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OPTIMIZING SHARED MOORING AND ANCHORING STRENGTH FOR FLOATING OFFSHORE WIND TURBINE ARRAYS

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ABSTRACT

Energy from floating offshore wind could provide substantial power generation if further utilized, but design optimization is required for the concept to achieve financial viability. A method proposed to reduce substructure costs for floating offshore wind turbines is to connect mooring lines from multiple turbines to a single anchor. However, the complex coupling of components in this system presents a reduction in system reliability of the wind array due to the chance of cascading failure in survival load cases. A proposed hypothesis to correct without drastically increasing costs is to strengthen a small number of important anchors significantly more than the rest. A noise-resistant optimization algorithm was developed using elements of genetic algorithms and Bayesian optimization to identify the optimal anchors to strengthen to improve system reliability. A previously developed simulation that evaluates the reliability of a hypothetical floating wind array with multiline anchors in the loading scenario of a 500-year storm was used as an objective function. While the resultant reliability values were uncompetitive compared to slightly strengthening all anchors, analyzed trends showed opportunity for the concept to work if a higher number of anchors are overstrengthened.

Keywords: optimization, mooring, multiline

NOMENCLATURE

a_{ijk}	anchor *ijk*, multiline configuration
C_l	line capacity distribution
C_a	anchor capacity distribution
$F_{a,i}$	anchor loading in anchor *i*
$F_{l,i}$	mooring line loading in line *i*
FOWT	floating offshore wind turbine
GA	genetic algorithm
l_i	line number *i*
n_A	number of above-average arrays
n_{OS}	number of overstrengthened anchors
OSF	overstrength factor
P_f	probability of failure
RBDO	reliability-based design optimization
s	coordinate of position along mooring line
t_i	turbine number *i*
β	reliability index
B	normalized reliability index

INTRODUCTION

With the continuously increasing power consumption of the United States, new sources of energy must be found for sector growth to continue. Total national energy production is estimated to increase by more than 20% by 2040, largely from an increase in power generation from natural gas and renewable sources [1]. One area of significant potential in energy production lies with offshore wind energy. Deeper waters – beyond the point where pile-driven wind turbines can be installed – also typically allow for steadier, stronger winds, as well as presenting fewer conflicts with shipping lanes, fishing areas, and coastal land owners. While large offshore wind farms already exist – particularly in northern Europe [2] – the potential

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of offshore wind is being limited by current methods of turbine installation. Almost all offshore wind farms in commercial operation use a fixed foundation, using a driven-monopile underwater structure, where the base of the turbine is driven directly into the seabed in a manner analogous to land-based turbines. However, this method of installation becomes impractical and prohibitively expensive at depths greater than 60 meters.

To take advantage of this wind resource, floating offshore wind is an area of significant focus. Floating offshore wind turbines (FOWTs) consist of the wind turbine buoyed on a floating platform, with several mooring cables connecting the floating platform to anchors embedded in the ocean floor. Floating offshore wind turbines have been demonstrably shown to be functionally viable in simulations, full-scale prototypes, and in Hywind Scotland, the world's first commercial floating wind farm [3]. However, offshore wind is still too expensive to be commercially viable on a widespread scale. In a Carbon Trust review in 2015, the cost for a single 6 MW floating wind prototype was about £5.2m/MW, far above the £3m/MW limit estimated for commercial deployment [4]. To reduce these costs, optimization needs to be conducted for all components of the design for FOWTs. Since the costs of the substructure and foundation is the largest capital expenditure of a floating offshore wind project, optimization of anchors and moorings is of particular interest [5].

One hypothesized method to optimize mooring and anchors for FOWTs is to utilize shared mooring or anchors. In a scheme designed by Fontana et al., a single anchor is used to moor three FOWTs, as opposed to each platform using its own set of anchors [6]. A detailed visual depiction of the setup is shown in Figure 1, with a large array of 100 turbines is shown in Figure 2. Such a system is estimated to have cost reductions of 8-16% compared to a standard single-line anchor system due to the reductions in the number of anchors by nearly a factor of three, and a subsequent reduction in geotechnical site investigations required [7].

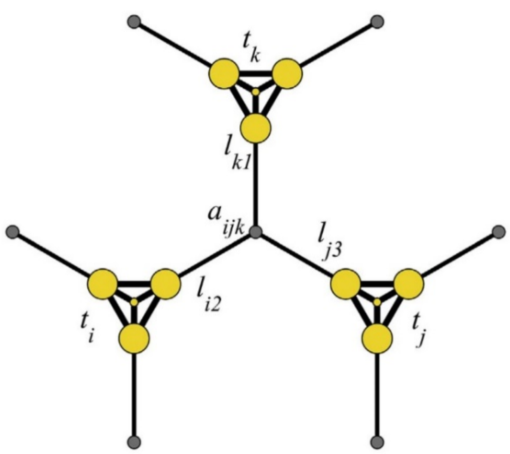

FIGURE 1: PLAN VIEW OF THE MULITLINE ANCHOR CONFIGURATION USED, SHOWING THREE FOWTS LABELED t_i, t_j, t_k CONNECTED TO THE SHARED ANCHOR a_{ijk} VIA THREE MOORING LINES l_{i2}, l_{j3}, l_{k1}

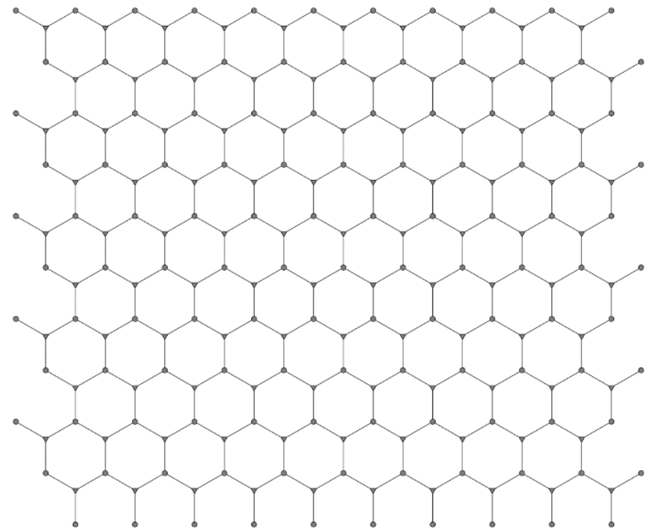

FIGURE 2: CONFIGURATION OF THE ANALYZED FLOATING OFFSHORE WIND ARRAY. CIRCLES INDICATE ANCHORS, TRIANGLES INDICATE TURBINES, AND LINES INDICATE MOORING LINES

However, a further finding of the shared anchor concept was that the dynamics of such a system would result in complex loading on the anchors due to the complicated coupling involved. In simulated survival load cases done by Hallowell et al., this would lead to significant reduction in system reliability compared to a single-line anchor system, largely due to an increased risk of cascading component failures [8].

To counteract this decreased system reliability, an increase in anchor strength is required, which introduces cost increase that could eliminate any cost benefit gained from utilizing the multiline anchor concept. However, it is possible that the complex dynamics caused by the component coupling could actually provide a benefit. The authors hypothesize that having a small number of specific anchors strengthened a large amount would provide comparable system reliability to strengthening all of the system anchors to a lesser amount for significantly lower costs.

To receive the greatest reliability benefit from this hypothesis, both the specific anchors and the amount the anchors are strengthened beyond the "standard" strength in the system (henceforth referred to as "overstrengthened" anchors) need to be optimized. The primary goal of this work is to identify the 10 optimal anchors to overstrengthen to maximize reliability in an array of 100 floating offshore wind turbines (as shown in Figure 2), and to identify whether this provides comparable system reliability versus slightly strengthening all anchors.

PROBLEM FORMULATION

System Design

The optimization scheme outlined in this paper uses a large floating wind array consisting of 100 turbines and 120 anchors utilizing the multiline anchor system designed by Fontana et al., where a single anchor moor three OC4 / DeepCWind semisubmersible platforms supporting a standard NREL 5 MW turbine [6]. The mooring lines are catenary Grade R3 chains with a nominal diameter of 77.9 mm and a nominal break load capacity of 5111 kN. with specifications listed in Table 1. Suction caissons anchors are used, as the multiline concept necessitates multidirectional anchor loading, with a nominal capacity of 3460 kN. The farm is set up in a hexagonal design with all turbines beginning in specific locations at regular intervals, with 10 turbines per row and 5 per column. Adjacent rows and columns are offset by half of the distance between turbines within the same row. Each anchor has lines connecting from three different turbines (unless the anchor is on the edge of the array), initially at 120 degrees apart. Additional problem parameters are listed in Table 1. As the turbines are greater than 10 rotor diameters apart from one another, wake effects are considered negligible and are not accounted for in this work.

TABLE 1: PARAMETERS OF THE ANALYZED FLOATING OFFSHORE WIND ARRAY. THESE ARE IDENTICAL TO THE PARAMETERS USED IN PREVIOUS WORK WITH THIS MULITLINE CONCEPT [6]

Parameters of Analyzed Floating Wind Array	
Ocean depth	200 meters
Unstretched mooring line length	835 meters
Mooring line seafloor lay length	243 meters
Radial distance from fairleads to anchors	797 meters
Radial distance from center of platform to fairleads	41 meters
Horizontal distance between turbines	1451 meters

Objective Function and Simulation

The objective function of the problem being addressed is to maximize the reliability of an array of FOWTs, utilizing the multiline anchor scheme with a predetermined number of overstrengthened anchors, as discussed above. “Reliability” in this context is a unitless index factor representing the mean return period to failure of the array, typically falling between 1 and 2. The reliability of a particular array configuration is determined using a set of MATLAB functions created to evaluate this system, identical to the simulation functions previously used by Hallowell et al. for an identical 100-turbine array [8].

The MATLAB simulation sets the geometry of the array, then determines the demands on all mooring lines ($F_{l,i}$) and anchors ($F_{a,i}$) by sampling the demands from loaded FAST data on a lognormal distribution. The FAST data was acquired from several analyses that simulated the hourly loading response of the turbine components under loading of a 500 year storm approaching from the south. Different simulations were used to determine the loading response of the components in different failure situations, such as when a platform was only supported by two mooring lines in the event of the third mooring line failing. If the strength capacity is less than the demand for an anchor or at any measured point of the mooring line, it fails, and the function changes the component capacity and demands for the surrounding components to loads calculated from the respective FAST data. Once determined, the simulation runs again to determine if more failures occur as a result of the loading changes, and the process repeats. The simulation runs until every anchor and turbine has a demand less than its capacity. The entire process is then repeated 5000 times to create a Monte Carlo simulation.

At this point, the simulation determines which turbines fail each simulation (a turbine failure occurs when any of the adjacent anchors also fail). The reliability value for the configuration is defined as:

$$\beta = -\Phi(P_f) \quad (1)$$

where Φ is the cdf of the standard normal distribution, P_f is the hourly probability of failure in the simulation scenario. More specifically,

$$P_f = 1 - \prod_{i=1}^{3}(1 - P_{fl,i}) \prod_{i=1}^{3}(1 - P_{fa,i}) \quad (2)$$

where $P_{fl,i}$ is the ith mooring line failure probability and $P_{fa,i}$ is the ith anchor failure probability. As described above, the failure probability for each turbine component is determined by:

$$P_{fa,i} = \mathrm{P}(C_a < F_{a,i}) \quad (3)$$

$$P_{fl,i} = 1 - \prod_{k=1}^{n_l}\left(1 - \mathrm{P}\left(C_l < F_{l,i}(s_k)\right)\right) \quad (4)$$

OPTIMIZATION ALGORITHM

To find the maximum reliability and the optimal anchors to overstrengthen in this optimization problem, a binary genetic algorithm (GA) was used as the basis of the overall optimization algorithm. However, due to a significant amount of stochastic noise in the generated solutions created by the sampling of the FAST data in the evaluation, using only a GA failed to converge to an optimal solution. The stochastic noise combined with the very large number of potential configurations (about 116 trillion if overstrengthening 10 anchors) necessitated a unique hybrid optimization scheme that introduces elements of Bayesian optimization common in RBDO applications, and an inter-test archive of existing solutions.

Binary Genetic Algorithm

In the algorithm, overstrengthened anchors are denoted as 1, while normal strength anchors are denoted as 0. The algorithm takes the number of overstrengthened anchors per array (n_{OS}) and the overstrength factor (i.e. the multiplier placed on the anchor strength of the selected overstrengthened anchors) as inputs, with the best reliability value and the corresponding overstrengthened anchors as outputs. The anchor numbering begins in the southeast corner of the array and proceeds north, returning to the southern end of the next column of anchors to the west. At the start of the optimization process, a population is generated with n_{OS} randomly selected overstrengthened anchors in each chromosome. The MATLAB simulation discussed in the previous section is used as the fitness function, which evaluates each configuration of overstrengthened anchors and outputs a reliability value.

After sorting the solutions by reliability value and the corresponding arrays from best to worst, the best reliability is evaluated. If it is better than the existing best reliability, this value is overwritten, and the new best set of overstrengthened anchors is saved.

The fittest 20% of each set of solutions have their traits cloned directly to the next generation. This high cloning rate is used to decrease stochasticity and decrease the time to convergence.

The process of selection begins with a kill of all below-average chromosomes. The remaining solutions are normalized as B, where array j is normalized as follows:

$$B_j = \frac{\beta_j - \beta_{avg}}{\sum_{i=1}^{n_A}(\beta_i - \beta_{avg})} \tag{5}$$

where n_A is the number of above-average arrays. This normalization is done to exaggerate good solutions, as the range of reliability values within a population is relatively small (typically 0.05 or less), to which selection is sensitive.

Selection was accomplished by ordering the normalized reliability values linearly, then randomly selecting a value within the range of normalized reliabilities. Instead of using a crossover point, a random permutation of the overstrengthened anchors from the selected parents that match the inputted number of overstrengthened anchors is selected. 60% of the solutions for the following generation consisted of children.

The remaining 20% of chromosomes for the following generation were randomly generated in the same manner as the first generation. This is done because having all chromosomes be composed entirely of children results in convergence to local maxima instead of a globally optimal solution.

This optimization process iterates for 100 iterations. At the conclusion of the last iteration, the algorithm outputs the best overall reliability and the corresponding set of overstrengthened anchors.

The determined parameters of the GA formulation, as well as grounds for the selection of each parameter value, are included in Table 2.

TABLE 2: GA PARAMETERS, SELECTED VALUES, AND RATIONALE FOR SELECTING EACH VALUE

Binary Genetic Algorithm Parameters		
Parameter	**Value**	**Grounds**
Iteration Limit	100	Smaller values led to worse solutions; larger values did not converge any further
Population size	100	Smaller values led to worse solutions; larger values did not converge any further
Number of overstrengthened anchors	10 (typical)	Selected a small enough number to where the most important anchors would be obvious, but a large enough value to where configuration trends and patterns could be identified.
Crossover percentage	60%	Smaller values do not converge; larger values quickly converge to local maxima
Cloning percentage	20%	Smaller values converge too slowly; larger values converge quicker, but to local maxima
Mutation percentage	0%	Stochasticity in evaluation prevents further stochasticity from being required

Bayesian Optimization Elements

In order to combat the stochastic noise resulting in a lack of convergence when optimizing with a binary GA, elements of Bayesian optimization were added to the algorithm. Bayesian optimization is tolerant to stochastic noise, making it suitable for this optimization problem. For this problem, the normal distribution of the reliability results from the evaluation simulation takes the form of the Gaussian process prior of a Bayesian optimization problem. The typical evaluation step in a GA is thus replaced by a Bayesian evaluation process.

Specifically, the evaluation process now takes the following form:

1. The set of overstrengthened anchors for a given solution is read into the program.
    a. If the exact permutation of overstrengthened anchors has not been evaluated before, the simulation evaluates the reliability of that solution 25 times, then calculates and saves the mean reliability for that permutation of overstrengthened anchors.
    b. If the exact permutation of overstrengthened anchors has been previously evaluated, the previously saved mean reliability is extracted, and the simulation evaluates the reliability an additional time. The mean is then recalculated and saved for that permutation of

overstrengthened anchors, overwriting the previously saved mean.

2. Each permutation of overstrengthened anchors encountered, the corresponding reliability values, and the corresponding number of times a permutation was evaluated, are each saved in ordered arrays to be referenced in future iterations.

This evaluation process was tested in isolation with five randomly selected sets of overstrengthened anchors, each evaluated for 250 iterations, then repeated four additional times. The results of this initial test showed that the standard deviation of the reliability values had dropped below 0.001 for all tested overstrengthened anchor solutions by 25 iterations, as shown in Figure 3. Therefore, as discussed in the new evaluation process above, the optimization algorithm evaluated each new solution 25 times. Note that this decision disregards the temporary increase of the black line back above the 0.001 standard deviation mark. The benefits gained from increasing the number of initial tests to 40+ were assumed to be marginal compared to the detriment of increased computational expense.

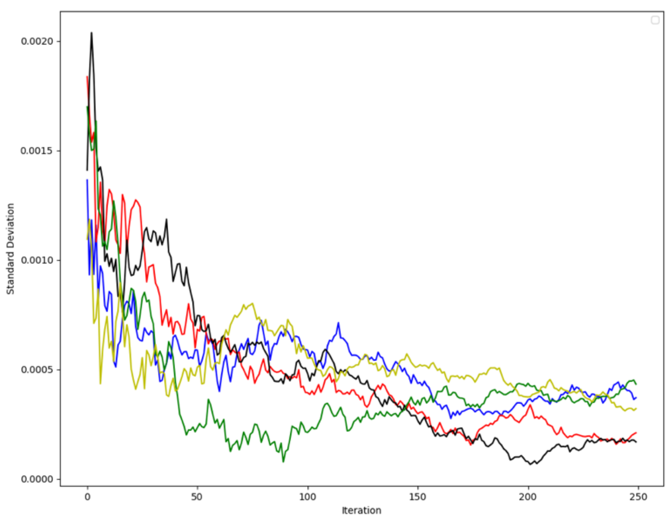

FIGURE 3: STANDARD DEVIATION VS. ITERATION COUNT FOR FIVE SETS OF OVERSTRENGTHENED ANCHORS

The cloning, selection, and crossover from the GA elements of the optimization algorithm act as the acquisition function of the algorithm from a Bayesian perspective, thus satisfying the two main components of a Bayesian optimization algorithm.

Due to the very large number of permutations of overstrengthened anchors, an archive of CSV files was established to save the arrays of overstrengthened anchor configurations, corresponding reliabilities, and the number of tests done for each configuration. These CSV files would be retrieved and read into the optimization algorithm each time it ran, effectively creating a running archive of all configurations that have been tested by the optimization algorithm throughout all of the times it has ever ran (within the specified directory). As the optimization algorithm was tested increasingly more, the archive saved an increasing amount of computation time.

RESULTS AND DISCUSSION

Overstrength Factor Results

One of the first notable results discovered was the behavior of the overstrength factor. As the overstrength factor was an algorithm parameter instead of an optimization variable, the optimization algorithm was simply run multiple times with varying overstrength factors and a varying number of overstrengthened anchors.

As shown in Figure 4, the lower overstrength values implicated reduced reliability, with the lowest overstrength factor of 1.1 diverging even at very low numbers of overstrengthened anchors, and 1.2 showing very little increase in reliability value if operating on more than five overstrengthened anchors. However, increasing the overstrength factor beyond 1.3 only gives marginal improvement in reliability, regardless of the number of overstrengthened anchors. It appears that the reliability for a 1.3 overstrength factor begins to separate itself from higher overstrength factors beginning after 15 overstrengthened anchors, although this was not further tested due to the majority of the testing for this problem being constrained to 10 overstrengthened anchors. As such, the overstrength factor was set to 1.3 for all optimization tests.

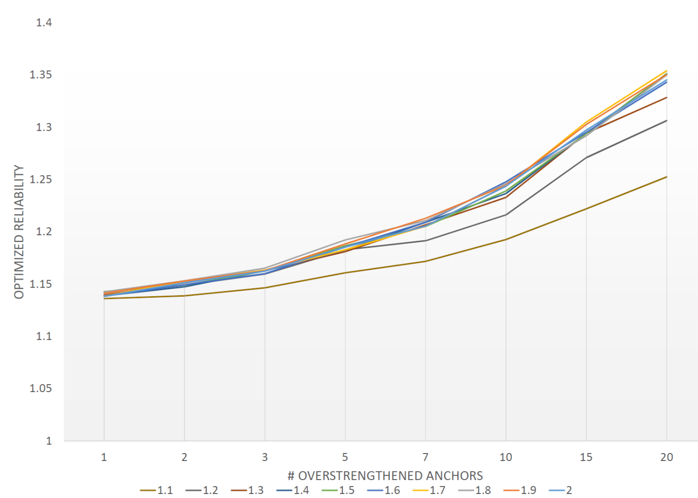

FIGURE 4: NUMBER OF OVERSTRENGTHENED ANCHORS VS. OPTIMIZED RELIABILITY FOR OVERSTRENGTH FACTORS RANGING 1.1 TO 2

Reliability Results

With the addition of the Bayesian optimization and archiving, convergence to an optimal fitness level was achieved, though multiple optimal solutions were found. Specifically, reliability values converged to an optimal value of 1.2315 ± 0.0005, but the selected set of overstrengthened anchors would be somewhat different every time the algorithm converged on this reliability value. An example of this through eight tests of the optimization algorithm is shown in Table 3.

TABLE 3: RESULTS OF EIGHT SUCCESSFUL OPTIMIZATION ATTEMPTS

Optimization Test Results – 10 Overstrengthened Anchors, 1.3 OSF		
Optimization Test	Reliability	Overstrengthened Anchors
1	1.2312	23 38 48 51 56 61 69 80 89 92
2	1.231	13 23 35 48 56 67 71 89 91 93
3	1.2319	23 27 49 51 56 73 78 83 90 92
4	1.232	23 36 40 56 59 60 68 83 89 92
5	1.232	9 34 36 51 56 70 72 78 89 94
6	1.231	5 34 47 56 59 73 78 83 89 92
7	1.2313	27 34 45 48 67 69 71 89 93 95
8	1.2311	9 23 39 45 56 70 73 78 93 100

These eight results were then charted simultaneously on a mapped wind farm layout, with different colors representing the number of times a specific anchor was selected across all optimization tests, functioning as a heat map. The results of this are shown in Figure 5.

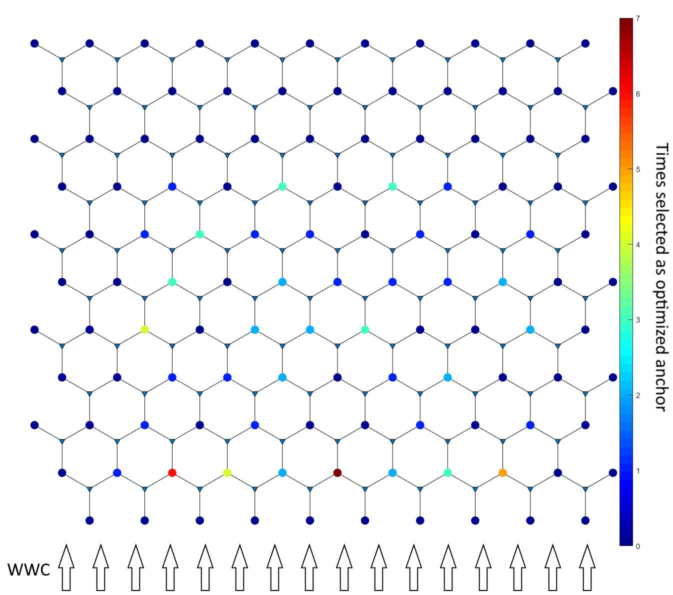

FIGURE 5: HEAT MAP OF THE ANALYZED WIND ARRAY, ILLUSTRATING THE FREQUENCY OF SELECTED OVERSTRENGTHENED ANCHORS FROM THE EIGHT SUCCESSFUL OPTIMIZATION TESTS IN TABLE 3

Upon analysis, there appears to be a moderate correlation between specific regions and the overstrengthening of anchors, as highlighted in Figure 6. Of note, Region A – the southernmost row of multiline anchors, always had at least three overstrengthened anchors in every optimized array. Regions B and C tended to each have at least one overstrengthened anchor present. Region D tended to have one to three overstrengthened anchors present, though almost never adjacent anchors.

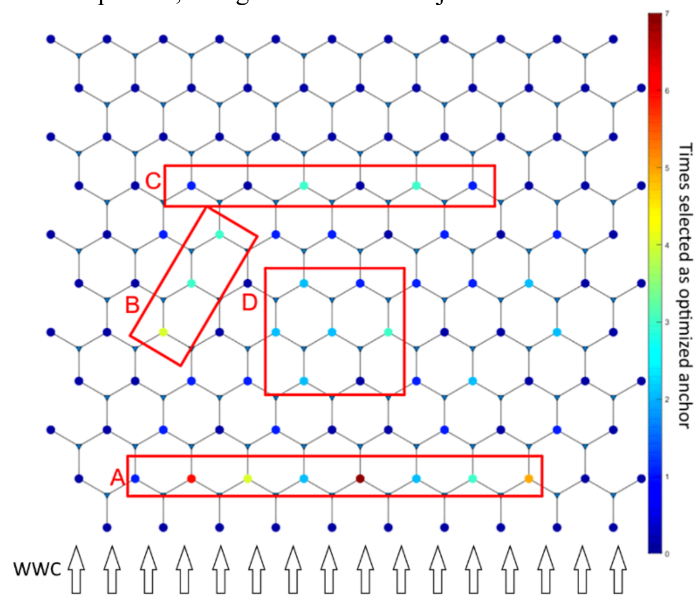

FIGURE 6: HEAT MAP OF THE ANALYZED WIND ARRAY, WITH BOXES ENCLOSING NOTEWORTHY REGIONS

Interestingly, with one exception (see Figure 7 below), nine of the 10 overstrengthened anchors would always fall within these four regions; there always is one overstrengthened anchor that falls in some other location in the array. This is likely a coincidence within the results rather than an indication of a specific behavior.

Figures 7 and 8 show two examples of optimized arrays, with red squares overlaying of the specified regions of interest. Note that Figure 7 provides several exceptions to several correlations discussed above.

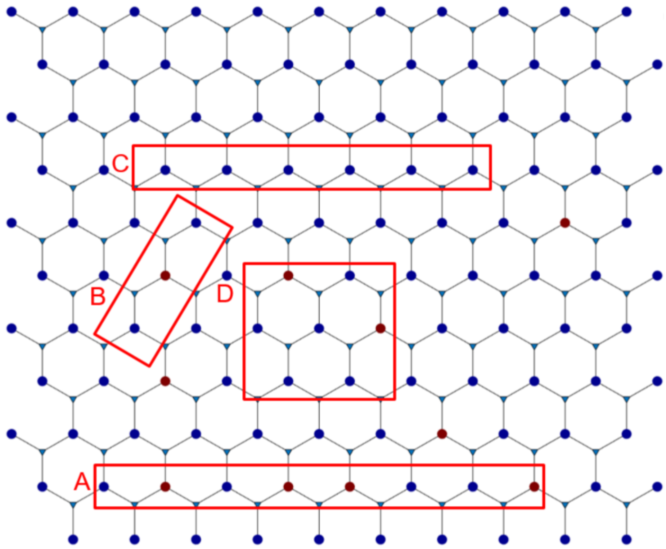

FIGURE 7: OPTIMIZED SOLUTION FOR 10 OVERSTRENGTHENED ANCHORS, WITH SOME DEVIATION FROM OBSERVED TRENDS, 1.3 OVERSTRENGTH FACTOR

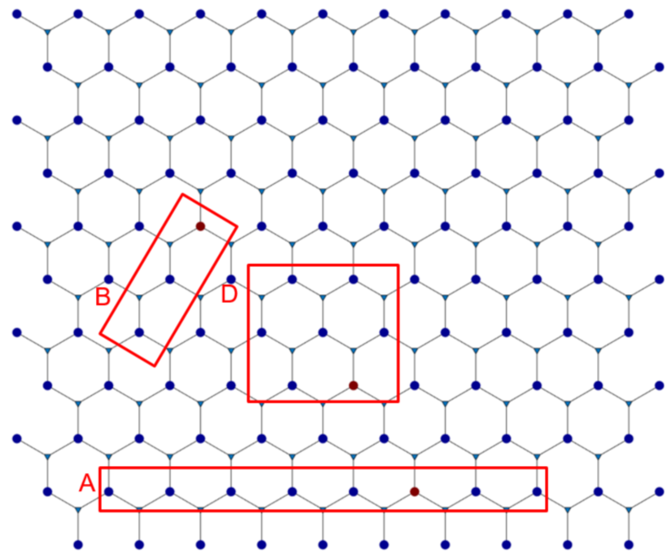

FIGURE 9: OPTIMIZED SOLUTION FOR THREE OVERSTRENGTHENED ANCHORS, 1.3 OVERSTRENGTH FACTOR

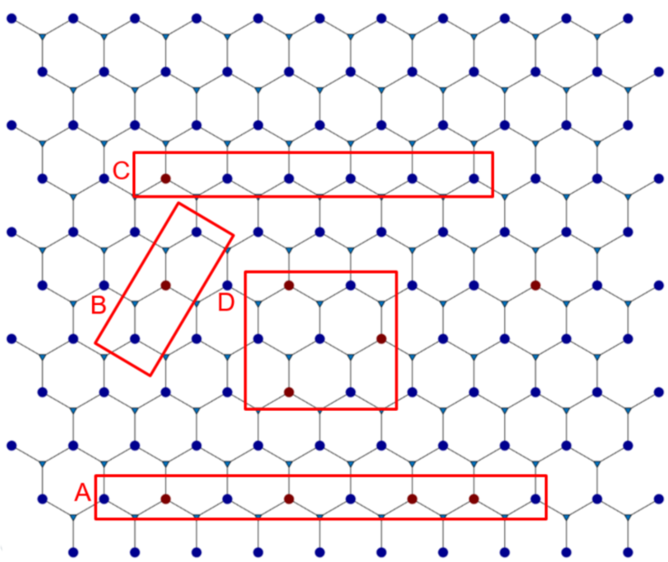

FIGURE 8: OPTIMIZED SOLUTION FOR 10 OVERSTRENGTHENED ANCHORS, WITH ADHERENCE TO OBSERVED TRENDS, 1.3 OVERSTRENGTH FACTOR

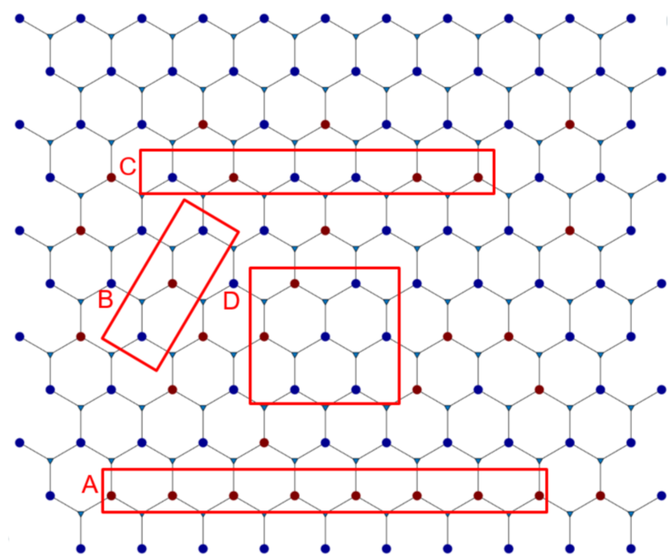

FIGURE 10: OPTIMIZED SOLUTION FOR 30 OVERSTRENGTHENED ANCHORS, 1.3 OVERSTRENGTH FACTOR

While many of the aforementioned regions and trends are only somewhat correlated, there appear to be two strong correlations:

1. The further south an anchor is within the array, the more likely it is to be overstrengthened.
2. The “center of mass” of all overstrengthened anchors falls close to the central column

To further test the behavior of the anchor selection, the optimization algorithm was tested with overstrengthening three anchors and 30 anchors. The results from these optimization tests are shown in Figures 9 and 10.

Overall, the same strong correlations found in the tests with 10 overstrengthened anchors also appear in the tests with three and 30 overstrengthened anchors. As shown in Figure 9, one overstrengthened anchor falls within each of Regions A, B, and D. for the test with three overstrengthened anchors. In Figure 10, every anchor in Region A is overstrengthened, and the concentration towards the southern half of the array still holds true, while maintaining east-west symmetry. The reliability values found for the differing numbers of overstrengthened anchors is listed in Table 4.

TABLE 4: RELIABILITY COMPARISON BETWEEN DIFFERENT NUMBERS OF OVERSTRENGTHENED OPTIMAL ANCHORS

Anchors Strengthened to 1.3 OSF	Reliability
3	1.151
10	1.2315
30	1.497

Despite a single optimized configuration not being identified, the rationale behind the trends for the selection of overstrengthened anchors offers insight into which anchors to target in the design of an array utilizing this multiline anchor theory. The concentration of overstrengthened anchors in the southern half of the array – especially in Region A – is likely due to the wind and wave forces acting on the array coming from the south. If an anchor in the southern part of the array fails, the coupling of the turbines and anchors makes it more likely for a single failure to lead to cascading failures than if an anchor in the north fails. This has the highest impact for multiline anchors near the edge of the array, explaining why Region A sees the highest concentration of overstrengthened anchors.

Comparison to Initial Hypothesis

Once a converged solution was identified, the resulting reliability evaluations from the optimization scheme were compared to the reliability evaluations of the same FOWT array where the strength of all anchors is increased to a lesser degree. The latter was acquired by testing the same simulation initially given (only all 120 array anchors were "overstrengthened") 500 times per overstrength factor and taking the mean reliability. The results of these tests are listed in Table 5.

TABLE 5: RELIABILITY VALUES WHEN OVERSTRENGTHENING ALL 120 ANCHORS IN THE ARRAY TO THE LISTED OVERSTRENGTH FACTORS.

Overstrength Factor	Reliability
1	1.1088
1.025	1.3216
1.05	1.518
1.075	1.6969
1.1	1.8638
1.125	2.0194
1.15	2.1624
1.175	2.3008
1.2	2.428

Comparing reliability values from Tables 4 and 5, the reliability from strengthening all anchors quickly surpasses the reliability for only overstrengthening a small number of anchors, even if the anchor selection is optimized. This suggests the reliability of a FOWT array using this multiline concept is much more closely tied to the number of anchors overstrengthened than which anchors are overstrengthened, or by how much. Notably, the reliability value for the optimization test with 30 overstrengthened anchors appears substantially more competitive with the mass strengthening reliabilities. Drawing from this, it is possible there is a point where overstrengthening some larger number of optimized anchors (more than 30, less than 120) provides increased benefit over increasing the overall anchor strength, and optimizing the anchors for that scenario could lead to some credence to the original hypothesis. The number and optimized location of these anchors, as well as the cost-benefit analysis of this concept versus simply strengthening all of the anchors to a lesser amount, is an area of substantial interest in future research.

CONCLUSIONS AND FUTURE WORK

Floating offshore wind provides a substantial untapped supply of energy that can be utilized to meet increasing energy demand in the United States. However, the substantial costs associated with floating offshore wind prevent it from currently being commercially viable, and design optimization is required for the floating offshore wind to approach viability. A method has been proposed to decrease the cost of anchoring by connecting mooring lines from multiple turbines to a single anchor, substantially reducing the cost of the anchors for a large farm. The hypothesis proposed by the authors was that a high system reliability level could be maintained for such an array by strengthening the most important anchors more than the majority of the anchors in the array. Optimization was required to determine the best anchors to strengthen.

The simulation used to evaluate the reliability of a hypothetical floating wind array uses data from prior FAST analyses to determine the mean number of turbine and anchor failures that would result from the loading scenario specified by the user. A binary genetic algorithm was initially attempted as a means to maximize the reliability of the simulation for a preset number of overstrengthened anchors and an overstrength factor, but this optimization algorithm proved to be sensitive to noisy evaluations resulting from probabilistic sampling within the provided simulations, and failed to converge as a result. To counter this, aspects of Bayesian optimization, such as treating repeated evaluations as a Gaussian process prior, made the optimization algorithm resistant to noise and succeeded in converging to a single reliability value, albeit with many optimal solutions.

The resulting configurations from optimized arrays show selected overstrengthened anchors being concentrated with respect to the direction of wind and wave forces, due to the effects of cascading failures if these components fail. However, optimizing and significantly strengthening a small number of anchors failed to match the reliability of slightly strengthening all array anchors, though the results suggest overstrengthening a much larger number of anchors in optimized locations could still provide substantial benefits to the overall reliability of the system.

Future work will entail identifying the relation between the number of optimized anchors and the reliability for a much larger set of overstrengthened anchors, and identifying if there is a point where the optimized overstrengthening method provides greater benefit than simply overstrengthening all array anchors.

The explicit costs of these two options – particularly the potential savings to the construction of a large floating offshore wind farm – also warrants future investigation. This could manifest by modifying the optimization algorithm to be multivariable, where the number of overstrengthened anchors is bounded by cost factors and solved by the algorithm in addition to the reliability.

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