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OPTIMIZING WIND FARM LAYOUTS USING HISTORICAL DATA AND COMPUTATIONAL FLUID DYNAMICS: A COMPUTATIONAL FRANDSEN WAKE MODEL AND DIFFERENTIAL EVOLUTION ALGORITHM

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Abstract: The increasing demand for sustainable energy solutions has heightened the importance of optimizing wind farm layouts to enhance efficiency and energy output. This study investigates the optimization of wind turbine placement using historical SCADA data, computational fluid dynamics (CFD), and Differential Evolution (DE) algorithms. We analyzed a comprehensive wind turbine dataset, which included wind speed, active power, theoretical power curves, and wind direction data. The analysis revealed a direct relationship between wind speed and power output, with discrepancies observed at both low and high wind speeds due to system inefficiencies and turbine power limits. The Frandsen wake model was employed to account for the wake losses, while the Differential Evolution algorithm was used to optimize the turbine positions to develop an optimal layout for 100 turbines within a minimum area of 21.6 km², aiming to minimize the wake effects and maximize the energy production. The results demonstrate that proper turbine alignment and spacing significantly improve the efficiency, allowing the turbines to operate closer to their theoretical maximum efficiency. The findings highlight the critical role of integrating historical wind data with CFD simulations to optimize turbine placement and performance. This work offers a valuable framework for future windfarm designs, emphasizing the benefits of data-driven approaches in maximizing renewable energy generation and operational efficiency.

Keywords: SCADA Data Analysis, Renewable Energy, Sustainability, Wind Turbine Spacing, Wind Turbine Performance, Differential Evolution Algorithm

1. Introduction

The escalation of global demand for clean, renewable energy sources has propelled wind energy to the forefront of sustainable power generation. Wind farms, which comprise multiple wind turbines, are becoming increasingly important in the energy landscape. However, maximizing the efficiency and production of these wind farms requires a comprehensive strategy that addresses multiple factors (Pollini, 2022). Incorporating past wind data into the optimization process provides a more comprehensive knowledge of local wind patterns, which can change greatly depending on geographical and meteorological variables. Pollini (2022) discovered the best circumstances for energy production and altered turbine locations based on past wind speed and direction data. The proposed data-driven method increases the accuracy of simulations and optimizations, resulting in designs that can be adapted to individual sites.

Wind turbine size and layout factors are critical in maximizing wind farm performance and economic advantages (Stanley *et al*., 2022); taller and bigger turbines are more susceptible to growing site limitations, which affects capacity density estimations. Geographical optimization techniques that incorporate turbine layout, economics, and wind resources emphasize the potential of bigger turbines to boost capacity and generation, especially when dealing with geographical restrictions. As technology advances, wind turbine proportions and designs evolve (Hartman, 2023), and taller towers and bigger rotor diameters are becoming more popular, allowing turbines to reach greater wind speeds while mitigating the effects of surface-level turbulence. Over the years, the average hub height for utility-scale land-based wind turbines has climbed dramatically, and offshore wind turbine heights are expected to rise further to capture even more wind energy.

Furthermore, the combination of computational fluid dynamics (CFD) and optimal modeling approaches can transform the way wind farm layouts are optimized. These technologies allow engineers to simulate wind flow patterns and turbine interactions, resulting in more accurate estimates of energy production and reduction of wake effects (Al-Addous *et al*. 2020). By integrating historical wind data with CFD models, designers can construct layouts that are not only efficient but also robust against shifting climatic conditions. The availability of historical wind data is critical for optimizing wind farm design (Mahoney *et al*. (2012), as historical data provide critical information on wind speed distributions, directional patterns, and seasonal fluctuations at the planned wind farm location. By analyzing historical wind data, engineers can determine the most typical wind conditions and create wind turbine layouts to capitalize on them. This strategy not only enhances the energy productivity of wind farms and decreases the possibility of energy losses due to misaligned turbines and unfavorable wake effects.

Despite breakthroughs in optimization approaches, windfarm design continues to face various obstacles (Hwang, Wu, & Chang, (2024). Wind behavior is complicated because it is affected by geography, meteorological conditions, and turbine interactions, making it difficult to correctly anticipate the wind performance. Furthermore, the computer resources required for thorough CFD simulations become significant, attaining efficient methods that can give results in a timely manner. CFD is quite useful in optimizing wind farm design, as it enables the modeling of airflow around wind turbines, offering insights into how alternative configurations influence performance. CFD predicts wake effects and their impact on power generation by modeling the interactions between turbines and their surroundings (Khanali *et al.*, 2018). This computational technique allows engineers to investigate multiple turbine designs and determine the ideal architecture that maximizes the energy extraction while minimizing the expenses.

Liang and Liu (2023) offered a variety of methods for optimizing wind farm designs, including using machine-learning techniques to forecast wake impacts and optimize turbine location based on past data. They provide a data-driven framework that uses machine learning models trained on CFD simulation data to improve layout optimization procedures. Other approaches include the use of genetic algorithms and other optimization techniques to successfully explore the design space. Pedersen and Larsen (2020) demonstrated the efficiency of combining CFD and historical wind data to optimize wind farm design. For example, in Tehran, Iran, actual wind speed data were used to optimize turbine layouts, resulting in considerable increases in energy output. Similarly, it has demonstrated that using probabilistic inference methods can lead to quick decision-making in the layout design process, thereby guaranteeing that windfarms are both efficient and cost-effective. Optimization algorithms should take turbine spacing, access roads, and maintenance areas into account to ensure that the layout design maximizes energy output while minimizing wake impacts to enhance turbine efficiency and overall wind farm performance (Peng *et al*., 2023).

As wind speed and direction are crucial parameters for determining the optimal layout of wind farms using CFD (Harish, 2016), areas with higher wind speeds are ideal for turbine placement to maximize energy output (McKenzie, 2023). In their research, Abdulwahab *et al*. (2024) developed innovative optimization approaches to predict ideal turbine locations based on historical wind direction and wake effects by combining CFD simulations with historical wind data. Wind turbines should ideally face the prevailing wind direction to maximize energy capture, and wind direction influences the path of turbine wakes, affecting downstream turbines. However, wind speed variations across a wind farm can influence the wake behavior and the turbine performance. A wind turbine's power output is directly linked to wind speed, affecting overall farm efficiency (Energy Education, 2018). Therefore, understanding the dominant wind directions helps in arranging turbines to minimize wake losses and optimize power output. Kirchner-Bossi and Porté-Agel (2024) have shown that applying genetic algorithms and self-adaptive optimization frameworks dramatically improves power production and reduces wake losses in wind farms, resulting in more efficient energy generation and lower costs.

Wind turbines create wakes, areas of low-pressure air behind the turbine (Platis *et al*., 2018), and the wind direction influences the wake effect on the turbine layout. These wakes can reduce the wind speed of downstream turbines, as shown in figure 1, affecting their power output (Sharaf, 2023).

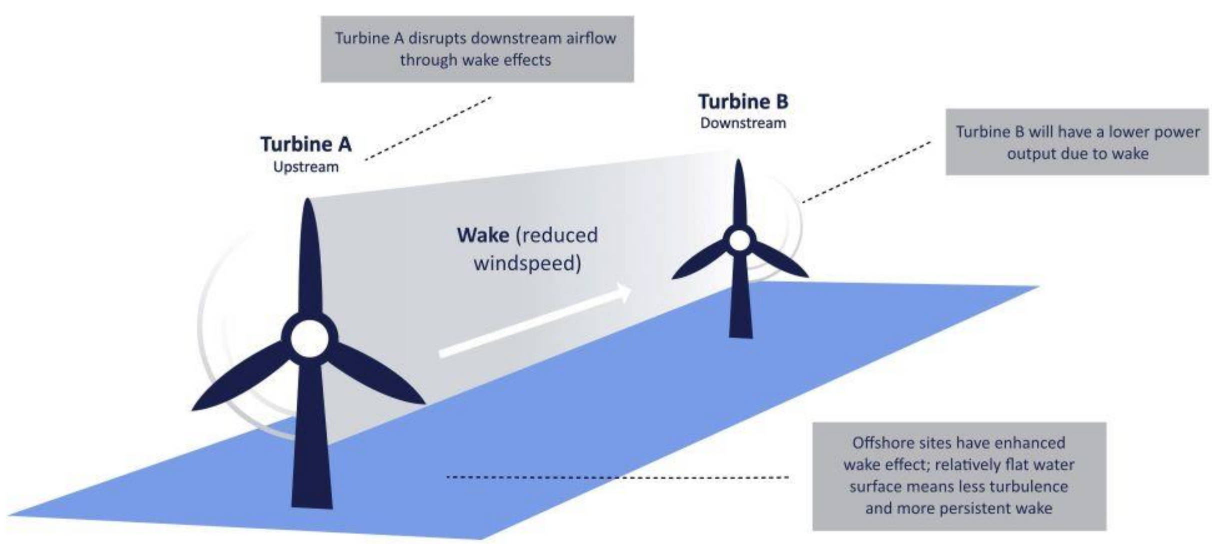

Figure 1. Wake effect of wind turbines (Sharaf, 2023)

The optimization of wind turbine layouts in large-scale windfarms presents substantial problems for total energy output and operating efficiency. Wind turbines are designed to efficiently use wind energy; nevertheless, variable factors such as the wake effects of turbine spacing can significantly affect their effectiveness. Inadequate turbine spacing, often caused by a lack of comprehensive planning, can worsen wake effects, resulting in inefficient energy harvesting. As a result, integrating CFD and historical wind data is crucial for developing successful wind farm layout optimization techniques. This work entails the performance analysis of a wind turbine and its historical wind SCADA data for a simulation on CFD with the use of python programing to optimize the wind farm layout.

1.1. Review of Related Literature

Various optimization methods can enhance wind farm layout efficiency by considering factors such as wake effects and energy production costs. Hou *et al*. (2015) utilized particle swarm optimization (PSO) to optimize turbine placement in offshore wind farms; their approach, which integrates historical wind data, achieved significant reductions in leveled production costs and improved energy yields. Wu *et al*. (2014) applied genetic algorithms and ant colony systems to optimize turbine layouts and transmission systems; their study considered wake effects and cable parameters, providing a framework for cost-effective design and demonstrating the benefits of integrating advanced optimization techniques. Herbert-Acero *et al*. (2014) reviewed various methodologies for wind farm design and optimization, including micro-siting and metaheuristic optimization; their review provides a comprehensive overview of recent advances and future research directions in wind farm performance modeling.

Fuglsang and Thomsen (1998) focused on cost optimization for offshore wind turbines, emphasizing the trade-off between initial costs and long-term benefits; their research highlights the potential for cost savings through optimized turbine layouts and supports the need for effective design strategies. Sun, Yang, and Gao (2019) proposed a Directional Restriction method for optimizing turbine spacing based on wind direction and rotor diameter. This method improves the utilization rate of nonuniform wind farms and is practical for real-world scenarios. Pillai *et al.* (2017) evaluated offshore wind farm layout optimization using genetic algorithms and particle swarm optimizers; their study identified layouts with reduced levelized energy costs, demonstrating the effectiveness of these algorithms in optimizing wind farm designs.

Advances in CFD, historical wind data integration, and various optimization methodologies provide tools to achieve these goals. The research on CFD applications, historical wind data utilization, and optimization techniques provides a comprehensive view of current practices and future directions in wind farm layout optimization. Dhunny, Lollchund, and Rughooputh (2017) validated the CFD tool WindSim by comparing its predictions with on-site measurements, focusing on the impact of computational parameters such as grid resolution and turbulence models on wind power estimates. This validation underscores the importance of accurate CFD modeling for wind farm site selection and turbine placement.

Tabas, Fang, and Porté-Agel (2019) reviewed CFD applications in urban wind energy, emphasizing the need for sophisticated turbulence models and validation processes; their review highlights the complexity of urban wind flow and the necessity of accurate CFD simulations for effective turbine placement and performance assessment. Sanderse *et al*. (2011) provided a detailed review of CFD methods for wind turbine wake aerodynamics, including both traditional and advanced approaches; their review outlines the evolution of CFD techniques and their role in understanding wind turbine wake dynamics, which is crucial for optimizing wind farm layouts.

Richmond *et al*. (2019) assessed the accuracy of wind farm CFD models by comparing simulations with operational data; their study highlighted challenges in wake effect modeling and error quantification, revealing that accurate wake simulation requires careful consideration of turbulence models and boundary conditions. Antonini et al. (2020) introduced an optimization methodology combining CFD with adjoint methods, addressing the high computational costs of direct CFD-based optimization; their approach demonstrated significant improvements in annual energy production by optimizing turbine placement in complex terrains, demonstrating the feasibility of integrating CFD with advanced optimization techniques.

2. Methodology

2.1. Data preparation

Accurate data are paramount for optimizing wind turbine layouts in large-scale wind farms. The process began by gathering a comprehensive dataset from kaggle.com: The Wind Turbine SCADA Dataset by Erisen (2019) contains 50530 rows and 5 columns. The columns include Date/Time, LV Active Power, Wind Speed, Theoretical Power Curve, and Wind direction. Once collected, the data were meticulously processed to ensure their quality and relevance. Key steps in the processing included:

- Removal of Zeros and NaN (Not a Number: Entries with zero values, especially in critical parameters like wind speed and LV Active power, can indicate sensor malfunctions or data recording errors. Such anomalies were identified and eliminated to prevent skewing the analysis.
- Removing duplicate records: Duplicate records can lead to biased results and misrepresentations in the dataset. A systematic check was performed to detect and remove any redundant entries, ensuring that each data point uniquely contributed to the analysis.

2.2. Data analysis and visualization

The steps involved the analysis of wind turbine data with a focus on wind speed, wind direction, active power, and the relationship between these variables. The analysis also included the evaluation of wind turbine performance using a performance curve and the examination of correlations between key variables.

i. Distribution of Wind Speed: The distribution of wind speed was analyzed by creating a histogram. This visualization helps identify the most frequent wind speeds encountered by the turbine, providing insights into the wind resource quality at the site. Equation 1 is used to illustrate the wind speed distribution.

$$Probability\ Density\ Function\ (PDF), fV(v) = \frac{1}{\sqrt{2\pi\sigma^2 v}}\exp(-\frac{(v-\mu v)^2}{2\sigma^2 v}) \quad (1)$$

Where;

- μv is the mean wind speed
- $\sigma^2 v$ is the variance of the wind speed:

ii. Wind Speed vs. Active Power and Theoretical Power: A scatterplot is created to analyze the relationship between wind speed and active and theoretical power outputs. The wind speed was plotted on the x-axis, while the active power and theoretical power were plotted on the y-axis. This plot is essential for understanding how wind speed influences the power generation of the turbine and how the active power correlates with the theoretical power.

2.3. Wind farm configuration

2.3.1. Wind Farm Spacing Calculations

When proposing the optimal farm size for a given number of turbines, it is essential to consider factors such as turbine spacing (to minimize wake effects), access roads, and the need for maintenance areas. The general rule of thumb for the spacing between turbines is about 3-5 times the rotor diameter (D) in the crosswind direction and 5-7 times the rotor diameter in the downwind direction.

Wind turbine dimension:

- Rotor Diameter (D): 120 m
- Hub Height: 100 m
- Blade Length: 60 m

Farm area and spacing recommendations:

- Cross-wind spacing: 3D to 5D -> 360 meters to 600 meters
- Down-wind spacing: 5D to 7D -> 600 meters to 840 meters

Equation 2 was used to calculate the area of the wind farm spacing for 100 wind turbines, with the crosswind and downwind spacings being independent variables. The minimum farm area for a hundred wind turbines is 21.6 km2, and the maximum area is 50.4 km2. This work considered the minimum possible farm for 100 turbines.

$$A = \left(\sqrt{N} * S_{cw}\right) * \left(\sqrt{N} * S_{dw}\right) \quad (2)$$

Where:

- Here, N is the Number of turbines
- Scw denotes the crosswind spacing:
- Sdw is the downwind spacing

2.3.2. Computational Mesh Creation

A computational grid was created over the wind farm area to facilitate the evaluation of potential turbine positions. The grid was defined with a resolution of 100x100 cells, covering the entire farm area. This mesh allows the discretization of the continuous space for optimization.

Objective Function Development: A power output model was implemented using equation 5 by determining the wind power from equation 3 and the turbine efficiency from equation 4.

$$P_{wind} = \frac{1}{2} \times \rho \times A \times v^3 \quad (3)$$

$$Efficiency = \frac{P_{turbine}}{P_{wind}} \quad (4)$$

$$P = \frac{1}{2} \times \rho \times A \times v^3 \times \text{Efficiency} \quad (5)$$

Where;

- ρ is the standard air density (1.225 kg/m³)
- A is the swept area of the turbine.
- where v is the wind speed.

Implementation of the Frandsen Wake Model for the Optimization Process: The Frandsen wake model was used to calculate the wake losses between turbines because this model considers the velocity deficit caused by the wake from an upstream turbine on downstream turbines. The wake radius was computed using equation 6:

$$Wake\ Radius = Rotor\ Diameter + 0.5 \times \left(\frac{Distance}{Hub\ height}\right) \times \text{Rotor Diameter} \quad (6)$$

The objective function for optimization was defined as the difference between the total power output and the total wake losses. This function maximizes the net power output by minimizing wake losses. The optimization of the turbine positions was performed using the Differential Evolution (DE) algorithm from the “scipy.optimize” library in python programing. This global optimization method was chosen for its ability to handle complex, multi-modal objective functions. The algorithm iteratively searched for the optimal turbine layout by adjusting the turbine positions within the wind farm area.

2.3.3. Position Bounds and Visualization

The turbine positions were constrained to lie within the farm boundaries. Each turbine's x and y coordinates were bound between zero and the respective farm length and width. After the optimization process, the optimal turbine positions were extracted and plotted using “matplotlib”. The positions were visualized on a 2D grid representing the wind farm, with each turbine’s position indicated by a red dot. The plot provides a clear visual representation of the optimized layout, facilitating interpretation of the results.

3. Results and Discussion

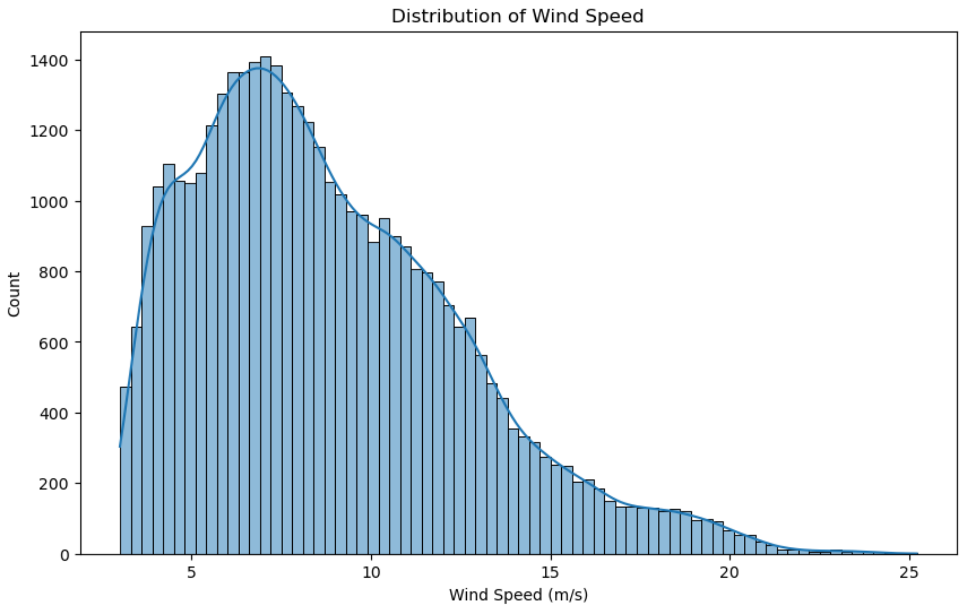

Figure 2. Distribution of wind speed

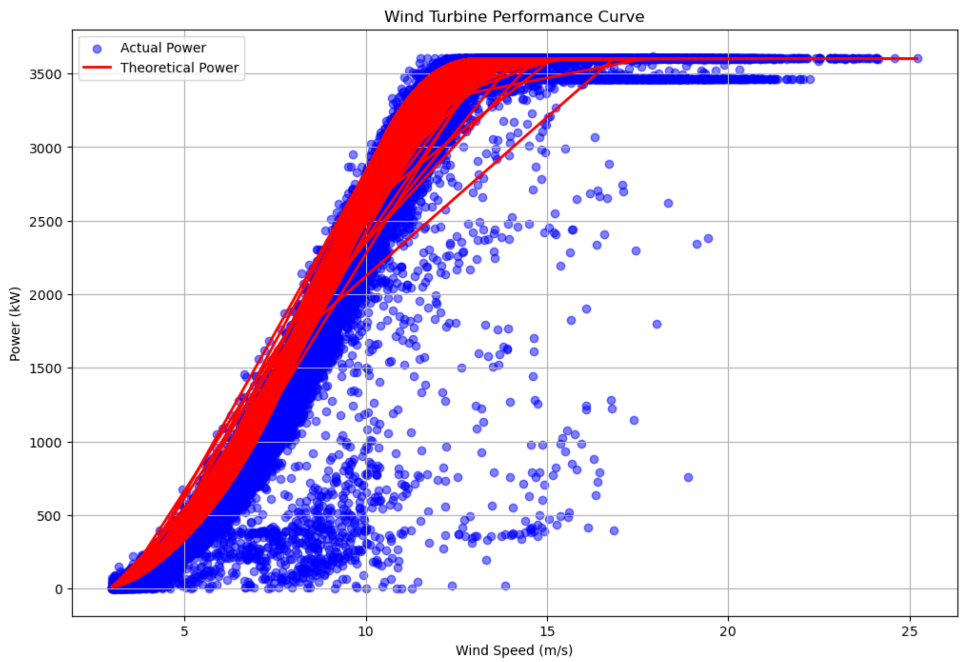

Figure 3. Actual and theoretical wind turbine performances

3.1. Performance at Wind Speeds

As the wind speed increases, the power output tends to increase, which is consistent with the physics of wind turbines, where the power output is proportional to the cube of the wind speed (Kasper, 2023). However, discrepancies are noticeable, especially at a certain wind speed ranges where the actual power is significantly different from the theoretical power. The mean wind speed recorded at the site of the wind turbine was 8.833 m/s, of which the bulk of the wind speed was distributed around this speed, as shown in figure 2. From figure 3, at lower wind speeds, there is a consistent gap where the actual power is lower than theoretical, which might be due to startup losses or inefficiencies in the system. At very high wind speeds (above 12 m/s), the actual power output often maxes out around 3600 kW, as shown in figure 3, of which the theoretical capacity limit of the turbine is 3600 kW. The maximum power output of the wind turbine was 3618.7329 kW at a wind speed of 17.914, while a power output of 3600.78 kW was attained at a maximum wind speed of 25.206m/s.

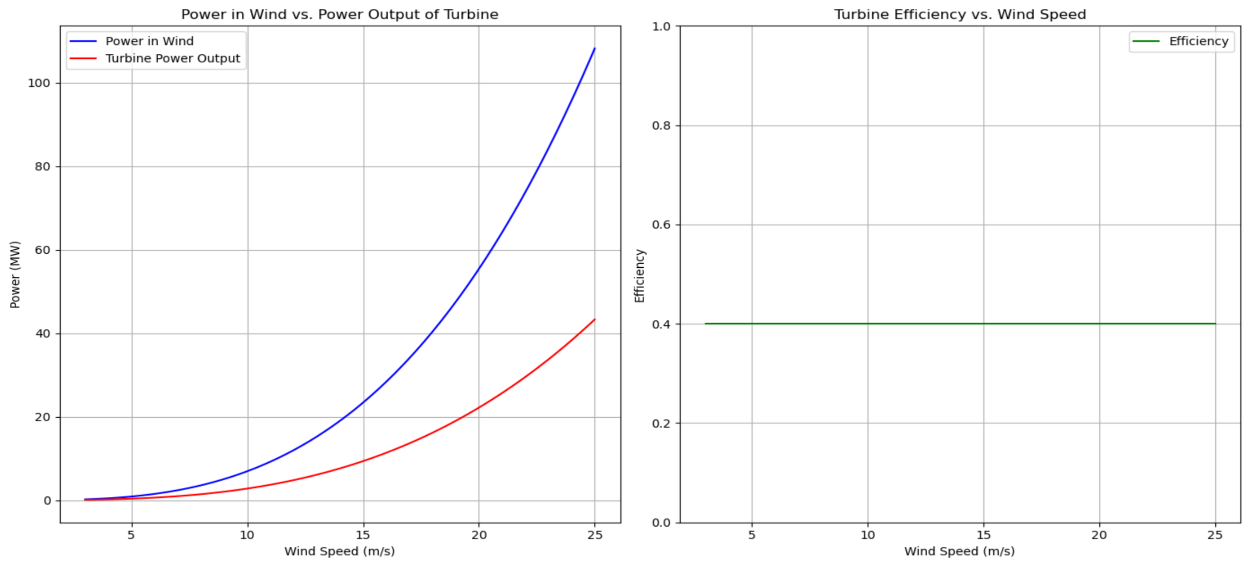

Figure 4. Wind turbine efficiency

The turbine efficiency refers to the ratio of the electrical output of a wind turbine to the kinetic energy available in the wind passing through the turbine rotor area. The maximum theoretical efficiency is defined by the Betz limit, which states that no turbine can capture more than 59.3% of the kinetic energy in the wind. Wind turbine efficiency is a critical factor in assessing a wind farm's performance and its overall viability as a renewable energy source. The turbine's efficiency of 40%, as shown in figure 4 indicates that the turbine converts 40% of the kinetic energy in the wind into electrical energy. Although this efficiency level is considered respectable in the wind energy sector, there are several dimensions to explore regarding its implications, advantages, and challenges.

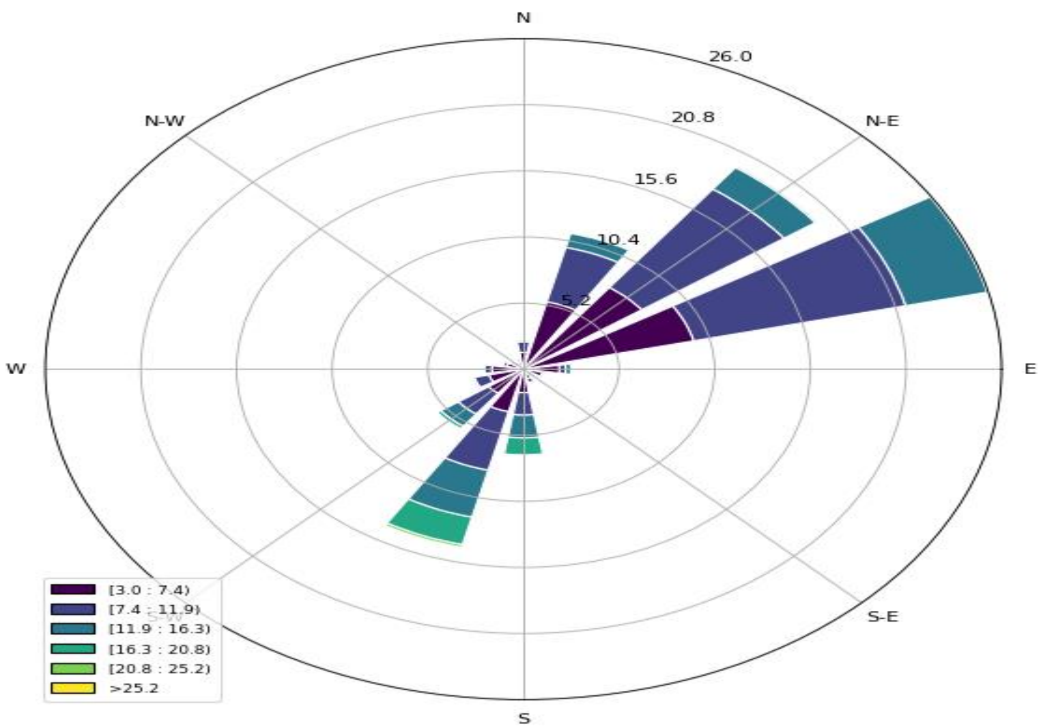

Figure 5. Distribution of wind speed across the direction

3.2. Direction Influence

The correlation between wind direction and power output provides insights into optimizing turbine positioning and orientation (Sohoni, Gupta and Nema, 2016). Wind turbines are designed to directly face the wind, as this maximizes their ability to capture wind energy and convert it into electricity (EERE, n.d.b). To achieve this, wind turbines have a mechanism called a yaw system that allows the entire turbine to rotate on its base to align with the changing wind direction (EERE, n.d.a). The components: anemometer and wind vane of a wind turbine work together to ensure that the turbine is always optimally positioned to harness the wind energy (NZWEA, n. d.). The wind direction may affect the turbine efficiency in a wind farm, potentially due to the suboptimal alignment of the turbine with the wind flow. From figure 5, the wind direction is primarily from the northeast and South West, with the northeast being more prominent. The wind direction exhibited significant seasonal or temporal variability; thus, the wind warm layout was designed to optimally accommodate this variability by having a more flexible or adaptable arrangement. Because there are seasonal shifts in the direction of wind coming from the northeast and southwest, the wind placement of the wind turbines had to be designed to accommodate both the southwest and northeast wind patterns.

The optimal wind farm layout plays a pivotal role in reducing the rift between the theoretical and actual performance of wind turbines. By reducing wake effects and aligning with prevailing winds, the layout allows the turbines to operate closer to their theoretical maximum efficiency. This leads to higher energy production, improved capacity factors, and better overall performance. Aligning the turbines with the prevalent direction of the wind optimizes the capture of wind and reduces the need for yaw adjustments, thus improving the efficiency of each turbine and bringing the actual performance closer to theoretical values. Advanced layouts that adapt to variable wind conditions and seasonal changes can help maintain higher efficiency and reduce the gap between actual and theoretical performance. By optimizing turbine placement and reducing performance losses, the overall capacity factor of the wind farm can be improved, leading to higher actual energy output than what would be predicted theoretically without considering layout effects.

Proper spacing and placement of turbines can enhance efficiency by reducing wake interference, and the cross-wind and down-wind spacing recommendations are based on minimizing wake effects. As the primary goal of a wind farm is to maximize energy production, the efficiency of the turbines directly influences the amount of electrical energy generated from the available wind energy. Wind turbines create wake effects. The downstream wind speed is reduced, and turbulence is increased, which, in turn, reduces the efficiency of the downstream turbines, and efficient turbines in optimal positions can extract more energy from the wind while minimizing losses due to turbulence and wake effects. With the use of a python programed computational fluid dynamics, an optimal wind farm layout for 100 wind turbines was generated for the minimum area the turbines can occupy to deal with these wake effects, to minimize the reduction in efficiency of downstream turbines and to maximize the overall farm efficiency, assuming a flat surface, as shown in figure 6.

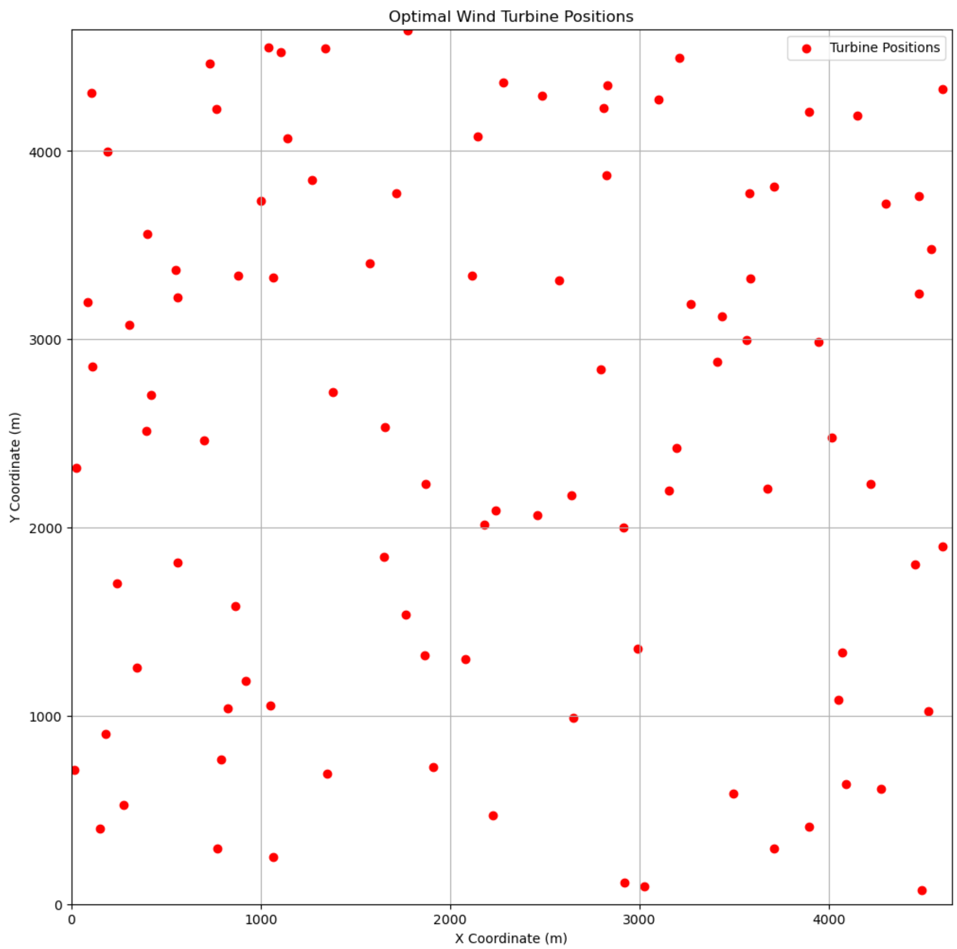

Figure 6. An optimal wind farm layout for 100 wind turbines for 21.6 km²

Optimal wind farm layout is crucial for maximizing energy output and minimizing operational costs, and by carefully considering the placement of the turbine, there can be a significant improvement to the efficiency of the entire wind farm (Stanley and Ning, 2019). Understanding the predominant wind direction helps in the computation of the wind turbine alignment for maximum energy capture. Topography can influence wind patterns and turbine placement (Wu *et al*., 2019) (Letzgus, Guma and Lutz, 2022), but this work assumed a flat plain for the dynamic layout of wind farms. As the wind turbines in the wind farm layout, as shown in figure 6 align with the prevailing wind directions, the turbines are able to capture wind more directly and consistently, thereby operating closer to their maximum power output more consistently, translating into higher energy production.

By carefully planning the arrangement of wind turbines, the mechanical loads on them can be distributed more evenly. An optimized layout can lead to a more uniform distribution of wind flow across the turbines, which helps in balancing the loads they experience. This balance is crucial for preventing excessive wear and tear on any single turbine, thereby extending its operational life (Tang *et al*., 2022). This optimal wind farm layout not only maximizes power generation but also minimizes the fatigue loads on the turbines by reducing the duration of high-fatigue-load conditions, thus reducing the overall mechanical stress on the turbines. Cao *et al*. (2022), in their work which entailed optimized wind farm layouts, indicated that the total duration of high fatigue loads can be reduced by up to 25%, which is beneficial for the structural integrity of wind turbines.

Understanding the performance of wind turbines involves comparing their actual output with their theoretical capabilities. Moreover, an optimal wind farm layout plays a vital role in bridging the gap between theoretical and actual performance. In theoretical models, turbines are assumed to operate in isolation with no wake effects from neighboring turbines, thereby simplifying the calculations. In practice, the wake effects from upstream turbines are the cause of the reduction in wind speed and also the increment in the turbulence experienced for turbines located downstream, and this effect decreases the actual power output compared to the theoretical maximum. Proper spacing allows wake recovery, where the wind regenerates and becomes less turbulent before reaching the downstream turbines. Therefore, the optimal layout involves placing turbines at appropriate distances and orientations to minimize wake effects. This ensures that the turbines operate in less turbulent air and are closer to their theoretical efficiency.

4. Conclusion

This study explored the optimization of wind farm layouts using historical SCADA data, computational fluid dynamics (CFD), and DE to maximize energy production and minimize wake effects. The analysis revealed a clear correlation between wind speed and power output, with discrepancies observed at lower and higher wind speeds due to startup inefficiencies and the turbine’s power limitations.

By employing the Frandsen wake model and Differential Evolution algorithm, an optimal layout for 100 wind turbines was developed, demonstrating the importance of precise turbine positioning. The optimal layout, which was configured over a minimum area of 21.6 km^2, significantly reduced wake interference, allowing the turbines to operate closer to their theoretical maximum efficiency. This not only enhances energy output but also reduces mechanical stress on the turbines, thus contributing to their longevity.

These findings underscore the critical role of wind direction and spacing in determining wind farm efficiency. Aligning turbines with prevailing wind patterns and optimizing their placement within the farm can bridge the gap between theoretical and actual performance. Moreover, this study highlights the value of integrating historical wind data with CFD simulations to create robust, site-specific windfarm designs.

In conclusion, optimizing wind farm layouts through data-driven approaches and advanced modeling techniques is essential for maximizing energy production, reducing operational costs, and extending the lifespan of wind turbines. This work provides a framework that can be applied to future windfarm projects to ensure that renewable energy sources are harnessed more effectively and sustainably.

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