Boosting wind farm productivity: smart turbine placement with cutting-edge AI algorithms

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Article Info

Article history:

Received Dec 24, 2023
Revised Mar 1, 2024
Accepted Apr 5, 2024

Keywords:

Fatigue
Genetic algorithm
Optimization
Wake
Wind farm

ABSTRACT

Efficient wind farm development necessitates careful planning of wind turbine placement. The primary aim of this optimization process is to strategically position turbines to minimize the wake effect. The ongoing study seeks to standardize wake losses across all turbines in the wind farm through the adoption of a novel diagonal layout. To achieve this objective, an objective function has been devised and employed by a genetic algorithm, aiming to maximize the energy production of the farm while avoiding the concentration of wake on specific turbines. This methodology was applied to the Gasiri wind farm using simulation. The results of the optimization show great promise, indicating a potential energy increase of 17% following the implementation of the optimized layout. Furthermore, the study highlights that the new turbine placements, characterized by higher nominal power, are more favorably aligned forward, in accordance with the wind direction, compared to their original positions. Additionally, a substantial reduction in the mechanical fatigue of the turbine blades was noted.

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1. INTRODUCTION

In recent years, there has been a growing commitment to expanding global clean energy production [1], driven by the urgent need to mitigate environmental degradation and achieve a sustainable balance in energy resources [2]. Wind power has emerged as a prominent source of green energy worldwide, with governments increasingly investing in wind energy infrastructure. Notably, wind farms constitute a significant portion of European investments in renewable energies [3], [4], underscoring their importance in the transition towards sustainable energy sources. However, optimizing wind farms remains crucial for maximizing energy output and minimizing energy losses, particularly due to wake effects that significantly impact efficiency [5].

Previous research has addressed wind farm optimization using various algorithms, including different artificial intelligence algorithms [6], [7]. While many studies have focused solely on optimizing energy or cost [8], some have combined both criteria, reflecting the complex considerations involved in wind farm design. Additionally, recent studies have explored the effects of consolidating nearby offshore wind farms [9], [10], highlighting evolving trends in wind energy development.

Despite advancements in wind farm optimization, challenges persist, especially in smaller wind farms where certain turbines may suffer disproportionately from wake effects [11], leading to reduced energy production and turbine fatigue. To address these challenges, this paper aims to develop an algorithm that can diminish and standardize wake impacts throughout all turbines within a wind farm, with a focus on maximizing energy output and mitigating wake effects. The primary contribution of this paper lies in its novel approach to wind farm optimization, which considers both energy and cost objectives while addressing wake effects. By combining these criteria and incorporating insights from recent studies [12], [13] on offshore wind farm consolidation, the paper offers a comprehensive framework for optimizing wind farm layouts.

The following sections of the paper will detail the methodology employed, starting with the wind farm modeling and the employed wake model. Subsequently, the paper will present the objective function and outline the optimization algorithm utilized for the Gasiri wind farm. Finally, the paper will conclude with an analysis of the results and key insights drawn from the study. In addition to addressing wake effects and optimizing wind farm configuration, this study highlights the importance of considering the challenges faced by small wind farms. These farms often face disproportionate impacts from wake effects [14], leading to increased turbulence, wind turbine blade fatigue [15], [16], and reduced overall energy production. To alleviate these challenges, the paper proposes the development of an objective function aimed at maximizing energy production while minimizing the detrimental effects of wake turbulence on specific wind turbines [17], [18]. By focusing on these smaller-scale wind farms, the research aims to provide information and solutions that can improve the efficiency and sustainability of wind energy production in various operational contexts. This approach highlights the importance of tailoring optimization strategies to meet the unique characteristics and constraints of different wind farm configurations, thereby contributing to a more robust and resilient renewable energy infrastructure.

2. MODELING OF WIND FARM

2.1. Wake modelling

The phenomenon of wake effect alters the wind speed as it passes through the upstream wind turbines (WT). The increasing impact is characterized by a decrease in wind speed and an increase in turbulence in the windiest area. Notably, wind turbines positioned in the wake zone produce less energy and require more maintenance compared to those upstream. Consequently, modeling the wake effect becomes crucial in deciding the placement of wind turbines, and it should be given significant consideration during the optimization of wind farm design layouts (WFDLO).

Certainly, various wake models have been employed to illustrate wind speed loss characteristics [19], [20]. These models fall into two primary categories: analytical wake models and computational wake models, which involve solving the Navier-Stokes equation and offer greater precision compared to other models. However, their application in wind farm design layout optimization (WFDLO) is hindered by increased computational requirements and higher costs [21]. On the other hand, analytical wake models are built on the foundation of analytical wind speed solutions and find extensive use in optimization methods, particularly for large wind farms with numerous wind turbines [22], [23]. Among these models, Jensen's wake model is widely utilized, incorporating a linear expansion of the wake as an underlying assumption [24]. Figure 1 illustrates the principle of the Jensen model developed. These models exhibit high efficiency due to their reliable power loss predictions, demonstrating reasonable accuracy compared to alternative models as demonstrated in [24]. Consequently, in this study, we opt for the Jensen model to calculate various wind speeds. Thus, the speed deficit is expressed as (1).

$$V_{df} = V_f \; [\left(1 - \sqrt{1 - C_T}\right) \left(\frac{D}{D_{wake}}\right)^2 \tag{1}$$

In this given context: D: represents the rotor diameter, measured in meters; D_{wake}: Denotes the wake diameter, measured in meters; C_T: Stands for the thrust coefficient; V_f : Represents the free incoming wind speed, measured in meters per second; and V_{df}: Signifies the wind velocity deficit, measured in meters per second. It's important to note that the wake diameter is not a constant value but varies based on the rotor diameter and a consistent wake minimization coefficient. The detailed calculation of this coefficient can be found in references [24] and [18].

2.2. Energy production modelling

Estimating energy production in the presence of the wake effect involves computing the power generated by each wind turbine. Various expressions, frequently utilized for estimating wind turbine power, have been investigated in [24]. Therefore, the approximate calculation of the energy production of each wind turbine is conducted as (2).

$$P_{WT} = \frac{1}{2}\rho\pi\frac{D^2}{4}C_{EF}(V_f - V_{df})^3 \quad (2)$$

C_{EF} denotes the efficiency factor, and it is expressed by (3).

$$C_{EF} = C_p\eta_m\eta_g \quad (3)$$

In this investigation, the efficiency factor C_{EF} is presumed to be 40%. The overall power generated by wind turbines operating under the influence of wake effects can be calculated as (4).

$$P_{WF} = \sum_{i=1}^{N_t} P_{WT} \quad (4)$$

The efficiency of the wind farm is defined by (5).

$$\eta_{WF} = \frac{P_{WF}}{(\frac{1}{2}\rho\pi\frac{D^2}{4}C_{EF}{V_f}^3)} \quad (5)$$

To streamline the optimization process of the examined wind farm, the wind turbine positions are identified using Cartesian coordinates (x, y). The computation of distances between turbines and the determination of the total wind speed deficit, accounting for overlapping zones, are outlined. Preview study [18], [25], the expression for the total velocity deficit is articulated as (6).

$$V_{dft} = \sqrt{\sum_{i=1}^{N_{up}} \left(\frac{A_{OV}}{A}\right)(V_{df})^2} \quad (6)$$

In this context, A_{OV} denotes the overlap area in square meters, A represents the swept area of the wind turbines in square meters, and N_{up} signifies the number of upstream wind turbines.

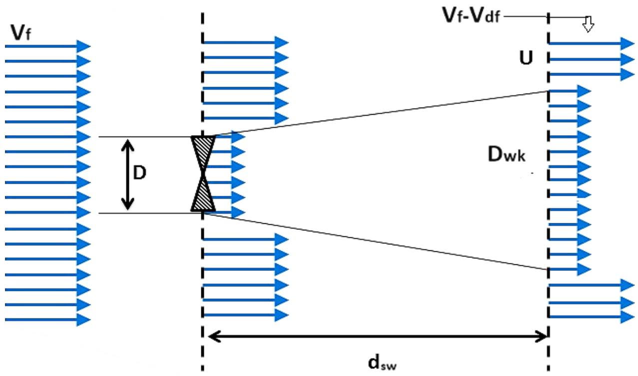

Figure 1. Jensen model [25]

3. METHODOLOGY

The research method entails the assessment of an objective function with the dual purpose of maximizing power output and minimizing wake losses within a wind farm through standardization. To scrutinize this methodology, we conducted an optimization of our objective function within the Gasiri wind farm employing genetic algorithms. It is noteworthy that the computational calculations were executed utilizing MATLAB software on a computing system comprising an i7 processor with 16GB of RAM. Comprehensive details and data are referenced in the subsequent section.

3.1. Objective function

The primary goal is to enhance the power output of the wind farm and normalize the wake losses for each individual wind turbine within the facility. Certain turbines in a wind farm may experience more pronounced wake effects, leading to operational challenges and a shortened lifespan. The proposed objective function aims to maximize the energy production of the wind farm while minimizing the standard deviation of wake losses experienced by the wind turbines. The objective function, designated as FOBJ, is derived as (7).

$$FOBJ = max\left(\frac{P_{WF}}{1-\sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(W_a-W_i)^2}}\right) \quad (7)$$

3.2. Algorithm for optimization

Genetic algorithms offer several advantages for the optimization of wind farms. Firstly, their global search capability allows them to effectively explore a broad solution space, making them well-suited for finding optimal configurations in complex, multi-dimensional problems. Additionally, the parallelism inherent in genetic algorithms enables the simultaneous consideration of multiple scenarios, accelerating the optimization process. These algorithms exhibit adaptability, dynamically adjusting to changing conditions and uncertainties, which is particularly beneficial for addressing variations in wind patterns. Genetic algorithms are also adept at handling conflicting objectives, making them suitable for the simultaneous optimization of multiple goals, such as maximizing energy output and minimizing wake effects. Furthermore, their ability to function without requiring derivative information makes them versatile for scenarios where obtaining derivatives may be challenging or computationally expensive. As illustrated in Figure 2 the steps of this algorithm are as follows, steps of genetic algorithm for wind farm optimization: i) Initialization: create an initial population of potential wind farm layouts; ii) Evaluation: assess fitness based on the objective function; iii) Selection: choose individuals for reproduction based on fitness; iv) Crossover: exchange genetic information to create a new generation; v) Mutation: introduce random changes to maintain diversity; vi) Evaluation (again): assess fitness of the new generation; vii) Elitism: retain the best-performing individuals from the previous generation; viii) Termination criteria: check if termination criteria are met; and ix) Repeat: if not met, repeat steps 3 to 8 until convergence to an optimal solution.

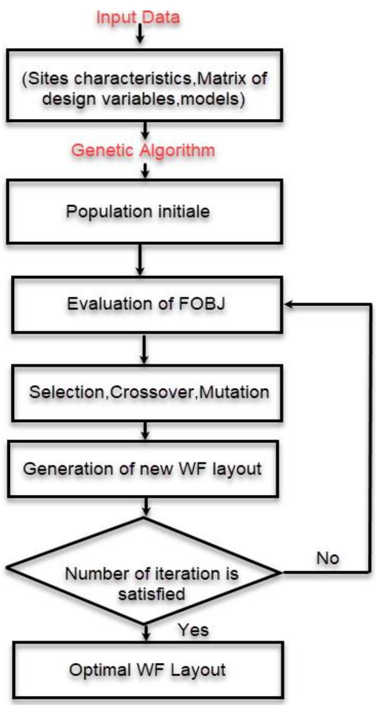

Figure 2. Processing process diagram of GA algorithm

Table 1 summarizes key parameters for a genetic algorithm: initial population size, selection pressure, crossover probability, mutation probability, and iteration number. Initiating the proposed algorithm necessitates essential information about the wind farm's characteristics and the selected model for the current study. Table 2 gives the characteristics of the turbines used for the simulation and Table 3 encapsulates the requisite data crucial for successfully commencing the genetic algorithm.

3.3. Case study: Gasiri wind farm

In this section, the emphasis is on optimizing the arrangement of wind turbines within the Gasiri wind farm using the previously defined objective function. The outcomes of this study will be juxtaposed with findings from earlier investigations on the same wind farm. The Gasiri wind farm is situated on Jeju Island, South Korea, and is illustrated in Figure 3, showcasing the distribution of wind turbines and the wind rose. Consisting of 13 wind turbines categorized into three types (HS50-750 kW, U50-750 kW, HJWT77-1500 kW), the turbines are positioned in a grid pattern oriented towards the NNW direction, recognized as the predominant wind direction at the Gasiri wind farm. Implementing the optimization of the wind farm requires a MATLAB code utilizing the wind data outlined in Figure 3, Table 1, Table 2, and Table 3.

Table 1. Prescribed factors in a genetic algorithm

GA parameter	Size of initial population	Selection pressure	Crossover probability	Mutation probability	Iteration number
Value	150	3	0.75	0.25	355

Table 2. Fundamental details about three distinct types of wind turbines

Power rating (kW)	U50	HJWT77	HS50
Hub height (meters)	750	1500	750
Rotor diameter (meters)	50	70	50
Cut-in wind speed (m/s)	50	77	50
Rated wind speed (m/s)	3	3.5	3.5
Cut-out wind speed (m/s)	12.5	13	12
Power rating (kW)	25	25	25

Table 3. Information provided as input for the genetic algorithm

Site characteristics	Wind speed and direction	Wf size	Roughness
Variables matrix	Arrangement	Constrain the distance between	Design variables for wind turbine
Models	Wake model	Power model	WT design variables

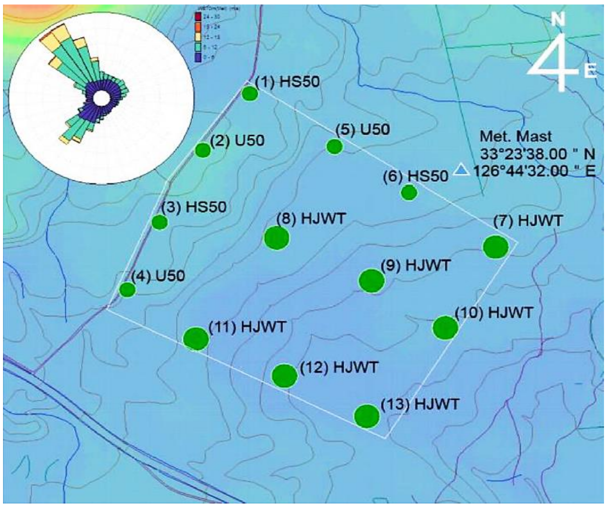

Figure 3. Current position of turbines in the Gasiri wind farm

The computed results of the annual energy production (AEP) energy production are compared with actual electricity production data collected from the Gasiri wind farm, as depicted in Figure 4. While there is a minor variance between the real data and the calculated results, the accuracy is notably improved compared to previous literature results [25] obtained using alternative algorithms. The disparity primarily stems from the choice of the wake model used and the specific operational characteristics of each wind turbine. Notably, 750 kW wind turbines are excluded from the calculation due to their low recovery rate based on the collected data. Figure 5 provides a summary of the collected and computed results.

The annual production of the wind farm is computed under the assumption of a 365-day operational year, equivalent to 8760 hours. The formula for calculating the annual production is stated as (8).

$$AEP = 8760 \sum_{i=1}^{N_t} \sum_{j=1}^{N_d} \sum_{k=1}^{N_s} F(U_{ijk}) P(U_{ik}) \quad (8)$$

Here, $F(U_{ijk})$ represents the likelihood of wind blowing within speed category k for turbine i within direction sector j, denoted as $P(U_{ik})$, represents the power generated by turbine i at wind speed category k. N_d and N_s

represent the partitioning by direction interval of the total bearing and the value obtained by dividing the wind speed range (3-25 m/s) by the range of wind speed, respectively.

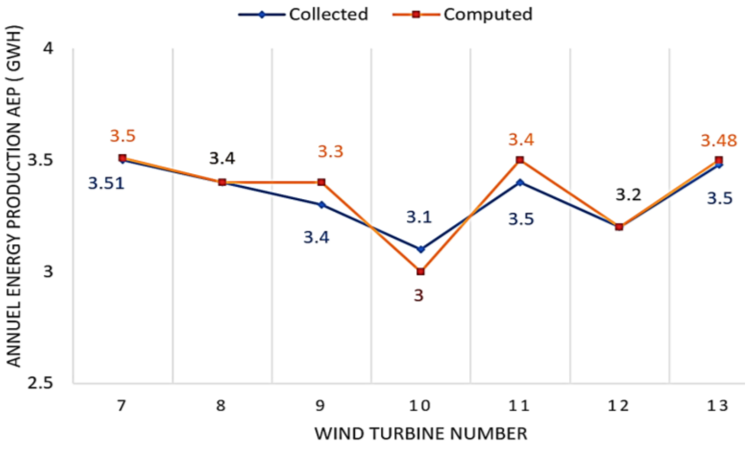

Figure 4. Contrast in annual energy productions (AEPs) derived from the Gasiri wind farm between the observed values and the computed AEPs

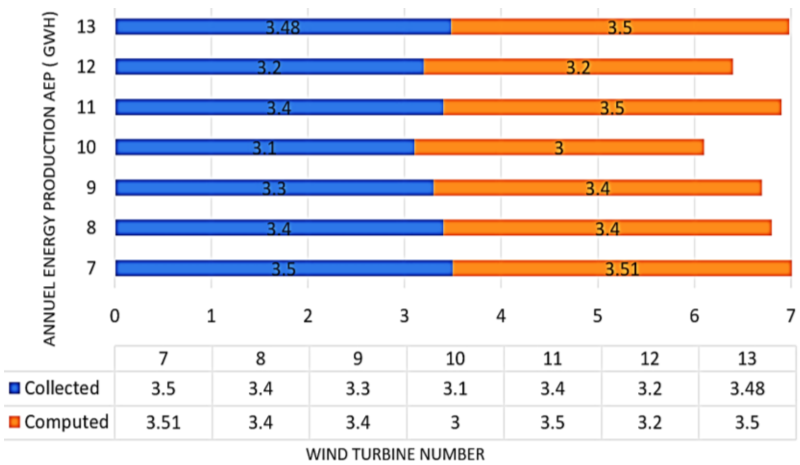

Figure 5. Discrepancy in annual energy output between the measured and calculated energy values

4. RESULTS AND DISCUSSION

Starting with Figure 6, which illustrates the fluctuation of the objective function, we observe a notable enhancement and convergence in algorithm performance after 350 iterations, with the objective function reaching a value of 0.85. This increase signifies progress towards optimizing the layout, showcasing the efficacy of our methodology. Compared to previous studies, our approach demonstrates superior performance in optimizing the layout, resulting in enhanced energy production, and minimized wake losses. The convergence indicates that our algorithm effectively navigates through various layouts, converging towards an optimal solution.

Figure 5 illustrates the difference in annual energy output between the observed and computed values. The collective annual energy production of the wind turbines amounts to 23.51 units. However, a minor disparity of 0.03 units is observed when comparing the collected production data (23.48 units) with the calculated value. This deviation can be attributed to the simplifying assumptions and uncertainties inherent in the wake model employed in our analysis. While the overall agreement between observed and calculated values is reasonable, this slight deviation underscores the need for further refinement and validation of the wake model to improve the accuracy of our predictions.

The computation domain for our wind farm, as delineated in Figure 7, is meticulously constrained. By enforcing a minimum spacing of 3 times the rotor diameter (3 * D) between turbines, we have established a separation of 230 m. This strategic spacing is critical for minimizing wake interference and optimizing energy production. Furthermore, to augment the flexibility in wind turbine placement, we have subdivided the designated area into 120 by 110 cells, each measuring 10 m by 10 m. This meticulous division accounts for restricted zones where turbine placement is prohibited, ensuring a comprehensive and efficient layout. However, while this approach enhances flexibility and accommodates various constraints, further refinement may be necessary to address potential limitations in capturing site-specific dynamics and optimizing energy production to its fullest potential.

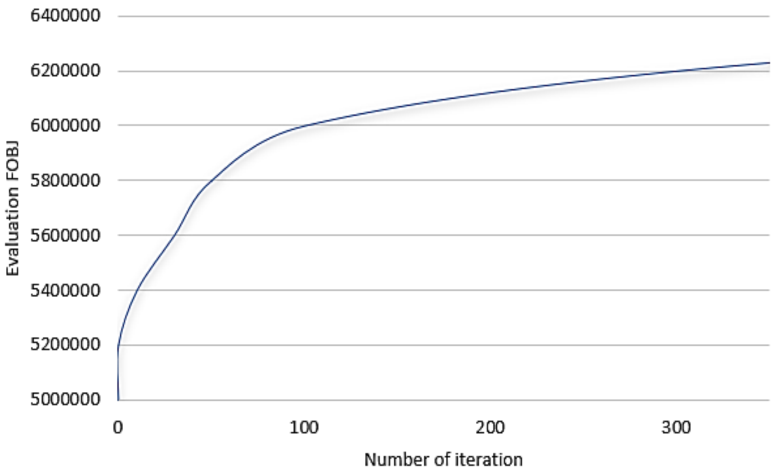

Figure 6. Assessment of the objective function (FOBJ) through the application of a genetic algorithm (GA)

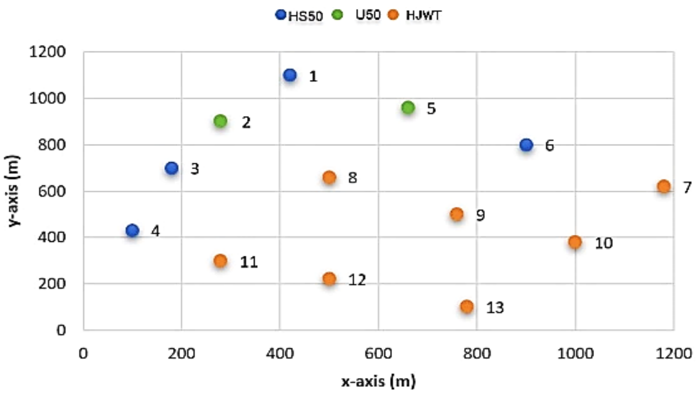

Figure 7. Geographical positions of the wind turbines within the Gasiri wind farm

The optimization procedure for the Gasiri wind farm, as depicted in Figure 8, is executed and subsequently juxtaposed with the current layout. Notably, wind turbines of the HJWT77 type, renowned for their high-rated power, display a proclivity to shift forward along the wind direction. This observation can be attributed to the minimized wake losses in forward positions, as visually illustrated in Figure 8. While this phenomenon aligns with theoretical expectations, it raises concerns regarding potential wake effects on downstream turbines and overall energy production efficiency. Additionally, our analysis reveals that lower-capacity wind turbines deviate from their initial positions in the existing configuration to align with the prevailing wind, consistent with prior studies employing simulated annealing algorithms for optimization, as documented in [24]. However, while this alignment may optimize individual turbine performance, it could lead to increased wake interference and reduced overall energy production efficiency.

Furthermore, it is worth noting that our proposed optimization technique demonstrates superior accuracy in terms of annual production levels compared to the findings presented in [22]. While this indicates progress in optimizing wind farm layouts, it is crucial to interpret these results with caution. Factors such as variations in wind conditions, terrain, and wake models can significantly influence the accuracy and reliability of production estimates. Overall, while our optimization approach shows promise in improving energy production efficiency, further refinement and validation are necessary to address potential shortcomings and ensure the robustness of our findings. Additionally, future studies should consider integrating more sophisticated optimization algorithms and comprehensive validation methods to enhance the reliability and applicability of wind farm layout optimization strategies.

In Figure 9, the increased annual energy production resulting from turbine repositioning underscores the superiority of our optimization technique compared to existing approaches. Turbines 7, 8, 9, 10, 11, 12, and 13 show notable increases in energy production, ranging from 0.35 to 0.95 units, while turbine 1 experiences a decrease of 0.1 units. While previous studies may have utilized similar optimization algorithms, our methodology demonstrates superior accuracy and effectiveness in achieving higher energy yields. The redistribution of turbines based on the optimization process leads to enhanced energy production across the wind farm.

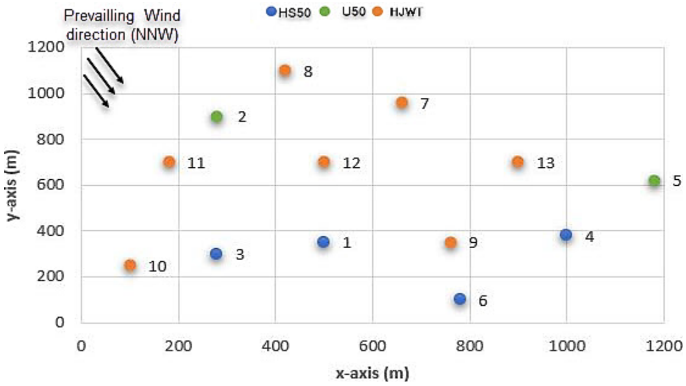

Figure 8. Results of the optimization for the layout of the Gasiri wind farm achieved through the utilization of the objective function

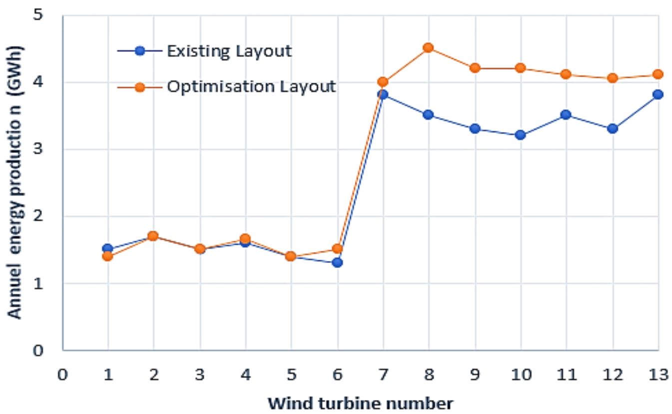

Figure 9. Annual energy yield for the existing arrangement versus the optimized layout, computed through the implementation of the objective function

Table 4 provides quantitative evidence of the improvement in net annual energy production between the current and optimized layouts. The notable disparity of 5.68 units underscores the success of the optimization approach in maximizing energy production. However, it’s important to interpret these results in the context of trade-offs between energy production, wake losses, and other factors, such as land use and cost. The increased net annual energy production indicates the effectiveness of our optimization method in achieving higher energy yields.

In Figure 10, the reduction in wake losses for the optimized layout is visually evident, with a decrease of -18.67%. This reduction surpasses the wake loss reduction achieved in previous studies, highlighting the effectiveness of our methodology in optimizing wind farm layout design. However, it’s essential to acknowledge potential uncertainties and variability in wake modeling, which may influence the accuracy and reliability of the results. The decrease in wake losses signifies improved efficiency and reduced energy losses across the wind farm.

Figure 11 further explores the consistency of wake losses across turbines in the optimized layout. This uniformity mitigates disparities in energy losses within the wind farm, surpassing the results of previous studies. The minimal variance in wake loss results in the optimized layout suggests a more consistent pattern, indicating a significant improvement over existing optimization technique. Consistent wake losses contribute to stable energy production and improved overall performance of the wind farm.

Table 5 quantifies the differences in wake loss percentages between the current and optimized layouts, revealing a notable decrease of -18.67%. This reduction surpasses the wake loss reduction achieved in previous studies, highlighting the effectiveness of our methodology in optimizing wind farm layout design. The significant decrease in wake losses indicates improved efficiency and reduced energy losses, leading to enhanced energy production and overall performance of the wind farm.

Table 4. Contrast in annual energy output between the current arrangement and the optimized layout

Wind turbine identification number	Net AEP/gross AEP	
	Current configuration	Enhanced configuration
1	1.49/1.54	1.44/1.61
2	1.62/1.71	1.76/1.82
3	1.45/1.52	1.49/1.55
4	1.53/1.57	1.64/1.73
5	1.40/1.53	1.43/1.58
6	1.39/1.55	1.51/1.63
7	3.65/4.05	4.00/4.80
8	3.48/4.02	4.45/5.05
9	3.32/3.97	4.20/4.95
10	3.35/3.98	4.25/4.80
11	3.46/4.02	4.10/4.85
12	3.36/3.90	4.03/4.48
13	3.38/3.88	4.08/4.70
Total	32.95/37.55	38.4/43.70
Difference	(+)5.86	

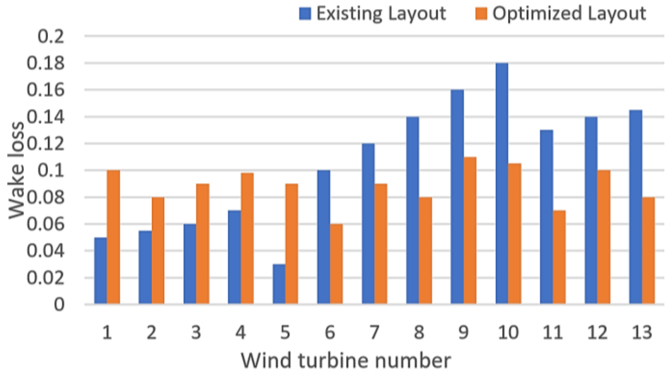

Figure 10. Differences in wake losses between the existing and optimized layouts

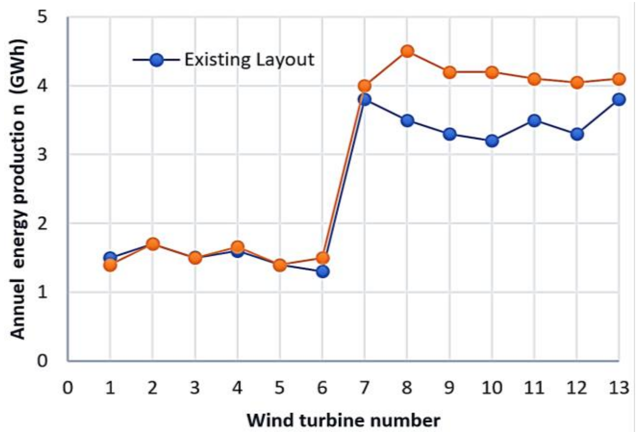

Figure 11. Consistency of wake losses in the optimized layout

Table 5. Differences in wake loss percentages between the current layout and the optimized arrangement

Wind turbine identification number	Percentage of wake loss	
	Current configuration	Enhanced configuration
1	5.16	10.02
2	5.72	8.10
3	6.13	9.02
4	2.32	9.8
5	8.13	9.06
6	10.06	7.05
7	10.39	8.50
8	13.87	8.3
9	16.17	12.1
10	17.83	11.13
11	13.04	7.09
12	13.87	10.17
13	14.38	8.06
Total	137.07	118.4
Disparity	(-)18.67	

5. CONCLUSION

This article presents a novel approach to optimizing a wind farm, employing an objective function through a genetic algorithm to refine the layout of wind turbines. The primary goal is to optimize energy generation while mitigating wake losses across all turbines within the wind farm. The application of this method to the Gasiri wind farm has yielded promising results, not only in the reduction of wake losses but also in their uniform distribution across the turbines in the farm.

The optimized arrangement indicates that wind turbines with greater rated power are typically situated ahead, aligning with the direction of the wind. Moreover, findings from the simulation in this research exhibit a noteworthy 17% enhancement in energy output relative to the current layout, along with a considerable decrease in estimated wake losses by around 18%. The optimization of the layout investigated in this study revolves around a cost function focused on minimizing wake losses. Future research endeavors aim to explore the relationship between wind turbine arrangement, utilizing a multi-objective function, and the associated costs involved in such optimization.

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