revenue, which is the total income generated by the wind turbines through the sale of electricity. Cm: Denotes the operation and maintenance (O&M) cost, which represents the expenses associated with the regular upkeep and maintenance of the wind turbines. IN: Represents insurance costs, which are the expenses related to insuring the wind turbine equipment and operations. Lin: Refers to loan interest, which represents the interest payments associated with any loans or financing used to fund the wind turbine project. Lp: Represents the loan principal, which is the original amount borrowed or financed for the wind turbine project. D: Stands for depreciation deduction, which is an accounting method used to account for the reduction in the value of the wind turbines over time. IT: Denotes income tax, which represents the taxes payable on the income generated from the wind turbine project. CFi: Represents the cash flow, which is the net financial result of the wind turbine project.

The annual depreciation value of the wind turbines is calculated using the Sinking Fund Method. This method considers various financial factors and cash flows to determine the annual reduction in the value of the turbines over their operational lifespan.

$$q = (P - S) \times \left(\frac{r}{(1 + r)^n - 1} \right) \quad (13)$$

$$D(n) = q[(1 + r)^{n-1} + (1 + r)^{n-2} + \cdots + (1 + r)] \quad (14)$$

In the given equation, the variables are defined as follows: P: This represents the initial value or cost of the wind turbines, typically the purchase or installation cost. S: S denotes the scrap value, which is the estimated residual or salvage value of the turbines at the end of their operational life. It's the value the turbines are expected to have when they are no longer in use. r: The variable 'r' stands for the annual rate of interest, which is the interest rate applied to calculate the financial aspects of the wind turbine investment, such as depreciation and the present value of future cash flows. n: This variable represents the equipment's life span, indicating the expected duration over which the wind turbines are expected to remain operational and generate power.

3.2.2. Wind Turbine Cost Analysis

The benchmark price for wind-generated electricity in Spain remains consistent and is not impacted by the geographic placement of wind farms. As per the Spanish Royal Decree 661/2007, a fixed onshore reference rate of 7.3228 c€/kWh is set for the initial 25 years of a wind farm's operational period. Subsequently, this rate decreases to 6.12 c€/kWh for the remaining duration[26]. However, due to ongoing economic challenges in the country, the Spanish government agreed with energy organizations aimed at reducing the cost of wind energy production by 35%. Consequently, the benchmark rates for wind farms have been adjusted to 4.7598 c€/kWh for the initial 25 years and 3.978 c€/kWh for the subsequent period.

It is noteworthy that the operational and maintenance (O&M) costs associated with onshore wind turbines typically fall within a range of 1.2-1.5 c€/kWh. In the Spanish context, the data indicates that around 60% of these expenditures are designated for the operation and maintenance of turbines, as well as installation costs. The remaining 40% encompasses expenditures associated with insurance, overhead costs, and land rental.

It should be noted that the overall system expenditure for wind farms is expected to be consistent in both deployment scenarios, with an estimated value of 1,250,000 € per MW. This uniformity arises from the similarities in the geographical characteristics of the proposed installation areas in various cities.

However, the cost of land is directly contingent on the load factor of the specific location in which the wind turbine is intended to be erected and the sustainability attributes of the area. Even though the distribution of wind farms across multiple different sites may lead to increased transportation expenses, the land cost in Tarifa exceeds that in the other locations. It is primarily due to the variance in annual working hours, with Tarifa offering 4,204 hours of annual working capacity compared to 3,943 hours in the three alternative locations. More detailed information concerning O&M costs can be found in Table 1.

Table 1: Wind farm operation and maintenance costs.

Percentage		O&M (kW/h)	One location (Tarifa)	All locations considered
0.6	0.2	Servicing wind turbine	0.2900	0.3225
	0.14	Disposable goods	0.2025	0.2025
	0.1	Repairing wind turbine	0.1500	0.1500
	0.1	Backup components	0.1500	0.1500
	0.04	Localized technical outlays	0.0850	0.0850
	0.01	Turbines power demand	0.0270	0.0270
0.4	0.32	Land leasing	0.4312	0.4000
	0.04	Operating expenses	0.0750	0.0600
	0.04	Service subscriptions	0.0750	0.0600
Ultimate O&M cost per kilowatt-hour			1.4857	1.4570

3.2.3. Economic Analysis for a Wind Farm

In this section, we examine the economic feasibility of distributing wind farm turbines across three distinct locations as opposed to a single location. We perform an in-depth economic analysis to assess the applicability of this approach. Our analysis is conducted using a typical wind farm configuration comprising 130 turbines, with the assumption that the benchmark pricing in the region remains unchanged.

To facilitate this assessment, we have organized the key economic parameters, which are essential for the analysis, in Table 2. These parameters provide a comprehensive overview of the financial aspects and considerations that underpin the comparison between the two deployment strategies.

Table 2: Key technical and economic indicators for wind projects.

Variables	Symbol	Value
Installed capacity in MW	P	3
Number of generators	n	130
Initial investment cost per €/MW	s	1,250,000
Loan time in years	N_2	10
Construction time per year	T	1
Fixed assets residual rate of in percentage	λ	5
Average IRR in percentage	υ	8
Insurance in percentage	i_n	2
Value-added tax rate in percentage	Z	3
Return of equity in percentage	-	12
Tax bracket in percentage	B	35
Utility escalation rate in percentage	e_s	4
Depreciable life per year	T_d	20
Concession time per year	N_1	20
Loan rate in percentage	i	3
Private capital	ρ	20

Leveraging the information presented in Table 2, we have formulated an annual cash flow model to depict the investment in wind turbines for both deployment scenarios. It is important to note that our analysis assumes a projected lifespan of 20 years for the wind farm. Additionally, we have designed the cash flow model with the objective of ensuring that the entire loan amount is repaid to the government within the first 10 years of the farm's production. This financial approach allows us to assess the long-term financial viability and sustainability of the proposed wind farm configurations.

3.2.4. Assessing Wind Turbine Economic

3.2.4.1. Analyzing wind energy costs without considering power fluctuations

Based on the data provided in Table 2, we have calculated the internal rate of return (IRR) ratios for the wind farm deployment scenarios, specifically for Tarifa and the distributed setup across three cities. It's worth noting that these calculations have been performed without factoring in the influence of power output fluctuations. The results indicate that if the variability in power generation is not considered, the IRR ratio for the Tarifa location significantly surpasses that of the three cities by 11.55% and 9.86%, respectively. This observation underscores the higher profitability of deploying the wind farm in a singular location, Tarifa, if the fluctuations in power output are neglected.

To provide a more comprehensive analysis, we have employed equations (7 to 14) to accurately determine the annual cash flow for each of the specified deployment scenarios. These equations enable us to account for the intricate financial dynamics associated with each option, taking into consideration various parameters and costs and ultimately aiding in a thorough evaluation of the financial feasibility of the wind farm deployment strategies.

Table 3: Yearly cash inflow for the agricultural operation in both situations.

Resource Area	Unit	Tarifa site	Three Locations
CF_0	millions €	-97.50	-97.50
CF_1	millions €	1.18	-1.73
CF_2	millions €	1.34	-1.59
CF_3	millions €	1.48	-1.47
CF_4	millions €	1.62	-1.36
CF_5	millions €	1.75	-1.26
CF_6	millions €	1.86	-1.17
CF_7	millions €	1.96	-1.09
CF_8	millions €	2.05	-1.03
CF_9	millions €	2.12	-0.98
CF_{10}	millions €	2.17	-0.95
CF_{11}	millions €	47.93	44.79
CF_{12}	millions €	48.44	45.27
CF_{13}	millions €	48.93	45.75
CF_{14}	millions €	49.43	46.22
CF_{15}	millions €	49.92	46.69
CF_{16}	millions €	50.40	47.16
CF_{17}	millions €	50.88	47.62
CF_{18}	millions €	51.35	48.07
CF_{19}	millions €	51.81	48.52
CF_{20}	millions €	52.26	48.96

The cumulative revenue for both deployment scenarios has been visualized in Figure 6. The chart reveals that the owner of the wind farm in Tarifa can repay the loan within the initial 11 years of the farm's operational lifespan. Beyond this point, the revenue generated consistently surpasses that of the deployment across three locations. This graphical representation underscores the substantial financial advantage of concentrating the wind farm in Tarifa, as it enables quicker loan repayment and results in higher overall gains when compared to the distributed setup.

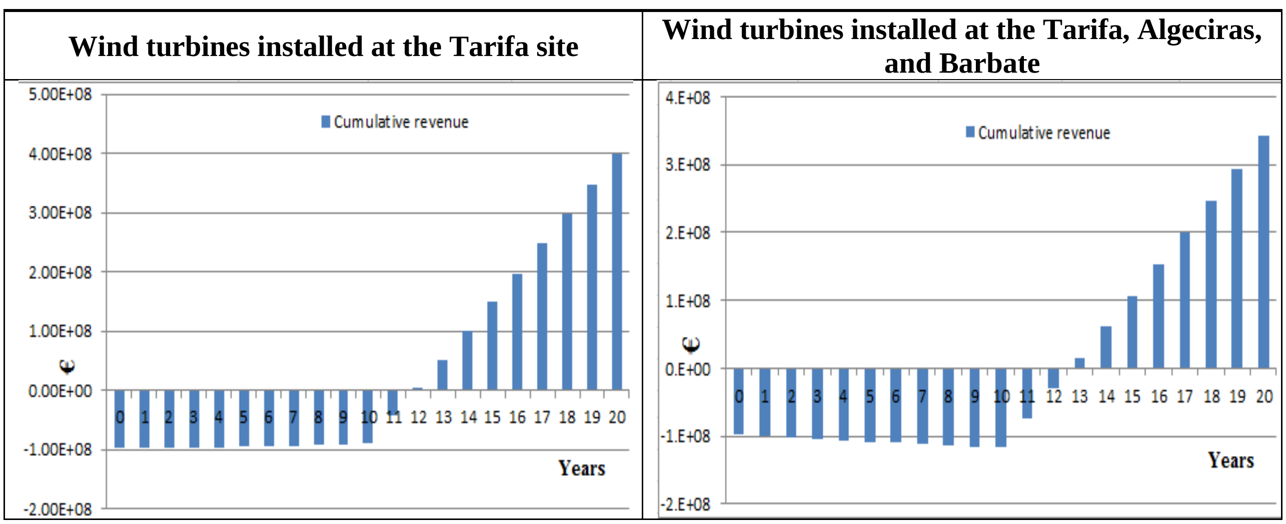

Figure 6: Accumulated income from both scenarios, excluding considerations for farm power fluctuations.

3.2.4.2. Wind Power Associated Costs Considering Power Deviation

The national grid authority has introduced a penalty factor to motivate wind power developers to address the output power deviations of the wind turbines. This recent addition to national grid regulations involves incorporating the penalty factor, achieved by multiplying the wind farm's base price. The magnitude of the penalty factor is determined by regulatory authorities and is contingent on the degree of output power fluctuations observed in a particular wind farm.

When the power fluctuations within a wind farm fall below the district average of power fluctuations, the penalty factor surpasses one. As a result, the income prices for the farm rise above the baseline. Conversely, if the fluctuations surpass this regional average, the income may face a reduction. This strategic mechanism is designed to incentivize wind farm operators to minimize uncertainties in wind turbine output, thereby promoting the sustainable development of wind farms.

This research paper employs a specific criterion for assessing the quality of wind farm output, namely the percentage of root mean square error (ePMRSEi). This criterion relies on a comparison between the targeted power output, set at 200 MW in this study, and the error calculated from the actual output of the wind farm. The percentage error is then incorporated as a penalty factor (δ) through the utilization of Equation (15). This approach provides a quantitative measure to assess and encourage the improvement of wind farm output quality, which is crucial for the stable and efficient integration of wind power into the grid.

$$e_{PMRSEi} = \sqrt{\frac{\left(\frac{P_{Target} - P_{act}}{P_{act}}\right)^2}{No.}} \tag{15}$$

In the equation mentioned, the variables are defined as follows: PTarget: This represents the required power output from the wind farm, which is set at a specific value of 200 megawatts (MW). It serves as the target or desired level of power generation that the wind farm should ideally achieve. Pact: This variable corresponds to the actual power generated by the wind farm. It reflects the real-world output of the wind farm, which may vary from the target due to factors like wind variability and other operational conditions. No.: Denotes the number of working days considered in the calculation. It represents the duration of the specific timeframe over which the comparison between the required power (PTarget) and actual power (Pact) is being made.

The average percentage of root mean square error, denoted as ePMRSE, can be mathematically expressed using Equation (16). This equation provides a quantitative representation of the ePMRSE metric, which plays a vital role in evaluating and characterizing the accuracy and consistency of wind farm output. It serves as a crucial tool for evaluating the effectiveness and caliber of wind power generation, especially in the context of its integration into the electrical grid.

$$e_{PMRSE} = \frac{1}{M}\sum_{i=1}^{M} e_{PMRSEi} \tag{16}$$

In the equation provided, the variable M represents the number of selected data points used for calculating the ePMRSEi metric. The value of M is indicative of the sample size or the number of data points considered when evaluating the accuracy and consistency of wind farm output. The larger the value of M, the more comprehensive and representative the assessment will be in characterizing the performance and quality of the power output.

The penalty factor can be computed using Equation (17). This equation outlines the specific mathematical relationship that allows for the determination of the penalty factor based on the calculated ePMRSE value. The penalty factor serves as a crucial component in the regulatory framework that incentivizes wind farm operators to enhance the quality and consistency of their power output while facilitating the integration of wind energy into the grid.

$$\delta_i = 1 + \alpha \times (e_{PMRSE} - e_{PMRSEi}) \tag{17}$$

The determination of the penalty factor (δ) is influenced by the variability control parameter (α), which is employed to regulate the degree of punitive measures imposed. The value of α is subject to the discretion of the regulatory authority and is directly proportional to the magnitude of power fluctuations observed in a wind farm. Essentially, as power fluctuations increase, the value of α also increases. The final payment made to the farm owners is then adjusted by multiplying it by the penalty factor (δ). If the penalty factor exceeds one, the farm owners receive higher income, while a value below one results in reduced income. This penalty mechanism is closely linked to the regulation of feed-in tariffs and serves as a means to encourage improvements in the reliability and consistency of wind power generation.

In this study, an illustrative value of $\alpha = 1$ has been chosen to demonstrate how this mechanism works in practice. This value is applied to penalize the Tarifa wind farm, which exhibits higher power fluctuations compared to the combination of the three alternative locations, as discussed in Section 3. As a result, the Internal Rate of Return (IRR) ratio for Tarifa, standing at 10.57%, is lower than that of the aggregate from the three locations (10.76%). This shift in cumulative revenue implies that the suggested distributed technique offers greater benefits compared to the sole implementation of the wind farm in Tarifa. By applying a relatively modest penalty factor in Tarifa, as illustrated in Figure 7, the owners of the three locations attain a more favorable income return. This strategic approach aligns with the goal of maximizing income while enhancing wind farm performance and grid integration.

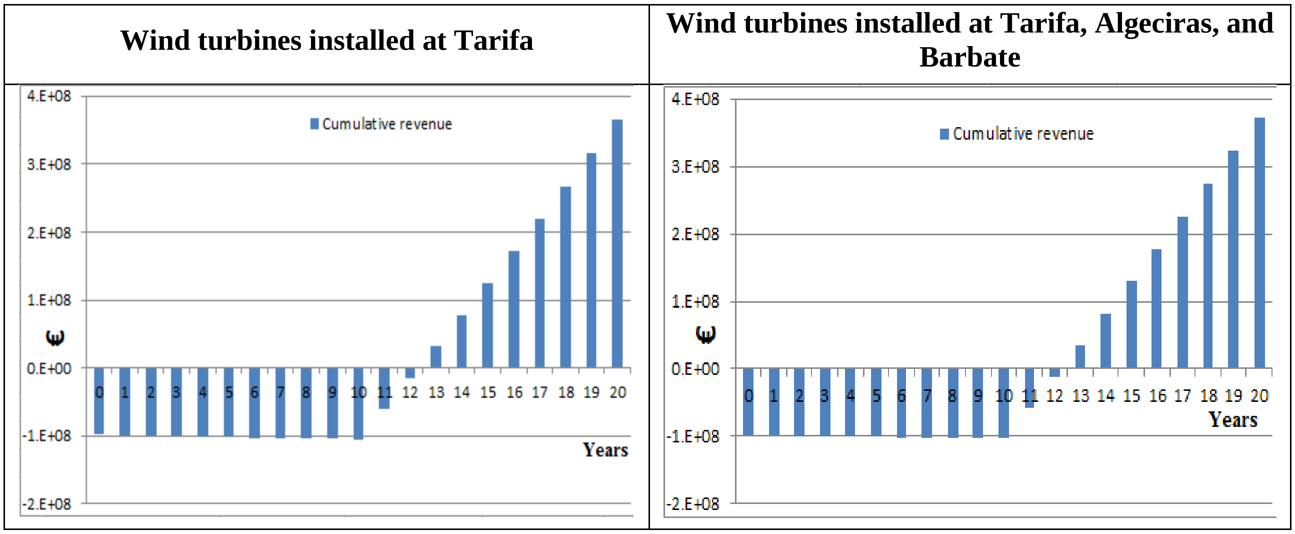

Figure 7: Total income from both scenarios, factoring in the fluctuations in farm power.

In examining the economic advantages and disadvantages of integrating large, fluctuating wind farms into the network, our cost analysis considers a crucial factor introduced by the national grid authority – the penalty factor. This factor serves as a regulatory mechanism, influencing the income prices for wind farm owners based on the degree of output power fluctuations observed. As outlined in Equation (17) and demonstrated in Figure 7, the penalty factor (δ) is calculated by assessing the percentage of ePMRSE as a measure of power output quality. The penalty mechanism, illustrated with an illustrative value of $\alpha = 1$ in our study, is designed to incentivize wind farm operators to minimize uncertainties in wind turbine output, promoting sustainable development. Our study sheds light on the economic implications of this penalty factor, showcasing its influence on the IRR ratios for different deployment scenarios. This nuanced analysis provides insights into how the introduction of a penalty factor can impact the financial viability of wind farm projects, guiding stakeholders in navigating the challenges and opportunities associated with integrating large, fluctuating wind farms into the network. It emphasizes the importance of optimizing power quality to maximize economic returns while meeting grid acceptance criteria.

It is crucial to emphasize that the premise of this study assumes that the power fluctuations of the three alternative locations meet the acceptability criteria established by the national grid. As a result, the imposition of a penalty is specifically allocated to the city of Tarifa, where more significant power fluctuations are observed. The extent of this penalty depends on the regulations and policies established by the national grid authority in their respective countries.

Based on the aforementioned discussions, it can be concluded that the suggested approach serves as an incentive mechanism for owners of wind farms. It serves as an incentive for these operators to proactively address and smooth their farm's power output, making it more suitable for grid integration. By reducing power fluctuations, they can not only enhance their chances of grid acceptance but also reduce the magnitude of the penalty factor imposed on their operations. This approach promotes a win-win situation where both the grid and wind farm owners benefit from improved power quality and greater economic returns.

In summary, our findings reveal a nuanced understanding of the economic feasibility of dividing a large wind farm into smaller groups distributed across different locations. Notably, our analysis, presented in Tables 2 and 3 and illustrated in Figures 6 and 7, provides a comprehensive overview of the Internal Rate of Return (IRR) ratios and yearly cash inflow for both scenarios, considering the deployment in a singular location (Tarifa) and the distributed setup across three cities. It is important to highlight that the calculations have been performed without factoring in the influence of power output fluctuations. This deliberate choice allows us to isolate the economic impact of deployment strategies from the complexities introduced by power deviations. The observed higher profitability in the singular location, particularly Tarifa, when fluctuations are neglected, underscores the financial advantage of concentrating the wind farm. However, we acknowledge the importance of considering power fluctuations, as demonstrated in Figure 7, where the distributed approach gains prominence. This aspect adds a layer of complexity to decision-making in the renewable energy sector, emphasizing the need for a careful balance between centralized and distributed deployment strategies to maximize economic returns while ensuring grid integration and power quality.

4. Discussion

Our analysis provides valuable insights into the disparities in costs, revenues, and overall economic feasibility between centralized and decentralized wind turbine deployment methods.

While the overall system expenditure for wind farms remained consistent in both deployment scenarios, we observed variations in land costs. This was particularly influenced by the load factor of specific locations, with Tarifa exhibiting higher land costs compared to the alternative locations. Moreover, O&M costs were analyzed in detail, considering factors such as servicing wind turbines, disposable goods, repairing wind turbines, backup components, localized technical outlays, and turbines' power demand. The distributed setup across multiple locations showed variations in these costs compared to a singular location (Tarifa).

The annual cash flow projection considered various revenue streams, including power sales, subsidies, and tax incentives. Disparities in power generation, particularly influenced by wind variability, led to variations in revenue between the centralized and decentralized scenarios. Furthermore, the introduction of a penalty factor as a regulatory mechanism played a crucial role in influencing revenue. The penalty factor, based on the percentage of root mean square error (ePMRSE), contributed to the economic feasibility of wind farm projects, particularly highlighting the impact of power fluctuations on revenue.

The IRR ratios for both deployment scenarios were compared, providing a comprehensive view of the overall economic feasibility. The findings shed light on the profitability of each strategy, considering factors such as initial capital investment, ongoing operational costs, and revenue streams.

Our analysis elucidates the disparities in costs and revenues, offering a nuanced understanding of the overall economic feasibility of centralized and decentralized wind turbine deployment methods. By examining the specific components that contribute to these disparities, we contribute to the broader discourse on optimizing wind farm investments for economic efficiency.

5. Conclusions

In conclusion, the proposed wind turbine deployment strategy aligns seamlessly with the broader goal of transitioning towards a cleaner and more sustainable energy future, both economically and environmentally. The escalating prices of conventional fossil fuels, coupled with increasing concerns about climate change, underscore the urgency of embracing renewable energy sources. Our research addresses a critical aspect of this transition by offering a strategic solution to mitigate the inherent variability in the power output of wind farms.

The recommended strategy involves the thoughtful distribution of wind turbines across multiple locations, effectively reducing power fluctuations. This not only enhances the economic viability of wind turbine investments, as evidenced by our comprehensive cost analysis but also contributes to environmental sustainability by fostering the integration of renewable energy into the grid. The introduction of a penalty factor further incentivizes wind farm owners to optimize power quality, aligning economic interests with environmental objectives.

For Spain and other nations committed to a renewable energy future, formulating economically viable policies is imperative. Our study advocates for the incorporation of the penalty factor as a motivational tool, providing a tangible strategy for minimizing output power fluctuations. This not only ensures the stability of the electrical grid but also promotes the continued growth of renewable energy projects.

As we look ahead, future work should consider the dynamic interplay of fluctuating fossil fuel prices and the evolving landscape of climate change on the economic rationale for renewable energy projects. By incorporating these factors into the assessment, policymakers can craft more resilient and adaptive strategies, steering the energy landscape toward sustainable development and addressing environmental concerns. Our research contributes valuable insights to this ongoing dialogue, emphasizing the pivotal role of strategic wind turbine deployment in achieving a cleaner and more sustainable energy future.

Conflict of interests

None

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