Realistic Floating Offshore Wind Farm Optimization

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Offshore wind farm design is multifaceted and complex. It involves a vast amount of design decisions that are all dependent on each other. However, in common wind farm design practice, these decisions are made iteratively and can thus ignore the dependence that they have on each other. An iterative approach leads to sup-optimal design which can diminish the economic viability of a wind farm project. It also requires more time to compare results and iterate on final designs. In this study a coupled optimization approach is introduced and analyzed to compare and contrast the economic benefits of acknowledging the interdependence of wind farm design decisions. The coupled optimization approach is able to design a floating offshore wind farm's cabling, mooring, and layout in about the same amount of time required to design only the layout, while also reducing the overall levelized cost of energy (LCOE) by 5%-23% depending on the ocean floor depth. Not only is there a significant reduction in the LCOE, the annual energy production (AEP) of the coupled optimization design is essentially the same as the optimal design of the standard optimization approach.

I. Introduction

Lately, there has been a renewed focus on floating offshore wind farms in order to diversify and increase the availability of renewable energy sources for growing electrical demand [1]. However, among the options for wind energy, floating offshore wind energy has the highest LCOE [2]. The main contributing costs originate from the electrical infrastructure, and the substructure which account for about 38% of the total balance of system (BOS) costs [2].

The more common approach to designing wind farms involves iterating between designing the placement of the turbines in order to reduce wake effects and designing the cabling layout with the objective of minimizing the total cable cost [3, 4]. While this approach can lead to higher annual energy production (AEP), it can also result in turbine layouts that place turbines close to the wind farm boundaries and spaces the turbines as far apart from each other as possible in order to reduce wake effects [5]. However, turbines spaced further apart results in higher BOS costs due to the electrical infrastructure required for longer cables.

In floating offshore wind farm design there has been ample development in mooring design, substructure design, cabling design, and wake modeling [6, 7]. However, there has been sparse efforts in coupling all the design elements into a comprehensive gradient-based optimization [8]. Layout optimizations that solely consider wake effects and AEP do not account for bathymetry data and the effect of the ocean floor depth on the cost of mooring lines and cabling. For example, in order to reduce wake effects, an AEP layout optimization may blindly place turbines above an area with a deep ocean floor where the mooring and cabling cost significantly increases. Thus, even if the layout increases the AEP, it may also increase the LCOE.

An optimization approach that couples cabling, mooring, and turbine layout design can enable more affordable floating offshore wind farms by aiming to reduce the LCOE. By reducing the LCOE the coupled optimization seeks to simultaneously increase the AEP while decreasing the capital cost. Whereas an optimization approach that handles the turbine layout and cabling design separately can result in an AEP that requires unnecessarily costly cabling infrastructure. Previous efforts to define a coupled optimization have been restricted to gradient-free and Mixed-Integer Linear Programming (MILP) approaches which may work for smaller wind farms, but requires extensive time and often results in infeasible solutions for larger wind farms [9].

The main hurdle for a coupled optimization is the computational cost of designing the cabling layout for each iteration of the turbine layout. An accurate estimate of the total cable cost requires a MILP approach solved through a branch and bound optimization [4]. However, for a wind farm with 50 turbines the MILP approach can take up to 2

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hours, which is highly impractical to solve in between iterations of a gradient-based wind farm optimization. In order to significantly reduce this computational cost we will demonstrate a deep learning approach that can estimate the total cabling cost of a wind farm layout with sufficient speed and accuracy.

Along with accurately modeling the cabling cost there are several realistic constraints that effect the resultant wind farm layout. In floating offshore wind there can be areas that are off-limit for placing turbines such as a shipping lane or protected fishing area [10–12]. For this study we model this type of constraint as an off-limit area that splits the wind farm area near the middle. Cabling can be placed in the off-limit area but turbines are prohibited.

In this study we demonstrate a realistic gradient-based floating offshore wind farm optimization that couples the electrical infrastructure, substructure, and mooring design and realistic constraints with the turbine and substation layout design. This will allow for the numerous dependent design factors in floating offshore wind farm design to effectively coordinate in reducing the overall LCOE. We will compare the coupled optimization approach with a layout optimization that only considers wake effects and maximizing the AEP.

II. Methods

Our coupled optimization approach pairs the BOS costs from NREL's (National Renewable Energy Laboratory) BOS code ORBIT (Offshore Renewables Balance- of-System and Installation Tool) and the AEP prediction from FLOW Farm [6, 13]. The objective of our optimization will be the levelized cost of energy (LCOE), where TCC is the turbine capital cost, BOS is the balance of systems cost, FCR is the fixed charge rate, OpEx is the operational expenditures, and AEP is the annual energy production (see Eq. 1).

$$\mathrm{LCOE} = \frac{(\mathrm{TCC} + \mathrm{BOS})\mathrm{FCR} + \mathrm{OpEx}}{\mathrm{AEP}} \tag{1}$$

The coupled optimization aims to reduce the LCOE with respect to the position of each turbine and the substation subject to boundary and spacing constraints (see Eq. 2). The boundary constraints prevents turbines from being placed outside the wind farm boundary and the spacing constraints places the turbines at least a minimum distance of 3 rotor diameters away from each other. The wind farm boundary considered in this paper is the Princess Amalia wind farm boundary with 50 NREL 5 MW reference floating offshore turbines [14].

$$\begin{array}{ll} \text{minimize} & \mathrm{LCOE} \\ \text{w.r.t.} & x_i, y_i (i = 1, ..., 50) \\ & \mathrm{x_{sub}}, \mathrm{y_{sub}} \\ \text{subject to} & \text{boundary constraints (wind farm boundary and off-limit area boundary)} \\ & \text{spacing constraints} \end{array} \tag{2}$$

The total BOS cost is equivalent to the sum of the substation, cabling, floating platform, and mooring BOS costs. Thus, the LCOE is dependent on the positions of the turbines and substation, and the depth of the ocean at each turbine position. ORBIT's current approach for designing cables involves a rigid grid structure that limits the design of the turbine layout. Therefore, in this study we demonstrate an approach for incorporating ORBIT's BOS cost estimates into FLOW Farm's gradient-based optimization framework where the total cable cost is predicted with a deep neural net trained on data from MILP optimized cabling layouts.

A. Cabling Cost Deep Learning Approach

The challenge with incorporating ORBIT's BOS cost estimates into a gradient-based optimization is the introduction of several discrete variables such as cable choice and changes in turbine array connections. Every iteration of the optimization requires a new evaluation of the cabling layout cost which requires a separate MILP optimization. The optimization used to define the cable layout cost can require an extensive amount of time due to the discrete nature of cable design. Thus, incorporating a MILP optimization is highly impractical. In order to accurately and practically estimate the total cabling cost a deep learning approach can learn how to estimate the total cabling cost based on any given wind farm layout.

1. Deep Neural Net Architecture

In order to generalize the layout data, the layout coordinates were converted into a 50x50 matrix where each element represents the distance between each turbine with every other turbine. The layout data is also used to develop a 50x1 matrix where each element represents the distance between the substation and each turbine. By separating the distance data into turbine-to-turbine distances and turbine-to-substation distances a neural network can be trained to learn the significance of the positioning of the substation. Since every turbine ultimately must connect back to the substation the turbine-to-substation distances are especially important to understanding the relationship between wind farm layout and total cable cost (see Fig. 1).

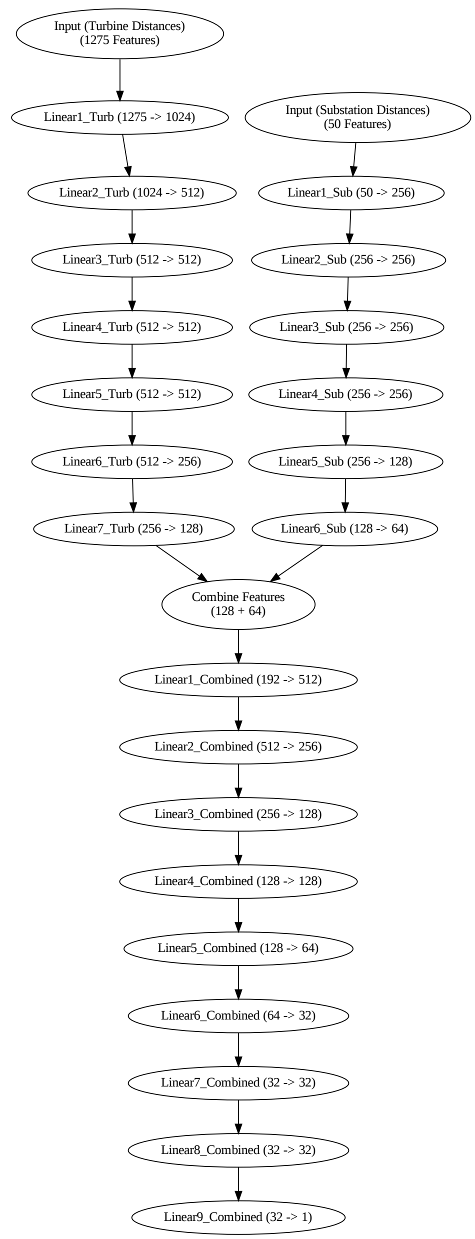

Figure 1 Each layer implements batch normalization and a ReLU activation function. There is also a dropout of 30% between the first three linear layers of both input paths as well as the first three linear layers of the combined features path.

Since the 50x50 matrix is symmetric the input values can be reduced by exclusively using the upper triangular portion. Thus, when both input matrices are flattened there is an input with 1275 features and another that has 50 features. Each of these inputs are then connected to separate linear layers. They continue independently through a few more linearly connected layers until they merge into a combined layer. Then the combined layer continues through more linearly connected layers before arriving at the single output value of total cable cost (see Fig. 1).

Batch normalization and ReLU activation functions were included between each linearly connected layer. In addition, we implemented drop out of 30% in the first three layers of both input layer paths in order to encourage learning in the deeper layers of the neural net. Similarly, in the combined layer we implemented drop out of 30% in the first three layers.

2. Training

In the area of a circle that is 7000 meters in diameter we generated random positions for 50 turbines and 1 substation. The 7000 meter diameter is about the width of the Princess Amalia wind farm boundary. Random positions were generated 300 times in order to run 300 unique MILP cabling layout optimizations. The branch-and-bound optimization in Gurobi was used to minimize the total cabling cost while constrained to the constraints defined by Fischetti and Pisinger [4] [15]. To develop the training and validation datasets a random even split was performed on the 300 random layouts scenarios.

The neural net described in Figure 1 was trained on the above described dataset for 2500 epochs where the loss function was the mean squared error (see Fig. 2). After 2500 epochs of training the deep neural net sufficiently converged and was able to predict the total cable cost of a random wind farm layout within 4.8% of the MILP optimization result for the total cabling cost.

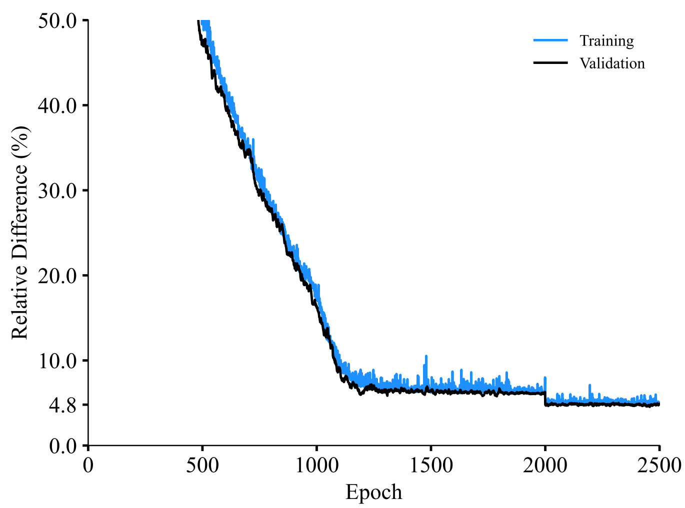

Figure 2 Relative percent difference between the deep neural net prediction of the total cabling cost and the MILP optimization result for the total cabling cost for both the training and validations datasets.

Figure 2 shows that the error of the deep neural net prediction is essentially identical for the training and validation datasets. This reveals that the amount of training data used in the training was sufficient to generalize the deep learning model and accurately predict the total cable cost over the validation dataset.

B. Bathymetry and Wind Rose Data

Since the deep neural net was trained on turbine-to-turbine and turbine-to-substation distances the coupled optimization will need to estimate the extra distance required for cabling to reach the ocean floor in addition to the horizontal distances between turbines and the substation. Bathymetry data is required in order to accurately estimate the extra cable length required to reach the ocean floor. Although the wind farm boundary and wind rose data are from the Princess Amalia wind farm, the bathymetry data used in this study comes from the coast of Virginia and was chosen for it's unique feature of having an ocean floor trench run through the wind farm. The properties of the wind speed and frequency are visualized in Figure 3.

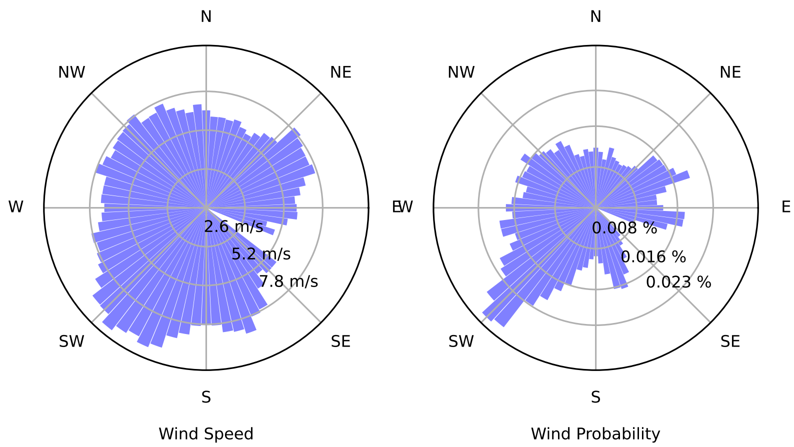

Figure 3 Wind rose for the Princess Amalia wind farm.

III. Results

In these results we compared the LCOE of a wind farm designed through the optimization defined in Eq. 2 and a wind farm designed through the same optimization definition but instead with the objective to minimize the -AEP. The AEP optimization doesn't involve cost estimates therefore it is blind to the effects of the ocean floor on cable and mooring costs. The comparison of these two optimization frameworks allows for an analysis of the potential benefits of a more realistic wind farm optimization as well a framework to identify differences in the resultant optimal layout designs. To assess the effect of the ocean floor depth on optimized LCOE and AEP we also ran the optimization over increasing ocean depth scenarios. Each ocean depth has the same trench but with differing maximum ocean depths; 219 meters, 274 meters, and 365 meters.

Both optimizations were run for each of the three depth scenarios with 10 random starts for the initial guess of the layout of the turbines and substation. For the LCOE optimizations, the lowest LCOE design was saved and for the optimization of the AEP the highest AEP design was saved. Each resultant optimal layout design was run through a MILP cabling layout optimization to estimate a more accurate LCOE as well as an AEP with a high resolution of wind rose data and rotor swept area sampling points for accurate estimation of the wake effects (see Fig. 4-5).

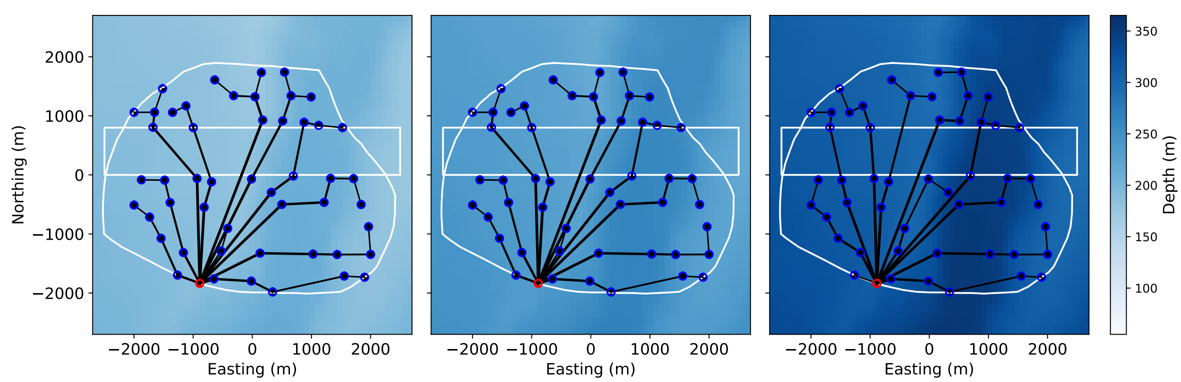

Figure 4 The optimized wind farm designs based on AEP for the three depth scenarios.

Figure 4 reveals that the optimal layout, with respect to maximizing AEP, pushed the substation to the edge of the boundary. This is most likely due to the constraints trying to move the substation out of the way. However, having the substation at the edge can result in higher cable costs since every turbine must eventually be connected to the substation. On the other hand, Figure 5 reveals that the optimal layout, with respect to minimizing LCOE, tends to pull the substation towards the center, especially when the ocean floor is deeper. This is most likely due to the cost of the cabling having an increasing influence on the LCOE with increasing depth.

In Figure 6 we compare the LCOE of the AEP optimization and the coupled LCOE optimization over three ocean

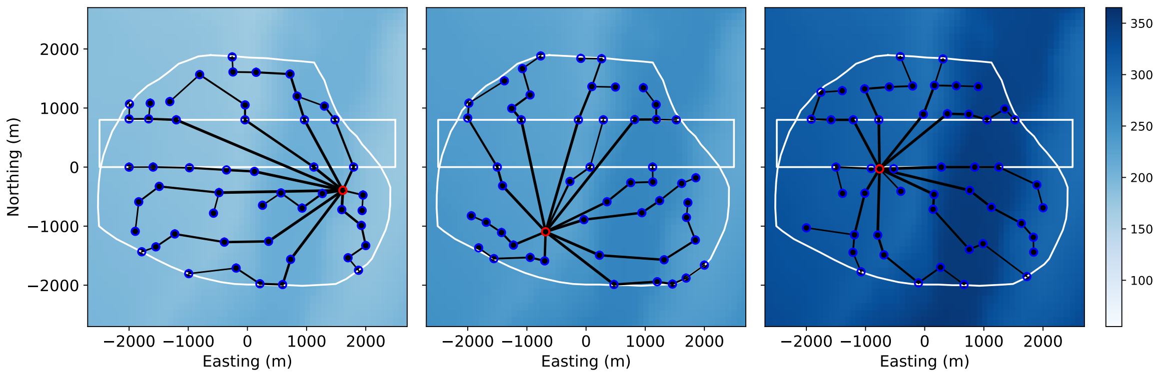

Figure 5 The optimized wind farm designs based on LCOE for the three depth scenarios.

depth scenarios. The LCOE values are normalized with respect to the highest LCOE of the optimal layout design from the AEP optimization (with a maximum depth of 365.2 meters). As ocean depth increases from 219 to 365 meters the AEP optimization resultant layout experiences a significant increase in the LCOE by about 15%. With increasing ocean depth the optimal layouts of the LCOE optimization result in a visible decrease in normalized LCOE.

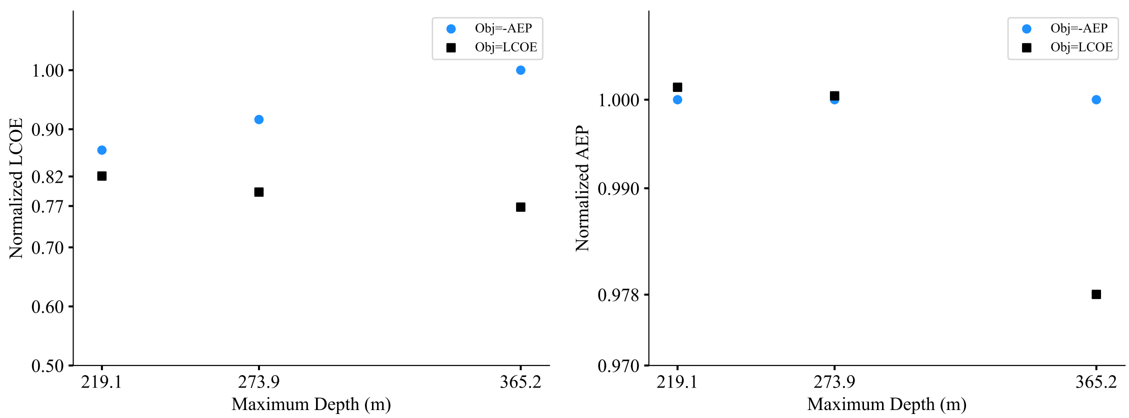

Figure 6 Normalized LCOE (on the left) and the normalized AEP (on the right) of the resultant optimal layouts from the AEP optimization and the coupled LCOE optimization over varying ocean depths

In Figure 6 we can also see that there is relatively little to no difference in the AEP of the optimal layout from the AEP optimization versus the AEP of the optimal layouts from the coupled LCOE optimization. The biggest difference is a 2% reduction in the AEP of the optimal layout from the coupled LCOE optimization at a maximum depth of 365.2 meters. However, a 2% reduction in AEP is insignificant compared to the 24% reduction in LCOE at the same depth when comparing the coupled LCOE optimization to the AEP optimization.

Figure 7 summarizes these findings by depicting the percent relative difference of the coupled LCOE optimization compared to the AEP optimization for their final design AEP and LCOE estimates.

When comparing both optimization approaches the coupled LCOE optimization is able to achieve a reduction in the LCOE by 5%-23% depending on the depth of the ocean while maintaining essentially the same AEP. This result reveals that when optimizing the layout of a floating offshore wind farm it is vital to the economic viability of a wind farm project to include more realistic modeling constraints in the optimization of the layout. Without these considerations, a simple layout optimization seeking to maximize AEP can result in an unnecessarily high LCOE and an unrealistic wind farm layout.

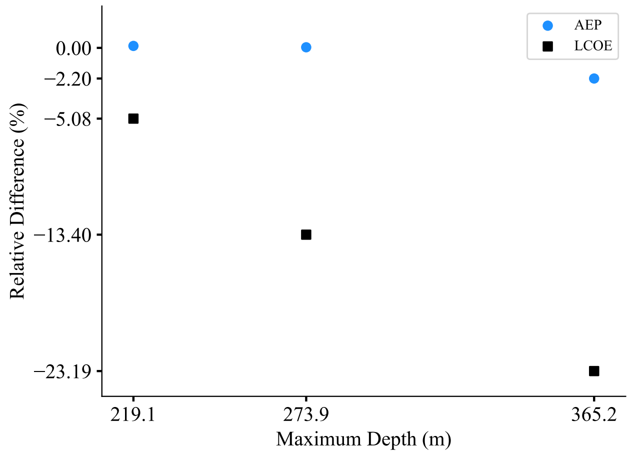

Figure 7 Percent relative difference of the coupled LCOE optimization compared to the AEP optimization for their final design AEP and LCOE estimates

IV. Conclusion

In conclusion, this study demonstrates the significant advantages of a coupled optimization approach for designing floating offshore wind farms, specifically focusing on reducing the levelized cost of energy (LCOE) while also maintaining a high annual energy production (AEP). By integrating the complexities of electrical infrastructure, mooring design, and realistic constraints—such as ocean depth and off-limit areas—we were able to create a more holistic optimization framework that significantly outperformed traditional methods that prioritize AEP alone.

Our findings reveal that layouts optimized solely for AEP often lead to a suboptimal LCOE, particularly in deeper waters where the costs of cabling and mooring can escalate dramatically. The coupled optimization strategy not only minimizes these costs but also achieves similar AEP levels, showcasing its efficacy in enhancing the overall economic viability of floating offshore wind projects. Specifically, our results indicate that the coupled optimization approach achieved reductions in LCOE ranging from approximately 5% to 23%, depending on ocean depth, while maintaining nearly the same AEP.

Furthermore, the integration of deep learning to streamline the computationally intensive aspects of this process opens the door to incorporating a broader range of realistic considerations into the optimization framework. By leveraging deep learning to quickly predict costs associated with complex variables, we can reduce the computational burden, enabling the optimizer to iterate quickly and allowing for the exploration of additional design factors that were previously thought too computationally expensive to integrate into a gradient-based optimization. These factors may include environmental constraints, regulatory requirements, fatigue loading, and dynamic turbine performance. In future work we plan to generalize the cabling deep neural net by training it with more cable options, turbine types, wind farm sizes, and differing number of turbines.

In summary, the coupled optimization approach represents a significant advancement in floating offshore wind farm layout design, offering both economic and process efficiency. By leveraging deep learning to streamline computationally intensive tasks, this framework opens the door to incorporating a broader range of realistic considerations into the wind farm optimization framework. As the renewable energy sector continues to expand, the adoption of such optimization techniques will be crucial in enhancing the viability and competitiveness of floating offshore wind energy.

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