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Parametric Analysis of Inter-Farm Wake Interactions in Offshore Wind Farm Projects Along the US East Coast

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Abstract. This study explores the effects of various parameters on wake interactions between offshore wind farms, with a particular focus on the Revolution-Southfork Wind and Vineyard Wind projects. The research examines how factors such as Euclidean distances, turbine-rated power, rotor diameters, and the number of turbines at upstream farms impact the annual energy production (AEP) of downstream installations. The results reveal significant variations in AEP losses, with the Nygaard model demonstrating a marked sensitivity to changes in turbine-rated power, rotor diameter, and the differing Euclidean distances between farms. Our findings indicate that strategic planning regarding turbine characteristics and farm placements is essential for optimizing energy output and reducing wake-induced power losses. These insights lay the groundwork for further analytical research.

1. Introduction

Wind energy is increasingly important in the global shift toward sustainable and renewable sources, particularly offshore wind, due to its ability to harness stronger and more consistent winds at sea[1]. A significant challenge in deploying offshore wind systems is the wake effect, where turbines extract kinetic energy from the wind, creating slower-moving air downstream. These wakes can extend far behind turbines, reducing wind speed over large areas and diminishing the efficiency of turbines within and between farms [2]. As offshore wind installations expand, particularly along the U.S. East Coast, addressing wake interactions becomes essential to realizing the full benefits of wind energy.

Previous studies have highlighted substantial power losses due to wake effects. Pryor and Barthelmie observed noticeable power reductions in densely installed U.S. wind farms [3], and Danish studies reported losses between 8.6% and 10.1% when wind farms were spaced 8 km apart [4]. Research on the Sandbank and DanTysk wind farms showed production losses of 10-15%, exceeding 30% under stable conditions [5]. Various experimental and modeling studies [6, 7, 8, 9, 10] — including mesoscale models [11, 12, 13, 14], Computational Fluid Dynamics (CFD) [15, 16], and engineering wake models [17, 18, 19, 20] — have addressed these issues, but significant gaps remain regarding optimal turbine spacing and characteristics.

Our research expands upon existing work by performing a comprehensive parametric analysis using simulation tools to study power losses from inter-farm wake interactions. We analyze wake

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effects by varying critical parameters like farm spacing, turbine-rated power, rotor diameter, and turbine numbers in upstream farms. Employing benchmarked engineering models, this approach helps identify key characteristics influencing inter-farm wake-induced power losses, guiding better decision-making and risk mitigation for future offshore wind farm developments.

2. Methodology

Understanding how upstream wind farms influence the power production of those located downstream calls for a systematic approach isolating key parameters and examining their contributions to wake interactions. In the context of the U.S. East Coast—where offshore wind development is in its early stages, and numerous projects are currently under review or recently permitted—this research provides a timely opportunity to anticipate efficiency losses linked to inter-farm wakes. By focusing on specific variables that govern wake propagation and quantifying their impact on Annual Energy Production (AEP), our work aims to offer actionable insights for developers, ultimately guiding informed decisions about wind farm placement to support more sustainable and productive installations.

2.1. Wind Farm Data and AEP Calculations

Before running simulations, it is essential to ensure that input data are accurate and compatible with the chosen modeling environment. For our study, we selected two U.S.-based offshore wind projects: Vineyard Wind 1 and the combined Revolution Wind–South Fork Wind configuration. Both projects are currently in the construction stage, allowing us to gather more realistic data, such as the models of wind turbines being used, the number of turbines, and the layout of their positions. Thus, we use Sea Impact [21] to digitize boundary geometries and turbine positions. Moreover, we integrate site-specific atmospheric conditions derived from the Global Wind Atlas [22]. Using the Generalized Wind Climate (GWC) files, we extract sector-dependent Weibull distributions that capture variations in wind speed and direction at the study site. These distributions are incorporated into PyWake's UniformWeibullSite class, enabling the simulation environment to reflect realistic offshore wind conditions. Since offshore locations typically exhibit low surface roughness and relatively stable flow conditions, we assume near-zero roughness length. PyWake [23] was chosen for the AEP calculations, as multiple wake models have been implemented and are available to use. Additionally, PyWake has been used in many studies in the existing literature for wind farm modeling [1, 24, 25] and optimization [26, 27, 28]. Our study incorporates a range of engineering wake models, including Bastankhah [29], NOJ [30], Turbo NOJ [31], Nygaard [17], Zong [32], Niayifar [33], Carbajo [34], and SuperGaussian [35]. We examined the wake deficit profiles at distances 10km, 25km, and 50km downstream of the Vineyard-Revolution wake interaction to further analyze the potential wake loss between the two sites.

2.2. Influence of Euclidean Distance ($\boldsymbol{d}$) on Inter-Farm Wake Interactions

To initiate this analysis, we employ a parametric approach. By varying one factor at a time while keeping other conditions constant, we can understand how changes in a single parameter—specifically, the Euclidean distance $\boldsymbol{d}$ between two wind farms—affect the Annual Energy Production (AEP). We calculated the Euclidean distance $\boldsymbol{d}$ between Revolution-South Fork Wind and Vineyard Wind, as illustrated in Figure 1. Consequently, we computed the AEP of Vineyard Wind for different values of $\boldsymbol{d}$. This was done by determining the percent difference in AEP, comparing scenarios without wake interaction from the upstream wind farm to scenarios that included the influence of wake interactions from the upstream wind farm.

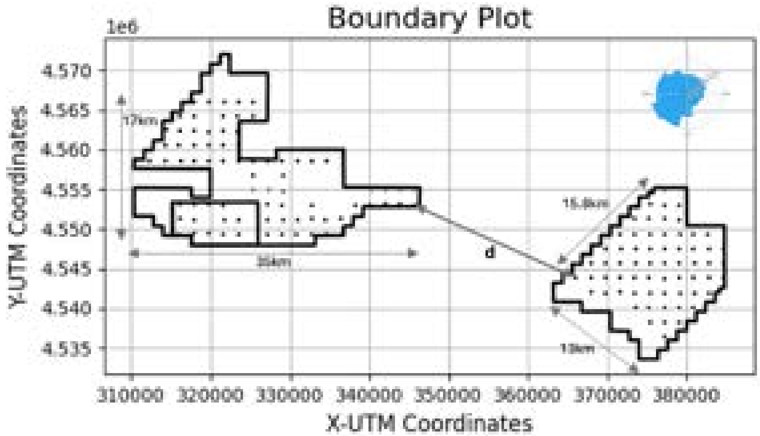


Figure 1: Distance ***d*** between the last turbine from Revolution-South Fork Wind and the first turbine from Vineyard Wind.

2.3. Influence of Wind Turbine Characteristics on Inter-Farm Wake Interactions

We investigate how specific turbine characteristics influence downstream wind farm AEP due to farm-to-farm wake interactions. Building upon our earlier inter-farm distance analysis, we focus on turbine-rated power and rotor diameter. Our scenario maintains a fixed 10 km distance between Vineyard Wind and the combined Revolution Wind–South Fork Wind, chosen to emphasize pronounced wake effects. Starting from an initial turbine model with original hub-height values, we systematically adjust turbine-rated power and rotor diameter using a custom Pywake GenericWindTurbine model. Changes apply exclusively to the upstream farm, aiming to clarify how these parameters affect wake interactions and downstream power losses. Site configurations and layouts remain consistent with Section 2.2.

2.3.1. Turbine Rated Power

Turbine-rated power defines the maximum electrical output achievable under optimal conditions. By modifying this specification, we alter the amount of energy each turbine extracts from the incoming wind, thereby influencing the strength and extent of the downstream wake. In this phase, we hold hub height and rotor diameter constant while systematically altering this specification, we modify the energy extracted from the wind and thus the magnitude and spread of the wake effects downstream. Additionally, Figure A1 demonstrates that these changes in rated power affected the turbine's Power and Thrust Coefficient (CT) curves, as variations in rated power directly influence operational characteristics such as efficiency and thrust loading, which subsequently impact wake intensity. Testing each rated power setting across selected wake models allows us to observe the response of each model to changes in power. An increase in rated power typically produces a stronger wake, leading to enhanced energy extraction and potentially greater downstream impacts. This approach helps us determine which turbine power settings best minimize or maximize wake-induced efficiency losses under various model assumptions.

*2.3.2. Rotor Diameter (**D**)*

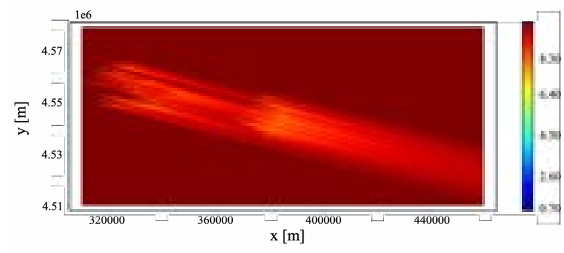
The diameter of the rotor plays a crucial role in determining the swept area of the turbine blades and, consequently, the amount of kinetic energy extracted from the wind. Larger rotors capture more energy but can create a more intense and widespread wake, while smaller rotors may generate milder wake effects, sacrificing energy extraction upstream. In this context, we keep the rated power and hub height constant and adjust only the rotor diameter. Furthermore, Figure A2 demonstrates how changes in rotor diameter affected the turbine's Power and Thrust Coefficient (CT) curves. This analysis is essential because rotor diameter directly impacts aerodynamic performance and thrust forces, influencing wake propagation downstream. By examining how each model responds to gradual increases in rotor diameter, we can identify which configurations optimize annual energy production (AEP) at the upstream site without causing significant losses for the downstream installation.

2.4. Number of Wind Turbines

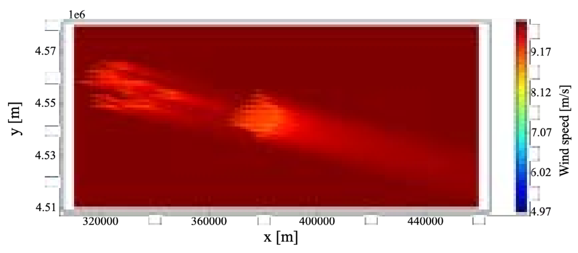
In this section, we examine how the number of turbines influences inter-farm wake interactions and resulting AEP. Specifically, we investigate how increasing upstream turbine counts amplifies wake effects downstream. Following boundaries established in Section 2.2, we set a 10 km distance between Revolution-South Fork Wind (11 MW, 200 m rotor diameter) and Vineyard Wind (13 MW, 220 m rotor diameter). We analyzed layouts for two different capacity densities, 3 to 4 MW/km², resulting in turbine counts ranging of 107 and 142, respectively. Comparing these configurations, we assess how increased turbine numbers affect wake interactions and downstream AEP, highlighting the relationship between upstream turbine density and intensified wake impacts.

3. Results

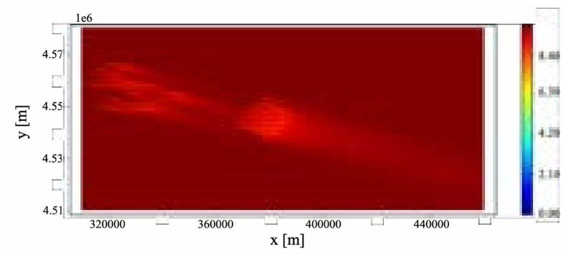
In this section, we present results from our parametric analysis on wake interactions between Revolution-South Fork Wind and Vineyard Wind farms. Initially, we provide visual insights through wake contours and deficit plots across different engineering models. Figure 2 shows wake contours at a wind direction of 285° and wind speed of 10 m/s, highlighting notable differences among models, particularly strong wake interactions captured by the Super Gaussian, Turbo NOJ, and Nygaard 2022 models. Figure 3 presents wake deficit profiles at distances of 10 km and 50 km downstream, illustrating the models' sensitivity to wind speed reductions and associated energy losses.



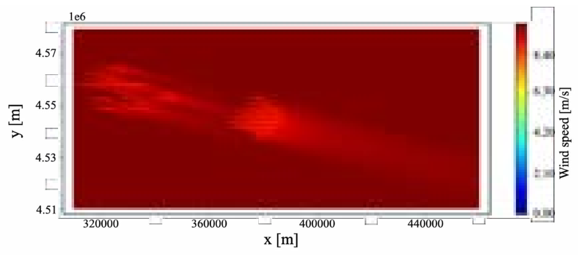
(a) Nygaard (TurboGaussian)



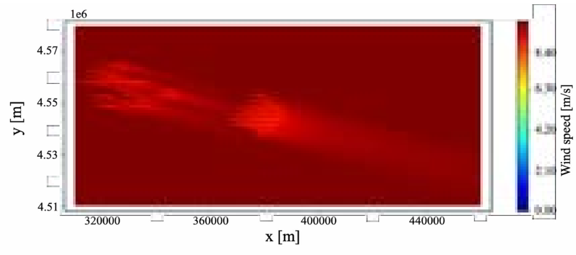
(b) Zong



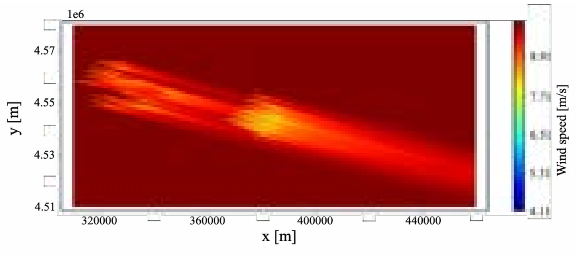
(c) Bastankha



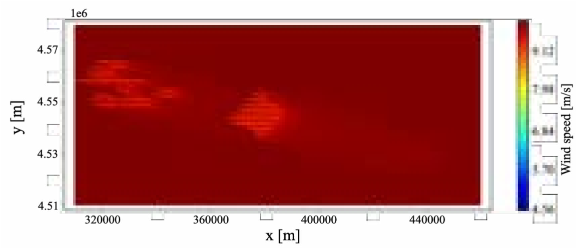
(d) Carbajo Fuertes



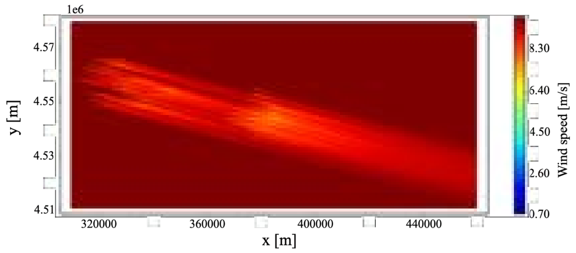
(e) Niayifar



(f) SuperGaussian

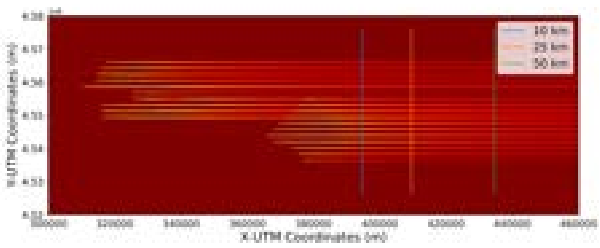


(g) NOJ

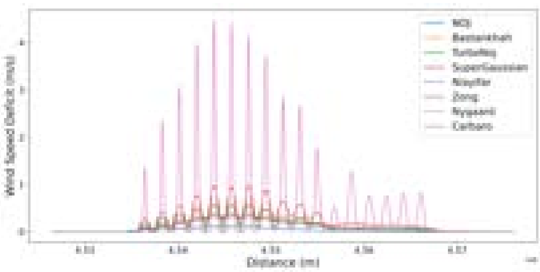


(h) Turbo NOJ

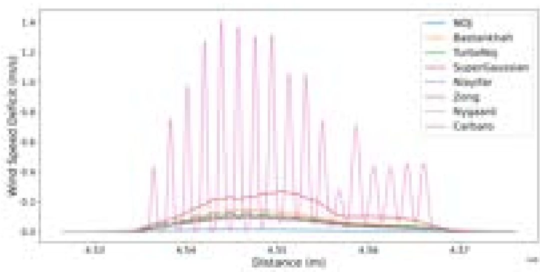
Figure 2: Wake contours for different engineering models, showing the Revolution-South Fork (left side) and Vineyard Wind (right side). The wind direction shown in the contours is 285°, and the wind speed is 10 m/s.



(a) Nygaard Contour Wake Map



(b) d = 10 km



(c) d = 50 km

Figure 3: Wake Deficit Profiles at different distance d downstream

3.1. Impact of Euclidean Distance on AEP

This section discusses the effects of varying the Euclidean distance (as indicated in Figure 1) on the AEP, aiming to assess to what extent this parameter influences the efficiency of energy generation in proximity to another wind farm. The first noticeable aspect in Figure 4 is the difference in the results provided by the various engineering models analyzed. Compared to the Nygaard and Super Gaussian, all the other engineering models underestimate wake effects. Second, Super Gaussian and Nygaard present a noticeable AEP difference at inter-spacing of 10km (approximately 0.6% and 0.7% respectively). However, the curves for Super Gaussian and Nygaard never really get flat, even for inter-distances approaching 60km. All the other models present curves that are much flatter after a certain distance.

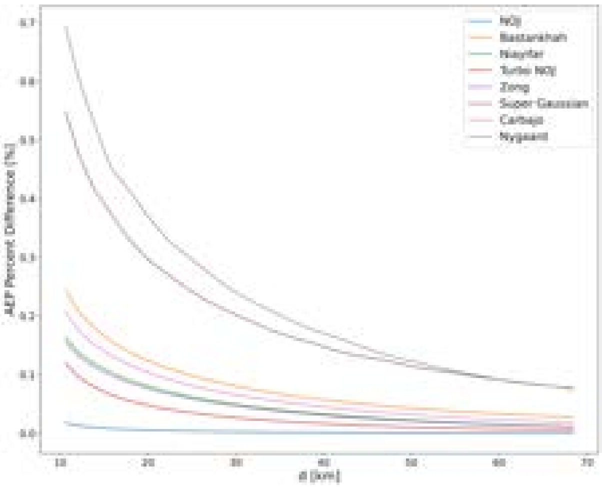


Figure 4: Impact of Euclidean Distances in the AEP of the Downstream Wind Farm across various engineering models

3.2. Effects of Turbine Rated Power on AEP

This section analyses AEP sensitivity concerning turbine-rated power. Here, we consider the same rated power for the two farms. The inter-distance is kept constant at a value of 10km. Our findings demonstrate that AEP losses increase as the rated power of the turbines increases. Specifically, the Nygaard model shows that the changes are quite significant. The curve for the model does not become flat when it approaches a value of 20MW, which is a power-rated value under consideration in the latest biggest turbines currently under development in the market. In terms of the behavior of the engineering models, they follow the same trends shown in Figure 5 where all the engineering models show negligible AEP differences except Super Gaussian.

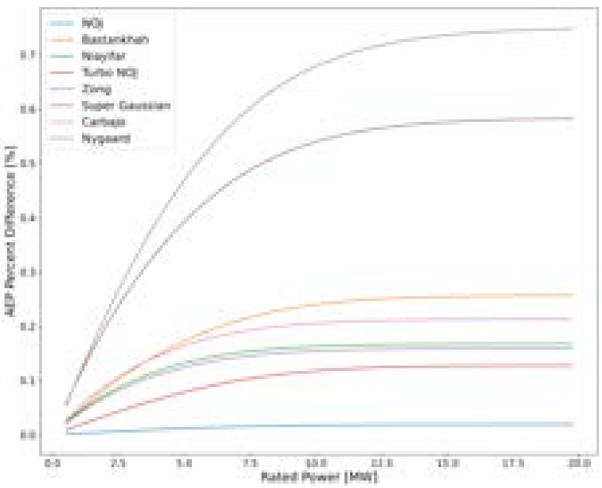


Figure 5: Relationship between turbine-rated power and downstream AEP loss across various engineering models

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3.3. Influence of Rotor Diameter on Wake Effects

Figure 6 highlights the AEP percent differences across varying rotor diameters, showing that larger diameters result in increased AEP losses at downstream locations, underlining the importance of careful turbine specification and placement in dense wind farm setups. Larger rotor diameters at the upstream site exacerbated wake effects, significantly reducing downstream AEP. Additionally, the curves for all the engineering models get flat after a certain value of rotor diameter. However, the Nygaard and Super Gaussian curves do not seem to get flat even when they reach 250m in diameter.

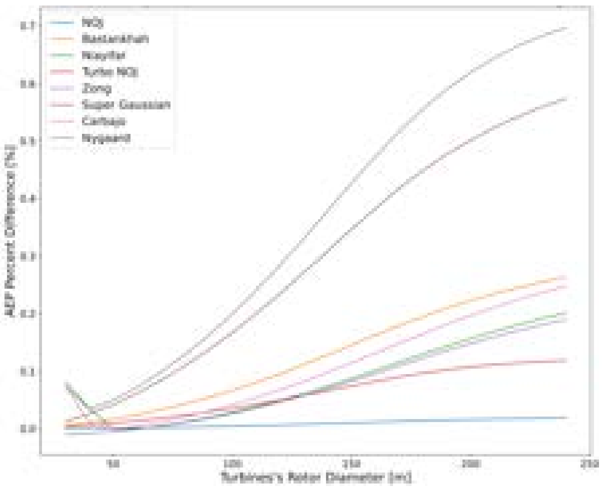
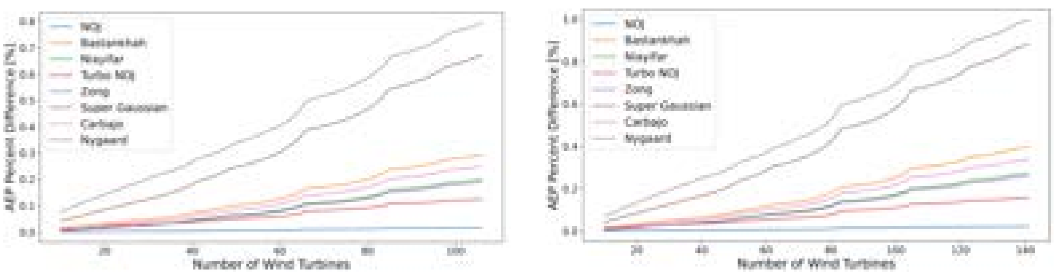


Figure 6: Impact of the Rotor Diameter on AEP of the downstream Wind Farm across various engineering models

3.4. Number of Wind Turbines

Figure 7 shows the AEP percent difference as a function of the number of wind turbines. For this case, it was established a distance of 10 km between the wind farms for a better analysis of the wake effect. Analyzing the number of turbines within a wind farm highlighted that as the turbine counts increase, wake interactions also intensify. This leads to a higher absolute AEP but can diminish the relative efficiency per wind farm. Therefore, we provided separate plots illustrating the variations in AEP percentage loss for different capacity densities, reflecting the influence of turbine count and placement. The results from Figure 7 suggest that higher power density in upstream wind farms can lead to higher wake losses in downstream neighboring farms.



(a) Capacity Density = 3 MW/km^2 (b) Capacity Density = 4 MW/km^2

Figure 7: Impact of the Number of Turbines of the upstream site on AEP of the downstream site across various engineering models

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4. Conclusions

This study investigated critical parameters affecting farm-to-farm wake interactions, focusing primarily on Revolution/Southfork Wind and Vineyard Wind. Four main parameters were analyzed: 1) the influence of inter-distances between farms, 2) turbine-rated power, 3) rotor diameter, and 4) number of turbines in the upstream farm. Regarding inter-distances, various engineering models indicated differing results, with the Nygaard and Super Gaussian models estimating Annual Energy Production (AEP) losses between approximately 0.7% and 0.1% for distances ranging from 10 to 60 km. Varying turbine-rated power up to 20 MW in the upstream farm (at 10 km separation) showed AEP reductions up to 0.72% (Nygaard model). Additionally, changes in turbine-rated power affected the power and CT curves, providing insights into efficiency optimization. The third scenario analyzed rotor diameter variations, with AEP losses reaching up to 0.7% for a 250 m rotor diameter (Nygaard model). Similar impacts on power and CT curves were observed, highlighting turbine efficiency. Lastly, the number of turbines at Revolution/Southfork Wind was increased to 142, maintaining actual distance and turbine ratings. AEP losses reached approximately 1% (Nygaard model) and 0.9% (Super Gaussian model) under denser conditions. The analysis also extended to Skipjack-Delaware Lease Wind and Maryland Offshore Wind (Appendix B), where assumed turbine layouts indicated wake-induced energy losses of around 1.3% (Nygaard) and 1% (Super Gaussian) at a 10 km distance. Limitations include model assumptions, and future studies should expand to additional U.S. sites for broader and more robust conclusions.

Appendix A: Power and Thrust Coefficient Curves for Varied Turbine

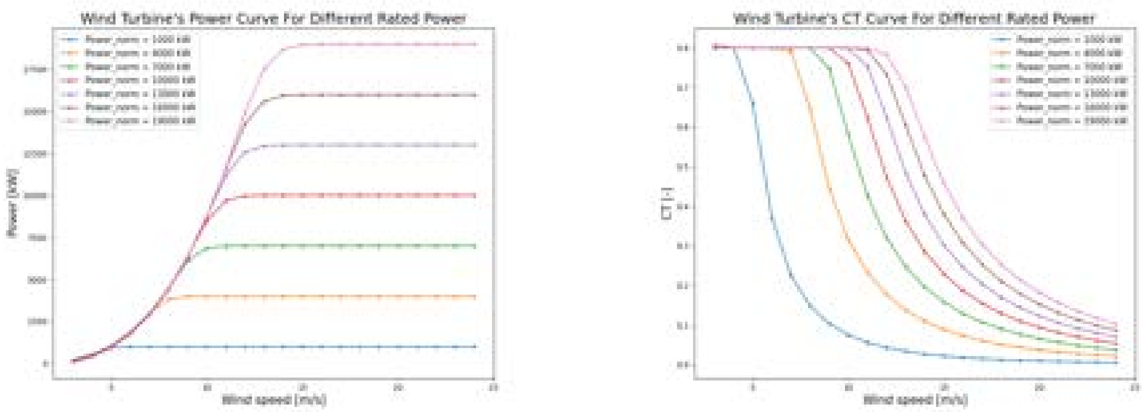

Figure A1: Power and CT Curves of Custom Turbines at Different Rated Powers

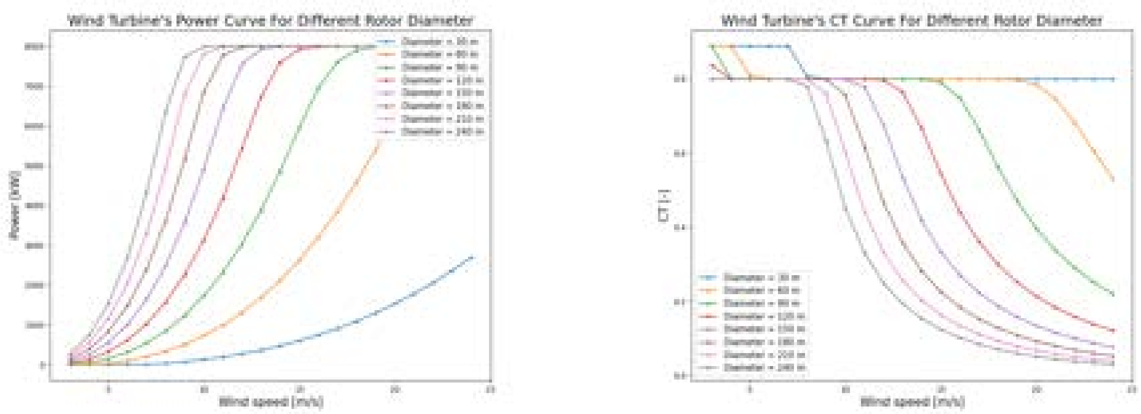

Figure A2: Power and CT Curves of Custom Turbines at Different Rotor Diameters

Appendix B: Parametric Analysis for SkipJack-Delaware Lease Wind and Maryland Offshore Wind

To further extend our analysis, we examined two additional wind farm sites—SkipJack-Delaware Lease and Maryland Offshore Wind. Although these sites lacked detailed turbine placement, information about their boundaries and the number of turbines allowed us to approximate layouts.

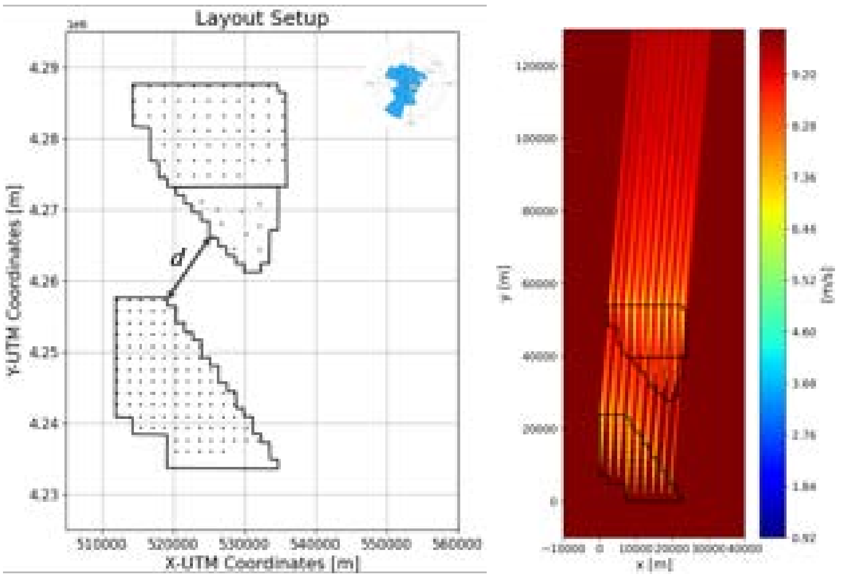

Figure B1: Layout and wake contour (Nygaard Model) visualization between SkipJack-Delaware Lease and Maryland Offshore Wind Farms at 10 m/s, 185°. Assuming a capacity density of 3 MW/km², we populated the boundary areas: SkipJack with 10 turbines, Delaware Lease (area: 282.87 km²) with approximately 71 turbines, and Maryland Offshore Wind with 114 turbines

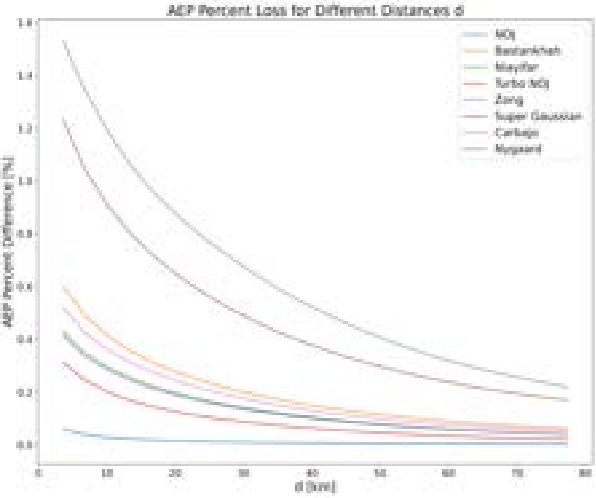

Figure B2: AEP percent difference versus Euclidean distance d between SkipJack-Delaware Lease (downstream) and Maryland Offshore Wind (upstream), across various wake models.

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