Floating offshore wind energy is anticipated to become a competitive source of renewable energy by the late 2020s, but the industry must reduce costs and uncertainties associated with the technology to do so. Identifying solutions to these problems frequently relies on computational modeling, which presents technical shortcomings limiting the versatility of the modeling results. This work presents two improvements that augment existing computational tools, allowing researchers to more accurately model floating offshore wind systems and reduce uncertainty. The first study presents a custom optimization algorithm to identify the relationship between cost and reliability for floating offshore wind farms using shared anchoring. The algorithm minimizes the added costs associated with failure by optimizing the strength of anchors for a case study of a large wind farm under simulated survival load conditions. The optimization algorithm merges a genetic
algorithm with elements of Bayesian optimization to account for uncertainty from
the probability of failure and the resulting repair costs. The second study presents
a numerical model created by modifying the OpenFAST floating wind turbine
simulation software. This numerical model solves for aerodynamic loading in a
real-time hybrid simulation, allowing for integration with physical wave basin ex-
periments with proper scaling and higher fidelity than computer simulations. Val-
idation shows that the model accurately generates aerodynamic loads efficiently
enough to be used in a real-time hybrid simulation setup. The study also identifies
modifications that will allow for modeling of tower top elasto-servo dynamics in
future work.
Advanced Computational Modeling Methods for Floating Offshore Wind Systems

by

Michael C. Devin

A THESIS

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Oregon State University

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Master of Science

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Master of Science thesis of Michael C. Devin presented on May 27, 2021.

APPROVED:

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Major Professor, representing Mechanical Engineering

______________________________
Head of the School of Mechanical, Industrial, and Manufacturing Engineering

______________________________
Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

______________________________
Michael C. Devin, Author
I’m tremendously grateful to all the peers who offered professional advise, guidance, and assistance to me as I conducted my research—

- Thanks to Spencer Hallowell, Sanjay Arwade, and Caity Clark for helping me establish my ideas and assisting me as I worked through my optimization journal paper.

- Thanks to Barb Simpson, Andreas Schellenberg, Jonah Gadasi, Pedro Lomónaco, and Christopher Neumann for your help and guidance on the real-time hybrid simulation project. I’m excited to see where the project goes in the future.

Going into graduate school, I knew it would involve a degree of turbulence and stress, but I did not anticipate a 2020 level of turbulence and stress. Thanks to all my friends, roommates, labmates, and colleagues who tackled the past two years alongside me—especially Nathan, Deetz, Aeron, Austin, Mel, Naser, Jared, Hannah, and Ali. You all brought me personal connection, support, and joy when the rest of the world decided those things should be hard to come by.

Lastly, to Bryony DuPont—I don’t know what made you decide to mentor my dumb 20 year old self who couldn’t get even my robot for ME 382 to work right, but I am forever grateful that you gave me a chance. I wouldn’t be where I am now without your belief in me and all the effort you put into helping me become successful. Working with you the past four years has been an absolute privilege.
CONTRIBUTION OF AUTHORS

The work to be published in Chapter 2 is built upon work conceptualized by Dr. Sanjay Arwade and Dr. Spencer Hallowell. Dr. Hallowell also contributed to the initial code development of the work. Dr. Bryony DuPont advised and assisted with critical revision of the article and final approval of the version to be published.
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Chapter 1: General Introduction

Wind energy has become one of the fastest growing sources of power generation in the United States, as the nation aims to address increasing power demand, achieve greater energy independence, and reduce carbon emissions to mitigate the harmful effects of climate change. This rapid growth is expected to continue in the coming years as states increase their renewable energy portfolio standards. Within the sector, focus has recently turned to offshore wind energy as it presents fewer land use conflicts, lower visibility from populated areas, and a better wind resource than onshore due to faster, more consistent, and less turbulent wind speeds. Using decades of industry experience from European nations, American offshore wind generation is expected to expand from its current deployed capacity of 42 MW across two projects to over 30 GW across 40 or more projects by 2030 [2].

In order to meet federal and state targets for offshore wind, floating offshore wind technology must soon become commercially viable. Unlike traditional fixed-bottom wind turbines, which have a fixed foundation installed directly into the ground or seabed, floating wind systems attach a wind turbine to a floating platform moored to the seabed to maintain stability. This allows for wind installations in ocean waters hundreds of meters deep, whereas fixed bottom offshore wind turbines are practically limited to about 60 meters. Crucially, this enables development in some of the best wind resource in the country off the coast of Maine,
Oregon, and California [3], the last of which already has projects in the development pipeline [4]. However, floating offshore wind technology is at a much earlier stage of development than onshore wind and fixed-bottom offshore wind technologies, and numerous issues still need to be addressed before commercial adoption is attainable. Among the most significant issues include a lack of design convergence on optimal platform and mooring system designs, higher construction and maintenance costs due to increased distance from shore and more severe metocean conditions, and a lack of well-established supply chains. Additionally, only two commercial-scale floating wind projects have been installed globally as of 2021—Hywind Scotland [5] and WindFloat Atlantic in Portugal [6]—and the lack of real world experience and data can further increase project risk and increase hesitancy for potential investors. Thus, further research is required to reduce project costs for widespread commercial development to be realized.

To achieve these goals, contemporary research in the offshore wind community is focused on reducing costs and uncertainty surrounding floating offshore wind system design and implementation, including design and array optimization, fatigue and extreme load modeling, and supply chain standardization. Due to the high costs and permitting limitations of installing demonstration projects in ocean waters, researchers in these areas often rely on computational modeling. While efficient and inexpensive, computational models are limited by the fidelity of the numerical modeling of physical phenomena, and there is limited real world data available to use for numerical model validation. Thus, significant uncertainty persists by emulating the full range of conditions expected in real world installations.
using purely computational modeling. Some researchers have begun analyzing reliability to address these shortcomings, but this research topic is not yet widely adopted. In particular, the correlation between different reliability levels and their corresponding increases in project costs is not well understood, making communication to potential project investors challenging.

The current state of floating offshore wind computational modeling research motivates two research questions of interest:

1. How can we establish better computational models reflecting the relationship between cost and reliability of floating offshore wind technologies?

2. How can we leverage existing computational modeling methods to better simulate real world metocean conditions?

In this body of work, I present two improvements upon existing computational modeling approaches for floating offshore wind, each addressing one of these research questions:

1. In Chapter 2, I present a method to identify the relationship between cost and reliability for floating offshore wind arrays using a custom optimization algorithm. The algorithm is applied to computer simulations of extreme loading conditions on a large floating offshore wind farm utilizing shared anchoring, a contemporaneous research topic in the community [7]. The optimization algorithm minimizes added costs of failure by altering the strength of the anchors in the simulated wind farm and applying a preliminary failure cost
model based on available data on offshore wind corrective maintenance. The model optimizes this cost using a genetic algorithm containing elements of Bayesian optimization in an inner loop to account for uncertainty associated with failure and repair.

2. In Chapter 3, I present and validate a numerical modeling approach using a modified version of the OpenFAST wind turbine simulation software integrated with Simulink. This model will interface in real time with a physical experiment in the O.H. Hinsdale Wave Laboratory at Oregon State University, allowing for computer modeling of aerodynamics and physical modeling of hydrodynamics. This hybrid approach allows the scale model experiment to be conducted without scaling issues, allowing the complex physical phenomena acting on a floating wind system to be modeled with higher fidelity.

The research presented here is significant in that it extends the capabilities of current computational modeling approaches in ways that make the simulation results more accurate and useful. This will help other researchers and industry partners use these tools to model floating wind systems more accurately and make design decisions with increased certainty. These efforts will ultimately lead to more rapid realization of floating offshore wind as a financially competitive technology in the United States.
Chapter 2: Optimizing the Cost and Reliability of Shared Anchors in an Array of Floating Offshore Wind Turbines

2.1 Introduction

The United States is beginning to adopt offshore wind power to meet state policy goals amid increasing national power demand. Seven states on the Eastern seaboard have now cumulatively committed to nearly 20 GW of offshore wind installations by 2035 [4]. Investment is also emerging for floating offshore wind projects on the West Coast, Maine, and Hawaii. The Bureau of Ocean Energy Management (BOEM) has established 13 call areas in US federal waters, including three off the coast of California and two near the Hawaiian island of Oahu [4]. The University of Maine recently partnered with Diamond Offshore Wind and RWE Renewables to install a full scale floating wind demonstration project off the coast of Maine, with completion expected in 2023 [8].

Floating offshore wind turbines (FOWTs) have shown to be viable in existing demonstration projects, and the first commercial scale FOWT installation off the Scottish coast has, at time of writing, exceeded production estimates [9]. However, floating offshore wind is currently too expensive to achieve widespread commercial viability. As of 2018, the levelized cost of energy (LCOE) of floating offshore wind is estimated at $132/MWh, far higher than the $42/MWh estimated for onshore
Additionally, uncertainty is high regarding the reliability of commercial development of FOWTs in the United States. The metocean climate of North American waters is more severe than seen in European waters, due to harsher wave climates (for the West Coast) and the risk of hurricanes (for the Atlantic and Gulf coasts) [11]. With little historical data about FOWT behavior in these conditions, offshore wind investors for American projects endure greater project risk and uncertainty. This is compounded by experience from Europe revealing, in some cases, higher repair costs and reduced turbine lifetimes than initially expected for offshore wind projects [12].

Research in floating offshore wind is currently addressing the problems of both cost and—to a lesser but growing extent—reliability. The relationship between these two parameters is important to consider in project planning to determine whether increased system reliability raises or lowers overall costs. For example, one proposed method to reduce costs for the mooring system is by utilizing shared anchors\(^1\). In a scheme designed by Fontana et al., a single suction caisson connects to three mooring lines instead of one [13]. For large wind farms, this method of sharing anchors reduces the number of anchor sites required by nearly a factor of three. This reduces overall capital costs of a system by 8-16% compared to an equivalent farm with a traditional single-line anchor system due to lowered material costs and fewer geotechnical surveys. Additionally, the symmetric loading

\(^1\)In other literature, this technology is also referred to as multiline anchoring or anchor mutualization.
from the three mooring lines has been found to reduce the overall force demands on an anchor by 11-16% [14]. However, sharing anchors also presents risks not present with traditional anchor systems. Hallowell et al. found the probability of failure for a given turbine in a survival load case with shared anchors increases by 12.2% compared to turbines using a traditional anchor system due to the risk of cascading failures when sharing anchors [1].

Despite the major implications the cost-reliability relationship can have in project planning and system design, it has not been explored for floating offshore wind systems at time of writing. To help address this, this research provides a computational method to examine the trade-offs between reliability and costs for the anchor sharing method developed by Fontana et al. Specifically, this work presents a novel optimization method, Rel-Opt [15], that selectively increases the strength of certain anchors in a large floating wind farm with shared anchors, with the goal of minimizing mooring system failure while balancing it with the cost of increasing anchor strength. The optimization method is a multivariable genetic algorithm modified to incorporate elements of Bayesian optimization to account for the inherent uncertainty related to failure. The evaluation function of the optimization algorithm expands on the system reliability evaluations by Hallowell et al. [1] by integrating a failure cost model. In the future, this algorithm could be adapted for other anchoring methods, which could inform strategies regarding the use of shared anchors and if the technology is cost effective. A cost sensitivity analysis is also performed to address cost uncertainties and identify critical areas of future research for this class of problem.
2.2 Problem Formulation

The objective function of the optimization algorithm in this work is to minimize the added costs of a floating wind farm in survival load conditions while controlling for anchor strength. This optimization problem examines a large floating wind farm consisting of 100 turbines in a 10-by-10 array with offset rows, shown in Figure 2.1. Except for perimeter anchors, each anchor moors three OC4/DeepCWind semisubmersible platforms, each platform supporting a reference NREL 5-MW turbine, requiring 120 total anchors [16, 17]. Wake effects are considered negligible as the turbines are greater than 10 rotor diameters apart, as per González-Longatt et al. [18]. A water depth of 200 meters is used with flat seabed bathymetry in a soft clay soil profile. This wind farm configuration is identical to that used in Hallowell et al. [1].

Additional relevant parameters of the anchor system are included in Table 2.1. The parameters are derived from the results of the mooring system design evaluation in Sections 5 and 6 of Hallowell et al. [1], which uses allowable stress design methodology and upper bound plasticity methods to determine mooring line and anchor capacity, respectively. The anchor adhesion factor, underpressure, and twist misalignment are also considered in the design.

2.2.1 Evaluation Function

Optimization algorithms require a clearly defined evaluation function in order to operate successfully. Discussion of the evaluation function is critical in under-
Figure 2.1: Schematic of the wind farm used in this work, illustrating the anchor sharing system.
Table 2.1: Parameters of the analyzed floating wind farm

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</tr>
<tr>
<td>Radial distance from fairleads to anchors</td>
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<table>
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<tr>
<th>Mooring Lines</th>
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<tbody>
<tr>
<td>Material</td>
</tr>
<tr>
<td>Grade R3 chains</td>
</tr>
<tr>
<td>Nominal diameter</td>
</tr>
<tr>
<td>77.9 mm</td>
</tr>
<tr>
<td>Nominal break load capacity</td>
</tr>
<tr>
<td>5,111 kN</td>
</tr>
<tr>
<td>Unstretched length</td>
</tr>
<tr>
<td>835 m</td>
</tr>
<tr>
<td>Seafloor lay length</td>
</tr>
<tr>
<td>243 m</td>
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</table>

<table>
<thead>
<tr>
<th>Anchors</th>
</tr>
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<tbody>
<tr>
<td>Nominal ultimate holding capacity</td>
</tr>
<tr>
<td>3,460 kN</td>
</tr>
<tr>
<td>Angle between padeye connections</td>
</tr>
<tr>
<td>120 degrees</td>
</tr>
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</table>

standing the problem the algorithm in this work aims to solve. Additionally, this helps clarify the rationale behind decisions made for other parts of the algorithm discussed in Sections 2.3 and 2.4.

The evaluation method used in this optimization algorithm is a modification of the system reliability calculation for this shared anchor concept derived in Hallowell et al. [1]. In the work of Hallowell et al., 12 1-hour simulations of a wind turbine in a survival load case (SLC) scenario are conducted in FAST, a time domain simulation software for wind turbines developed by NREL [19]. FAST simulates the nonlinear aero-hydro-servo-elastic interactions of a floating wind turbine, capturing the fully coupled dynamic response of this load case. The SLC scenario, developed by Viselli et al. [20], represent a southerly storm with a 500-year mean return period for the Gulf of Maine, which has a similar water depth and soil profile to
what is being considered here. The peak tensions at various points in each mooring line and at the anchor are fit to a lognormal distribution. This distribution is randomly sampled to determine the demands on every mooring line and anchor in the wind farm. Similarly, the load capacity for each component is determined from a lognormal distribution based on the nominal load capacities in Table 2.1. This simulates the structural variance in mooring system components, calculated from the risk of soil degradation failure with 20% covariance as per Choi [21]. If the demand for any component exceeds its load capacity, the component fails. All turbines associated with failed components recalculate the demands on the surviving mooring lines and anchors (sampled from different distributions generated from identical FAST simulations with the respective failed mooring lines removed), again capturing any mooring system failures. This process repeats until no new failures occur. The number of turbines connected to failed components is saved, and the process repeats many times (set by the user), allowing for a reliability analysis to be performed via the Monte Carlo method. This process is visualized in Figure 2.2.

The evaluation function used in this optimization algorithm (henceforth referred to as the *added cost evaluation*, visualized in Figure 2.3) builds upon the work of Hallowell et al. (henceforth referred to as the *system reliability evaluation*) by adding three modifications:

1. An additional safety factor can be specified for each anchor in the wind farm prior to the start of the evaluation. This extra safety factor is specified as a multiplier to the nominal load capacities in Table 2.1 prior to the lognormal
Figure 2.2: System reliability evaluation used in Hallowell et al. [1].
sampling. The multiplier is referred to as the \textit{overstrength factor} of an anchor for the remainder of this work. 20 discrete overstrength factors are available, ranging from 1.05 to 2.

2. The number of Monte Carlo samples performed is now controlled by the optimization algorithm, based on the reliability and cost of the wind farm given certain overstrength factors. This is explained in greater detail in Section 2.3.2.

3. Once the number of turbines with component failures in a given Monte Carlo simulation is determined, a cost analysis is added to calculate the costs from all applied overstrength factors and component failures. This is detailed in Section 2.4.

2.3 Optimization Algorithm

A custom optimization algorithm was developed for the added cost evaluation to solve this optimization problem. A multivariable genetic algorithm (GA) was used as the basis for the algorithm. However, given the uncertainty present in the added cost evaluation, a GA with traditional function evaluations would output highly stochastic data, making convergence to an optimal solution challenging. This challenge is addressed by using series of function evaluations instead of a single evaluation per individual, as per Painton and Campbell [22]. This is done in this work by incorporating elements from Bayesian optimization methods to combat
Figure 2.3: Added cost evaluation process. Changes from Figure 2.2 are in bold.
the stochasticity and reach convergence.

2.3.1 Multivariable Genetic Algorithm

Genetic algorithms are a set of heuristic optimization methods that uses principles of Darwinian natural selection to converge to a global optimum. Given a set population size, individuals are created using a random combination of the problem design variables, encoded into “bits”. A function evaluates and scores each individual based on desirable heuristics. A new population is then created using the process of crossover (where two individuals from the population share their genes to create offspring) and mutation (where a segment of the bits of an offspring is altered), with more fit individuals being more likely to be selected to reproduce. Over many generations, the population gradually “evolves” to an optimal solution.

A genetic algorithm was chosen for this work for two reasons. First, this optimization problem is non-differentiable, eliminating most classical optimization methods. Second, the problem has a large search space. This makes the problem prone to local (rather than global) convergence, which GAs can avoid more effectively than numerical optimization methods. Two-dimensional binary arrays are used to encode each individual in the GA, with each row representing a different anchor and each columns indicating the selected overstrength factor for that anchor (if any). 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.
Table 2.2: GA parameters of the optimization algorithm used in this work

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>Population size</td>
<td>100</td>
</tr>
<tr>
<td>Crossover percentage</td>
<td>70%</td>
</tr>
<tr>
<td>Cloning percentage</td>
<td>10%</td>
</tr>
<tr>
<td>Kill percentage</td>
<td>20%</td>
</tr>
<tr>
<td>Percentage of offspring mutated</td>
<td>10%</td>
</tr>
<tr>
<td>Bit mutation rate</td>
<td>10%</td>
</tr>
</tbody>
</table>

In order to ensure efficient convergence while avoiding local optima, the optimization algorithm was tuned extensively to strike a balance between population diversity and computational efficiency. This includes the introduction of other optional GA parameters, including elitism (where the most fit individuals are cloned directly to the next generation prior to crossover), using a kill (where the least fit individuals are ineligible from crossover to remove negative outliers), and including a set of random individuals in each population unaffected by the crossover in the previous generation. Uniform crossover is used, where each bit has equal chance of being selected from each parent. Mutation is incorporated to alter the overstrength factor of a select number of anchors ±0.1, as long as it stays within the range of 1 to 2. Algorithm parameter values were tuned empirically, and are given in Table 2.2. The algorithm is considered converged once the same configuration has been the fittest in the population for 100 consecutive generations. The algorithm stops once converged or if 5,000 generations elapse, whichever comes first.

Additionally, it was discovered that seeding the initial population resulted in
large increases in efficiency with negligible reductions in population diversity. The selection of initial seeds was also determined empirically. 40% of the initial population is seeded with turbine configurations expected to perform well. This set includes configurations considered to be good (though unlikely optimal) solutions to act as starting points to reduce computation time for the algorithm. The seeded configuration selections are shown in Table 2.3. Each seeded configuration has a uniform overstrength factor throughout all the overstrengthened anchors in the farm, though four overstrength factors were tested per combination of anchors (i.e. each cell in Table 2.3 corresponds to four configurations, each with its own uniform overstrength factor).

The remainder of the initial population is composed of random configurations, as is typical for a GA. However, this set of the population is split: two-thirds of the random configurations have a uniform overstrength factor but random overstrengthened anchor selections, and one-third have both random overstrengthened anchor and overstrength factor selections. This was done because a decrease in computation time to convergence was found by adding the uniform overstrength factor individuals without significantly affected population diversity.

The fitness function used in the algorithm is given in Equation 2.1. The fitness of an individual is equal to the cost difference between it and the worst surviving individual divided by the standard deviation of the costs of all surviving individuals.

\[ F_i = \frac{|C_i - C_{last}|}{\sigma_{gen}} \]  

(2.1)
Table 2.3: Details of the 40 initial seeds used in the optimization algorithm.

<table>
<thead>
<tr>
<th>Selection</th>
<th>Image</th>
<th>OSFs</th>
<th>Selection</th>
<th>Image</th>
<th>OSFs</th>
</tr>
</thead>
<tbody>
<tr>
<td>All anchors</td>
<td><img src="image1.png" alt="Image" /></td>
<td>1.05, 1.10, 1.15, 1.20</td>
<td>Southern half of anchors</td>
<td><img src="image2.png" alt="Image" /></td>
<td>1.10, 1.20, 1.30, 1.40</td>
</tr>
<tr>
<td>Shared anchors</td>
<td><img src="image3.png" alt="Image" /></td>
<td>1.10, 1.20, 1.30, 1.40</td>
<td>Shared anchors in long columns</td>
<td><img src="image4.png" alt="Image" /></td>
<td>1.10, 1.20, 1.30, 1.40</td>
</tr>
<tr>
<td>in short columns</td>
<td><img src="image5.png" alt="Image" /></td>
<td>1.10, 1.20, 1.30, 1.40</td>
<td>Shared anchors in long columns</td>
<td><img src="image6.png" alt="Image" /></td>
<td>1.10, 1.20, 1.30, 1.40</td>
</tr>
<tr>
<td>Southern row of shared anchors</td>
<td><img src="image7.png" alt="Image" /></td>
<td>1.25, 1.50, 1.75, 2.00</td>
<td>Center three anchor rows</td>
<td><img src="image8.png" alt="Image" /></td>
<td>1.10, 1.20, 1.30, 1.40</td>
</tr>
<tr>
<td>Outer box of shared anchors</td>
<td><img src="image9.png" alt="Image" /></td>
<td>1.25, 1.50, 1.75, 2.00</td>
<td>All anchors with 3 lines</td>
<td><img src="image10.png" alt="Image" /></td>
<td>1.05, 1.10, 1.15, 1.20</td>
</tr>
<tr>
<td>Even # anchors</td>
<td><img src="image11.png" alt="Image" /></td>
<td>1.05, 1.10, 1.15, 1.20</td>
<td>Odd # anchors</td>
<td><img src="image12.png" alt="Image" /></td>
<td>1.05, 1.10, 1.15, 1.20</td>
</tr>
</tbody>
</table>
2.3.2 Bayesian Optimization

Bayesian optimization is commonly used in optimization problems where the objective function is largely unknown and expensive to evaluate. A prior probability distribution is generated from the objective function, with evaluation points probabilistically sampled. A posterior distribution is created after analyzing the results of the evaluations, forming an acquisition function that determines where the next evaluation points should be.

Incorporating elements of Bayesian optimization proved useful in this optimization algorithm since its methods are inherently tolerant to stochastic function evaluations. For this hybrid algorithm, the lognormal distribution of anchor and mooring line demands discussed in Section 2.2 function as the Bayesian prior, and the GA cloning, crossover, and mutation discussed in Section 2.3.1 act as the acquisition function.

Functionally, this means that the number of evaluation simulations for a configuration is dependent on its fitness, with fitter individuals being evaluated more times than less fit individuals. For the initial population, each configuration is simulated 3,000 times, as this was the point at which good individuals could reliably be separated from mediocre and poor individuals (see Figure 2.4). The algorithm stores an archive of all configurations, the total number of simulations ran for each configuration, and the average cost across all simulations for each configuration. For all subsequent generations, the algorithm queries the archive after the population is generated to identify which configurations already exist in the archive. The
Figure 2.3: Reduction in cost variance due to additional simulations.

Algorithm then retrieves the archived cost, simulates the configuration an additional 1,500 times, calculates an updated average cost, and restores the new values to the archive. Configurations not stored in the database are simulated 3,000 times and subsequently stored, as was done with the initial population. This addition is shown in Figure 2.3 above.

With this process, the best configurations are simulated an increasingly large number of times, gradually reducing the variance in its cost. Meanwhile, poor configurations are only simulated enough times to confirm they are not evaluating
well before dying out via the GA selection process. In a simulation of 25 random configurations (sample data included in Figure 2.4), configurations could be reliably ranked after 150,000 total simulations, which determined the 100 generation threshold to decide convergence. Therefore, by convergence, the optimal cost should have very low error associated with its cost.

2.4 Cost Model

The optimization algorithm uses a cost model to evaluate (1) the added capital costs due to overstrengthening the selected anchors, and (2) the added costs from performing need-based maintenance to repair the failures from loss of stationkeeping.

The overall equation for the added cost of a configuration is

\[
C_i = \sum_{n=1}^{n_{sims}} \frac{C_{failure}}{n_{sims}} + C_{osf}
\]

The failure cost is averaged from all the evaluations as discussed above in Section 2.3.2. The failure cost for each simulation is based on the total number of turbines with at least one mooring line or anchor failure, at which point stationkeeping is lost. The cost components consist of the likeliest perceived costs that could occur in the event of a floating wind turbine losing stationkeeping. The total failure cost for a given simulation is given as

\[
C_{failure} = C_{moor} + C_{elec} + C_{turb} + C_{downtime}
\]
Each component of Equation 2.3 is detailed below in Sections 2.4.1-2.4.4.

The overstrength factor cost is the \textit{additional} cost of manufacturing the over-strengthened anchors compared to the normal strength anchors. Details of the overstrength factor cost are detailed below in Section 2.4.5.

It is worth noting that this cost model is not meant to be comprehensive. The addition of the cost model here is used as a tool to demonstrate the trade-offs between cost and reliability in the optimization algorithm. However, cost accuracy was approached with care, and values are derived from existing literature when possible. A cost sensitivity analysis is also performed to examine differences in algorithm behavior for different cost profiles (see Section 2.4.6).

2.4.1 Mooring System Repair

As no shared anchoring system has ever been tested, various assumptions had to be made regarding the anchor and line replacement process:

- The entire anchor is assumed to be replaced regardless of failure mode. On suction caissons, the padeye (the connection point on the anchor for the mooring line) is below the seabed for an installed turbine. Therefore, even if partial removal and reinstallation of a suction caisson were a repair option, it would be logistically challenging (particularly for a shared anchor), and a complete reinstallation is likely less expensive [23]. While the evaluation in this work only considers anchor failures from soil degradation, this rule would hold if torsional failures on the padeye were considered, as these have
also been reported to be likely during hurricanes [24].

- Similarly, in the event where a mooring line fails but its anchor does not, the entire anchor is still replaced.

- The reinstallation of failed anchors begins after all formerly connected turbines are towed to port.

- One anchor handling tug supply (AHTS) vessel with subsea equipment is used to reinstall an anchor. While AHTS vessels often drop anchors directly from the vessel without subsea equipment due to cost savings, precision in install location is vital due to the coupled nature of shared anchors, so subsea equipment must be used.

- Three AHTS vessels, one per turbine, are used to reconnect the mooring lines to the platform fairleads.

- A complete anchor reinstallation is assumed to take 14 hours total. Myhr et al. [25] used a 12 hour installation time for single line suction caissons, and one additional hour is added per extra mooring line due to vessel maneuvering and handling complexities from connecting multiple lines to one anchor.

The costs for different items considered are included in Table 2.4. All monetary values derived from literature are converted to 2020 U.S. dollars. The anchor material cost is assumed to be directly proportional to the anchor mass, which depends on the ultimate holding capacity. The required anchor mass for a given anchor strength (factoring in the overstrength factor of the anchor) is calculated
Table 2.4: Details of mooring system repair

<table>
<thead>
<tr>
<th>Item</th>
<th>Failure Cost</th>
<th>Notes</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mooring line material cost</td>
<td>$208,750 per line</td>
<td>$250/m in 200m water depth</td>
<td>[25]</td>
</tr>
<tr>
<td>Anchor material cost</td>
<td>Variable</td>
<td>See text</td>
<td>[25]</td>
</tr>
<tr>
<td>Anchor decommissioning cost</td>
<td>$903,828 per anchor</td>
<td></td>
<td>[27]</td>
</tr>
<tr>
<td>Anchor disposal cost</td>
<td>$495,887</td>
<td>Covers all failed anchors</td>
<td>[27]</td>
</tr>
<tr>
<td>Labor &amp; vessel costs</td>
<td>$343,720 per anchor</td>
<td>Method 1 from Castro-Santos et al.</td>
<td>[27]</td>
</tr>
<tr>
<td>Vessel transit time</td>
<td>3 hours</td>
<td>50 NM @ 16 knots</td>
<td>[28]</td>
</tr>
<tr>
<td>On-site repair time</td>
<td>14 hours</td>
<td>2 hours more than</td>
<td>[28]</td>
</tr>
</tbody>
</table>

from its density and volume; in turn, the anchor volume is calculated using the design equations for pile anchors given by the American Bureau of Shipping [26]:

$$L, D, T = c \times S_{ult}^d$$  \hspace{1cm} (2.4)

where $c$ and $d$ are (1.1161, 0.3095, 2.0580) and (0.3442, 0.2798, 0.2803) for $(L, D, T)$ respectively, using the ABS constants for suction piles in very soft clay. The material cost of a suction pile anchor is set at $12,300/ton, as used in Myhr et al. [25], and the density of steel is assumed to be 7,850 kg/m$^3$. 
2.4.2 Electrical Repair

The drift and rotation of a platform caused by even partial loss of stationkeeping will almost certainly result in damage or failure of the inter-array cable for the turbine in question. Therefore, every turbine in the simulation that suffers at least one component failure in its mooring system is assumed to require electrical repair.

The layout of the electrical cabling for the wind farm is shown in Figure 2.5, which uses a convention radial collection system, similar to what is used in the 100 turbine wind farm analyzed by Bjerkseter and Ágotnes [28]. Considering the location of the farm in the Gulf of Maine, the export cable continues east to the coast to connect with land-based transmission lines. The inter-array cables are assumed to be connected serially between turbines without redundancy. As a result, the electrical failure of one turbine results in the loss of power to all downstream turbines, even if those turbines maintain stationkeeping. This impacts the downtime power losses substantially, as explored in Section 2.4.4.

The electrical repair begins after the anchor system and turbine repairs are complete and all turbines have been reinstalled in the farm. The entire cable length for a particular unmoored turbine is assumed to be removed and replaced with a cable laying vessel. The costs and other relevant information associated with inter-array cable repairs are detailed in Table 2.5.
2.4.3 Turbine Repair

Virtually no literature exists regarding the expected damage to floating offshore wind turbines due to loss of stationkeeping. While the damage to an unmoored floating wind turbine in the midst of a 500-year storm has the potential to be catastrophic, the probability of these failures, which failure modes to consider, and isolating the damages that would not occur absent loss of stationkeeping is
Table 2.5: Details of electrical system repair

<table>
<thead>
<tr>
<th>Item</th>
<th>Failure Cost</th>
<th>Notes</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inter-array cable material cost</td>
<td>$805,916 per turbine</td>
<td>$481/m</td>
<td>[29]</td>
</tr>
<tr>
<td>Replacement cable length</td>
<td>1,675.5 m</td>
<td>Based on farm geometry</td>
<td></td>
</tr>
<tr>
<td>Vessel and labor costs</td>
<td>$258,027 per turbine</td>
<td>$154/m</td>
<td>[29]</td>
</tr>
<tr>
<td>Cable laying rate</td>
<td>400 m per day</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

impossible to approximate given the current state of research. Due to this, assumptions regarding turbine repairs from loss of stationkeeping are kept generalized and conservative.

The cost model assumes all turbines that lose stationkeeping are towed to shore by an AHTS as soon as it is safe to do so to undergo inspections, prior to the mooring system repairs. Each turbine is assumed to be quayside for one week to undergo major repairs to the gearbox, hub, blades, and yaw system, as specified by Carroll et al [30]. The mooring system repairs are assumed to occur while the turbines are quayside, and the turbines are towed back to the farm and reinstalled at the end of the week. Costs associated with turbine repair is detailed in Table 2.6.
Table 2.6: Details of turbine system repairs

<table>
<thead>
<tr>
<th>Item</th>
<th>Failure Cost</th>
<th>Notes</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbine tow vessel cost</td>
<td>$727,942</td>
<td>per turbine</td>
<td>[28]</td>
</tr>
<tr>
<td>Turbine quayside time</td>
<td>1 week</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gearbox repair material costs</td>
<td>$3,000 per</td>
<td>Major repair from Carroll et al.</td>
<td>[30]</td>
</tr>
<tr>
<td></td>
<td>turbine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hub repair material costs</td>
<td>$3,000 per</td>
<td>Major repair from Carroll et al.</td>
<td>[30]</td>
</tr>
<tr>
<td></td>
<td>turbine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blade repair material costs</td>
<td>$1,800 per</td>
<td>Major repair from Carroll et al.</td>
<td>[30]</td>
</tr>
<tr>
<td></td>
<td>turbine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yaw system repair material costs</td>
<td>$3,600 per</td>
<td>Major repair from Carroll et al.</td>
<td>[30]</td>
</tr>
<tr>
<td></td>
<td>turbine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quayside labor costs</td>
<td>$109,985</td>
<td>From annual labor crew costs</td>
<td>[25]</td>
</tr>
<tr>
<td></td>
<td>per turbine</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.4.4 Costs from Lost Power

Costs of lost production must be considered for turbines that go offline due to electrical failures. As with the other failure cost components, only downtime resulting directly from a loss of stationkeeping is considered in this research.

Levelized cost of energy (LCOE) is used to translate lost power production into a cost-equivalent to add to this cost model. An LCOE of $132/MWh is used as given by Stehly and Beiter [10]—while the LCOE at the point in the future when a floating wind farm of this scale is feasible will likely be far lower, estimating that extends beyond the scope of this work. The total cost-equivalent from lost power
is

\[ C_{\text{downtime}} = LCOE \ast P \ast k_{cf} \ast n_{tpr} \ast n_{rows} \ast t_{\text{repair}} \]  \hspace{1cm} (2.5)

where \( k_{cf} \) is assumed to be 0.44. The total repair time for each failed site is

\[ t_{\text{repair}} = t_{\text{weather}} + t_{\text{labor}} \]  \hspace{1cm} (2.6)

The total repair process, and the time required for each step, is summarized in Figure 2.6.

The maintenance delays due to poor weather for offshore wind installations are far higher than for onshore turbines, and floating installations are expected to have even longer delays than fixed-bottom offshore wind due to the increased travel times and generally more severe metocean climates further from shore [12]. For determining the delay time in waiting for a weather window for this particular site, 37 years of metocean data was collected from NOAA Station 44005, available from the National Buoy Data Center [31], to determine the frequency and length of weather windows. Weather window thresholds were set at 2 meters significant wave height, from the value given for AHTS vessels by Brons-Illing [32], and a maximum sea level wind speed of 12 m/s, as per Dowell et al. [33].

For every 12 hours of total repair time (excluding the time the turbine is quayside), a random sample is used to determine whether a 12 hour weather window occurs, in which case the repairs can proceed without delay. If the random sample falls outside the weather window probability, the delay is determined by randomly
Figure 2.6: Repair process following a mooring system failure. The sun symbols on arrows indicates a weather window must open before the next action can be performed.

sampling the downtime lengths from the NOAA data. This process is repeated until all repairs have been completed.

2.4.5 Capital Costs of Overstrengthening Anchors

The capital costs for overstrengthening the specified anchors in a particular configuration are computed as
The method of finding the costs of the overstrengthened anchors and an un-strengthened anchor are identical to the method discussed in Section 2.4.1 using the ABS equation.

\[ C_{osf} = \sum_{i=1}^{n_{os}} C_i - C_{unstr} \] (2.7)

2.4.6 Cost Sensitivity Analysis

Despite the floating offshore wind cost estimates made in previous works and cost parallels that can be made with onshore and fixed-bottom offshore wind, the cost model used here is highly speculative. Virtually no publicly available data exists for operations and maintenance costs for floating wind turbines due to the nascence of the industry. Furthermore, these values are difficult to even predict due to fluctuations in the cost of steel, duration of repairs, and vessel costs and availability. These uncertainties are exacerbated in the United States, which does not have an established supply chain for fixed-bottom offshore wind (let alone floating offshore wind), and is further complicated by restrictions on the use of foreign vessels in American waters by the Jones Act [34].

Because of these reasons, a cost sensitivity analysis is performed in this work to evaluate the differences in trade-offs between reliability and cost for different cost profiles. The profiles selected are meant to evaluate the elements of the cost model thought to have the highest uncertainty in cost, with the multiplier selected so Profiles B and C have roughly the same cost when tested with an optimal
configuration from Profile A. The three cost profiles are considered in this work:

- Profile A: The baseline cost model. All costs specified throughout Section 2.4 are unchanged.

- Profile B: Costs associated with mooring system repairs are increased by a factor of 3. This represents cost uncertainties related to cost of steel for anchors, vessel costs, and complications involving working with shared anchors.

- Profile C: Costs and downtime associated with turbine quayside repairs are increased by a factor of 5. This represents uncertainties regarding the severity of turbine damage caused by loss of stationkeeping during a severe storm.

2.5 Results and Discussion

For all profiles, the algorithm stopped after reaching the 5,000 generation limit. However, upon analyzing the results, it appears that a minimal cost is consistently achieved by around generation 2,000, but there are many combinations of overstrength factors that achieve the minimum cost. This is not surprising, given the size and symmetry of the wind farm. Additionally, all of the optimal configurations show very similar behavior, enabling us to draw valuable conclusions about the mooring system design and reliability. Statistical information about the optimal costs is included in Table 2.7.

The configuration with the lowest cost would change every few generations due to the continuously updating costs for each configuration, preventing the algorithm
Table 2.7: Added cost results of the optimization algorithm

<table>
<thead>
<tr>
<th>Cost Profile</th>
<th>Mean Optimal Cost</th>
<th>Standard Deviation</th>
<th>Mean Optimal Reliability Index</th>
<th>Mean Absolute Percentage Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$12,794,221</td>
<td>$53,397</td>
<td>2.2320</td>
<td>0.32%</td>
</tr>
<tr>
<td>B</td>
<td>$14,795,386</td>
<td>$53,402</td>
<td>2.3513</td>
<td>0.29%</td>
</tr>
<tr>
<td>C</td>
<td>$14,327,646</td>
<td>$57,660</td>
<td>2.3504</td>
<td>0.32%</td>
</tr>
</tbody>
</table>

from meeting the standard convergence criterion. While it is possible that this algorithm would eventually find a single optimal solution, it would likely take a prohibitively long time and would provide little new information or practical benefit than what is achieved here. As a test, Profile A was simulated for an additional 2,000 generations using a population entirely of optimal anchor configurations from earlier testing, with a much higher cloning percentage to encourage rapid reduction in cost uncertainty. Despite this, there was less than a 5% reduction in standard deviation, with no apparent convergence to a single optimal configuration.

2.5.1 Anchor and Overstrength Factor Selection

Sample configurations of different optimal selections are given in Table 2.8. These do not represent all of the optimal configurations for each profile, merely a subset that is representative of the diversity of patterns seen in the optimal set as a whole. Notably, despite the similarity in patterns between the optimal configurations, specific patterns of anchor numbers rarely appear. Due to this, it is probable
that the minimum costs here approach a global optimum, as it suggests that these configurations were discovered independently of one another by the algorithm.

All optimal configurations for all profiles overstrengthen every anchor in the wind farm except for the unshared anchors on the eastern, western, and northern edges of the farm. Overstrength factors are kept relatively low, with no factor ever exceeding 1.35. The unshared anchors on the southern edge of the wind farm are likely overstrengthened due to the wind and wave directions in the evaluation coming from the south, making this row of anchors (and the southernmost anchor on each turbine in general) suffer much higher failure rates than the other unshared anchors.

Profile C has the highest average overstrength factor, and Profile A has the lowest. The latter is expected, considering the lower failure costs make the risk of component failure less severe. Profile C having a higher average overstrength factor than Profile B is somewhat unexpected, considering the similar costs of the two profiles. It is likely that the failure of a single turbine in Profile C is far more severe than in Profile B since the costs from lost power are much higher, particularly if a single component failure causes the loss of power to several turbines. Profile C also shows markedly less pattern consistency in overstrength factor locations. This may be due to the amplifications of downtime costs making the impact of the variance in determining weather delays much greater, increasing the uncertainty in the optimization problem. Profile A had the lowest mean reliability index of $\beta = 2.2320$, which corresponds to a mooring system component failure rate of about 1.25%. Profiles B and C had somewhat higher reliability indices corresponding to
Table 2.8: Sample results of the optimization algorithm. Anchor color indicates its overstrength factor.

<table>
<thead>
<tr>
<th>Profile A</th>
<th>1.05</th>
<th>1.1</th>
<th>1.15</th>
<th>1.2</th>
<th>1.25</th>
<th>1.3</th>
<th>1.35</th>
<th>1.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profile C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Anchor color indicates its overstrength factor.
a 0.94% failure rate. This indicates a risk trade-off still exists between cost and reliability for all three profiles, with higher repair costs corresponding to a reduced number of allowable failures.

Noticeable patterns emerge when comparing the overstrength factors north to south. All three profiles show the center rows consistently have the highest average overstrength factor in the farm. This is likely due to the high impact of a electrical failure of turbines near the middle rows, as the serial connection of inter-array cables can cause up to five turbines to lose power due to a single component failure. Profile B also shows a concentration of higher overstrength factors at the southern end of the farm compared to the other two profiles. This is perhaps due to the risk of cascading failures propagating from the south, as the southernmost anchor of each turbine is at the highest risk of failure as discussed above. Due to the amplified mooring system repair costs in Profile B, it would make sense to reduce mooring system failure more than the other profiles. The north of the farm sees the lowest average overstrength factors for similar reasons, though this is less pronounced in Profile C.

No clear patterns emerge when comparing overstrength factors east to west. Spreading out the anchors with higher overstrength factors seems to occur more often than not, though there are many exceptions to this (some included in Table 2.8). Still, spreading out the highest strength anchors is logical since it reduces the risk of both south-to-north cascading failures and severe electrical losses. The lack of patterns east to west is not surprising, as both the evaluated storm conditions and inter-array connections propagate north to south in this work.
2.5.2 Added Cost vs. Reliability

Based on the results of the array optimization, an additional test was performed to identify a more detailed interaction between system reliability (as calculated by the system reliability evaluation discussed in Section 2.2) and added cost across the different cost profiles. A configuration was created for each profile where all the anchors selected in Section 2.5.1 are overstrengthened to a uniform factor ranging from 1.05 to 1.5. A configuration with no overstrengthening (i.e. an overstrength factor of 1) was also tested. Each configuration is evaluated 100 times, with each evaluation consisting of 3,000 simulations.

The results of this test are shown in Figure 2.7. As expected from the optimization results, added costs minimize with fairly low overstrength factors, at 1.15 for Profile A and at 1.2 for Profiles B and C, before slowly beginning to increase despite improved system reliability. The minimum cost occurs at $\beta \approx 2.25$, coinciding with the mean optimal reliability index from Profile A.

Profile C has drastically higher costs than Profile B for the farms with the lowest anchor strength, but these costs converge around an overstrength factor of 1.1, with Profile B eventually becoming slightly more expensive than C for overstrength factors 1.25 and above. This suggests that decreasing the overall number of failures reduces costs for Profile C much more drastically than for Profile B. This could point to the importance of further research into expected floating wind turbine damage in survival load cases, as farm design related to this could provide huge maintenance cost savings for relatively minor capital cost increases.
Figure 2.7: Comparison of system reliability evaluation and added cost evaluation for a farm with uniformly strengthened anchors.

Notably, the minimum costs are also around $3 million higher than the optimized results found despite equivalent system reliabilities, suggesting significant cost savings by optimizing strength selection. However, the cost model in this work does not consider the additional manufacturing costs associated with the need of producing multiple anchor sizes. The cost of this may be more impactful than any cost savings from having multiple anchor strengths with precise placement locations. Ultimately, this is difficult to conclude one way or another given the
uncertainties still surrounding costs and logistics in large floating offshore wind farm installations, whether included in the cost model or not.

2.6 Conclusions and Future Work

By the end of the 2020s, floating offshore wind will likely make a significant contribution to the renewable energy portfolio of the United States. At the present, however, the substantial costs, risks, and uncertainties associated with floating offshore wind prevent it from being commercially viable. The main objective of this work is to provide an optimization algorithm to analyze the trade-offs between system reliability and added capital costs. A large wind farm using a shared mooring system is considered due to known shortfalls regarding its system reliability. Accounting for cost-normalized system reliability can reduce risks and uncertainties that currently exist with both the shared anchoring concept and, more broadly, the development of floating offshore wind farms.

Results reveal that the reduced system reliability in the shared mooring system is best remedied by increasing the strength of all shared anchors and windward unshared anchors. The optimization study identifies many similar configurations with added costs very close to the global minimum. Anchors supporting turbines nearest the export cable have their strength increased the most across all cost profiles. When the costs of mooring system repair are amplified, the strength of windward anchors are increased nearly as much as the anchors near the export cables. The lowest cost solutions retain about a 1.25% probability of failure due
to loss of stationkeeping, indicating improving reliability above this point is not worth further capital cost investment into the mooring system.

Results also indicate that system reliability is particularly sensitive to changes in turbine-related repair costs. Based on this, refinement of expected failure modes for floating offshore wind turbines under extreme loads could drastically improve the precision of computational simulations similar to the one performed in this work. Ultimately, this could have major positive impacts on floating wind farm system design, and is recommended by the authors as an area of future research focus.

While the optimization problem here could be answered by merely approaching a global optima, this work demonstrates the challenge of solving optimization problems with high uncertainty, even when consciously addressing it using Bayesian methods. The high degree of uncertainty in floating offshore wind technology would likely have prohibitively high computation time for more complex non-differentiable optimization problems, such as detailed continuous field layout optimizations. Creating concrete decisions regarding supply chain logistics and maintenance strategies for the American offshore wind sector would reduce systematic uncertainty in these optimization problems, which could ultimately provide great benefit to system optimization work in the research community.

Imminent future work will entail applying this optimization algorithm to an equivalent floating wind farm with a traditional, single line mooring system. This could provide insight into whether the costs of an optimized farm with shared anchors provides financial benefit over traditional anchors despite the difference in
system reliability. Other topics of future work include using a more efficient sampling technique in the evaluation function to further reduce convergence time, and expanding the optimization algorithm beyond the specific demonstration case studied here. Adding elements such as altered metocean conditions, different mooring system dispositions, and different floating platform models are of particular interest, as these generalize the algorithm for use in other areas of research in the floating offshore wind community.
Chapter 3: Numerical Modeling for Real-Time Hybrid Simulation of
Floating Offshore Wind Turbines Using OpenFAST

3.1 Introduction

The demand for floating offshore wind in the United States is expected to rapidly
grow in the near future, as state governments continue to expand their renewable
energy portfolio goals. Floating offshore wind technology enables power generation
in water depths unreachable by standard fixed-bottom wind turbines, unlocking
vast areas of ideal wind resource, particularly for Maine, the West Coast and Hawaii
[35]. However, building large-scale physical prototypes of floating wind turbines
in ocean waters is often impractical due to their high costs, complex supply chain,
and difficulty in quickly acquiring the necessary data. As a result, the industry
instead relies on computer-aided engineering tools and scale model testing under
controlled environmental conditions.

Research and industry alike use computer-aided engineering simulations due to
their efficiency and low cost to model floating wind turbines with desired condi-
tions. Organizations have developed software specializing in time domain simu-
lations of various areas of interest for offshore wind turbines, including the hydrody-
namics [36, 37, 38], aerodynamics [39], structural dynamics [40], or a combination of
the above [41, 19, 42]. The FAST software in particular is a comprehensive, open-
source program developed by NREL that has gained popularity in the offshore wind research community. FAST is capable of performing efficient mid-fidelity, fully-coupled simulations encompassing aerodynamics, hydrodynamics, structural dynamics, and control dynamics of a floating wind turbine [19]. FAST has been verified to provide good agreement with real world phenomena, particularly regarding structural and aerodynamics responses [43, 44], though poor agreement has still been found for coupled wind-wave loading with complex wave dynamics [45, 46].

Scale model laboratory testing is frequently used in engineering to prototype designs with fewer practical constraints than large scale testing without relying on computational approximations of complex physical phenomena. To maintain correlation between geometric scaling of the model and dynamic scaling of physical phenomena, researchers have identified and validated many similitude laws to correlate the two to ensure measurements in the scale model can be scaled to accurately duplicate the full-scaled device [47]. While perfect similitude cannot be achieved across all physical phenomena, most physical systems are dominated by a particular type of phenomena, allowing uniform scaling using a single similitude law. However, the complex interaction of disparate physical forces in a floating wind turbine does not allow for a single similitude law to be assumed without introducing significant scaling error. In particular, Froude scaling laws, used to scale hydrodynamic and structural interactions, are incompatible with Reynolds scaling laws, used to scale aerodynamic interactions. This results in geometrically scaled floating wind turbines using Froude scaling predicting poor full scale projections
of aerodynamic loading on the turbine [48, 49]. Researchers have experimented with model adjustments to reduce the error with Froude-scaled aerodynamics with some success. Kimball et al. adjusted the airfoil geometry and blade chord of the NREL 5-MW reference turbine to provide more accurate thrust and power coefficients to adequately Froude scale the aerodynamics, and was used in the Offshore Code Comparison, Collaboration, Continued, with Correlation (OC5) project [50]. Others have also had success by performance scaling rotors, using ducted fans, and using porous drag disks on the rotor [51]. However, all these corrections generally lose accuracy for higher wind speeds, and are specific to a given wind turbine design, making replication for other designs impractical when given a limited amount of laboratory testing time.

Real-time hybrid simulation (RTHS) is being explored as a promising general solution for the discrepancy in scaling laws for offshore wind scale model testing. RTHS couples a scale model laboratory subassembly experiment with a synchronous computational model (usually referred to as a numerical model) simulating other subassemblies at full scale. The experimental and numerical models exchange data in real time to allow them to function as one fully assembled model. If partitioned correctly, the numerical model can simply model the subassemblies presenting scaling problems at full scale, allowing for scaling with a single set of similitude laws without reducing accuracy. RTHS is widely used in earthquake engineering, where it has found use dating back to the 1970s [52], and has expanded to other civil engineering applications since.

Research has emerged in the past decade exploring the capabilities of RTHS
for offshore wind turbine scale model testing to account for the Froude-Reynolds scaling conflict. Chabaud et al. first conceptualized the use of RTHS for floating wind testing by designing a linearized model in one degree of freedom using computationally modeled wind and physically modeled waves [53]. Sauder et al. [54] and Hall and Goupee [55] later constructed hybrid setups and verified this system design using a winch system to actuate a floating wind turbine in a wave tank using aerodynamic loads simulated in FAST. The work by Hall and Goupee was later validated with wind tunnel testing, finding good agreement with providing aerodynamic loads from a computational model [56]. Vilsen et al. later generalized the RTHS method from Sauder et al. for varied ocean structures, performing a case study with a physical buoy in a still-water basin with a numerically modeled mooring system using RIFLEX software [57]. Azcona et al. used a ducted fan at the tower top as their actuation method, with FAST simulating the rotor thrust using inputted platform motions [58]. Matoug et al. also used a top-mounted propeller to account for thrust using a lookup table to compare the response of a horizontal axis wind turbine and a vertical axis wind turbine using the same platform [59].

Bayati et al. [60] and La Mura et al. [61] have explored the reverse coupling, where the hydrodynamics are numerically modeled and actuated via a 6 degree of freedom robotic system moving a wind turbine in a wind tunnel. Campagnolo et al. conducted a wind tunnel experiment on a scale model floating platform with four wind turbines (one on each corner) using numerically modeled waves actuated via driving motors in one degree of freedom, aiming to maximize total power of
the turbines on the platform [62].

The most crucial aspect of RTHS is in the coupling between the physical and numerical models, as the success of the system communication is dependent on its ability to operate in real time. The numerical model is often the bottleneck for this, and developing a quick and accurate model is crucial. Since the performance and fidelity of the numerical model are competing objectives, some software and hardware limitations have been observed for RTHS for floating wind systems. Hall et al. analyzes sources of error for RTHS systems using a modified version of FAST that emulates measurement, actuation, and latency errors in a physical model partitioned either at the rotor or at the tower base. It was discovered that tower base coupling requires far less latency and resultant bandwidth error due to the high frequency structural loading that must be accounted for numerically [63]. Bachynski et al. developed a methodology for sensitivity analysis to determine which forces and moments should be actuated by modifying an aerodynamic numerical model to examine the effects of incomplete actuation. Gyroscopic moments were found to have limited effects, while pitch and yaw were both significant, second only to thrust and torque [64].

Floating wind turbine computational simulation tools, particularly FAST, have also been coupled together in real time systems to create a higher fidelity co-simulation. Li et al. developed a system using a real-time implementation of FAST to model the mechanical system of a wind turbine, and the Real-Time Digital Simulator (RTDS) to model the electrical system [65]. Whitby and Condon developed a real time interface between the AeroDyn module of OpenFAST and the
ProteusDS software to provide higher fidelity drive train loading than AeroDyn can provide by itself [66]. Previous versions of FAST (or AeroDyn, the aerodynamics module in FAST) have been used to model aerodynamics in RTHS setups in some aforementioned works [54, 55, 58], but the LabVIEW interface available in these previous FAST versions is no longer compatible with more recent versions of FAST (version 8 and above).

This work discusses the development of a novel numerical modeling method to simulate aerodynamics using the most recent version of the FAST software, OpenFAST. This numerical model is intended for use in an ongoing research project at Oregon State University (OSU), where it is intended to solve for the aerodynamic loading of a floating wind turbine model in the wave basin of the O.H. Hinsdale Wave Laboratory actuated by a robotic arm in six degrees of freedom. The method presented here expands the functionality of the existing OpenFAST integration with Simulink to allow for external platform motions to interact with the structural module of the program. The method processes the external inputs in a manner that avoids the need to decouple active and inertial hydrodynamic loads and bypasses the hydrodynamic-structural coupling in OpenFAST. The method is validated by building a Simulink model replicating feedback from a physical system, and extension testing is performed to identify whether the method is accurate enough to solve for tower top structural loads or incorporate control dynamics.

Section 3.2 describes the development of the numerical model in OpenFAST, including its theoretical basis and integration with the physical system. Section 3.3 presents results of the numerical mode validation and exploration of its potential
extended functionality. Section 3.4 summarizes the results and discusses future work.

3.2 Methodology

OpenFAST is composed of many loosely coupled modules, each responsible for solving some aspect of the loading or response of a wind turbine. After the solve procedure for a given module is completed, the module sends relevant outputs to other modules to be used as inputs. Those modules then perform their solve procedure and send outputs to more modules, including the modules it initially received input from, in order to correct the inputs for the next time step. This modular approach allows OpenFAST to simulate the full dynamic response of a floating wind turbine.

By its nature, the structural dynamics module, ElastoDyn, couples to nearly every module, as shown in Figure 3.1. In particular, the structural dynamics solver is closely associated with the aerodynamics module (AeroDyn) and the hydrodynamics module (HydroDyn). The ElastoDyn-AeroDyn and ElastoDyn-HydroDyn couplings are thus logical locations to partition the system in a RTHS setup. In the current project, we are aiming to partition the system to numerically model the aerodynamics based on the physical motions of the physical floating structure in a wave basin. Therefore, I focus on the ElastoDyn-AeroDyn partitioning for this method.

The detailed methodology for the numerical model is divided into three sections:
Figure 3.1: Coupling of the OpenFAST modules with ElastoDyn and partitioning of the real-time hybrid simulation setup used in the OSU project. Black lines indicate borders between OpenFAST modules, solid orange lines indicate initial RTHS partitioning, dotted orange lines indicates the proposed future RTHS partitioning.

- Section 3.2.1 discusses the theory underpinning the structural dynamics solver in OpenFAST and justifies the modifications made to the program.

- Section 3.2.2 discusses the modifications made to OpenFAST to allow it to run as a numerical model in the RTHS setup.

- Section 3.2.3 discusses how the modified version of OpenFAST communicates
3.2.1 Theory

ElastoDyn uses load inputs delivered from other modules to calculate (1) the internal forces and moments occurring within the turbine structure, and (2) the equations of motion describing how the turbine is moving in space. The module uses Kane’s method to describe the complex multibody dynamics of the wind turbine and solve for these outputs. Fundamentally, Kane’s methods solves for equations of motion in the form

\[ F_r + F^*_r = 0 \]  \hspace{1cm} (3.1)

where \( F_r \) comprises the generalized active forces in the system (i.e. external loading on the system in the global reference frame), \( F^*_r \) comprises the generalized inertial forces in the system (i.e. the forces describing the motions of objects due to their acceleration and momentum in local reference frames), and \( r \) is a summation of all the degrees of freedom analyzed from the global frame of reference. For computational methods, this is usually solved using matrices, where Equation 3.1 takes the form

\[ [f(\dot{q}, q, t)] + [C(q, t)]\{\ddot{q}\} = 0 \]  \hspace{1cm} (3.2)

where \( q \) and \( t \) are the positions of bodies in the global frame of reference and time,
respectively. Equation 3.2 is more commonly written in the form

\[
[C(q,t)]\{\ddot{q}\} = [-f(\dot{q}, q, t)]
\] (3.3)

In ElastoDyn, the turbine structure is broken down into nodes. The local loads and motions are solved at each node using input forces and previous positions, which are then compiled to construct \( C(q, t) \) and \( f(\dot{q}, q, t) \). \( \ddot{q} \) is then solved using matrix inversion and the generalized equations of motion are determined.

The degrees of freedom considered in ElastoDyn include the tower, blade edges and flaps, nacelle yaw, the drive train and generator, and the six degrees of freedom of platform motion. The total forces and moments \( F_p \) and \( M_p \) acting on the platform, as computed by ElastoDyn, are

\[
F_p = F_t + F_{hydro} - m_p (a_p + gz)
\] (3.4)

\[
M_p = M_t + M_{hydro} + r_{\bar{p}t} \times F_t - m_p r_{pp} \times (a_{\bar{p}} + gz) - I_p \cdot \alpha_p - \omega_p \times I_p \cdot \omega_p
\] (3.5)

where subscript \( p \) refers to the platform at its reference point (by default, its geometric center at the still water level), \( \bar{p} \) refers to the platform at its center of mass, \( t \) refers to the tower nodes, and \( hydro \) refers to the hydrodynamic loading.

Issues arise when performing this calculation in the desired RTHS setup. Since this project plans on using force control (i.e. the numerical model has displacement inputs and force outputs), the platform motions are observed post-hoc without consideration of the influence of each individual force, so \( F_t, M_t, F_{hydro}, \) and \( M_{hydro} \) cannot be solved. While this loading could hypothetically be measured
using force sensors, parsing the active forces from the inertial forces would be very
difficult, making ElastoDyn’s use of Kane’s method intractable when attempting
to solve for motions throughout the rest of the wind turbine structure.

The method proposed in this work avoids this problem by assuming that plat-
form motions are a result of active loading only. In other words, this method
considers the contributions of inertial couplings from other structural subsystems
to the motion of the platform negligible. This eliminates the need to apply the
platform motions in its six degrees of freedom in the structure of Kane’s method.
Instead, the platform motions can be easily applied directly to the local equations
of motion of the hub and blades, which are only dependent on the kinematics
of the platform. AeroDyn then returns the aerodynamic loading to ElastoDyn,
which is populated at various points in $C(q, t)$ and $f(\dot{q}, q, t)$ as it normally would,
completing the coupling between the two modules. This new coupling is shown in
Figure 3.2.

Modifying ElastoDyn in this manner also provides the opportunity to extend
the purely aero-elastic RTHS coupling to potentially include some tower top struc-
tural motions. Particularly, it is feasible that the negligible inertial coupling con-
tributions on the platform holds even when considering blade, generator, and drive
train degrees of freedom. The capability of this method to operate in this manner
is explored in Section 3.3.4.
3.2.2 OpenFAST modifications

The base version of OpenFAST natively integrates with Simulink using an S-Function to provide user generated control systems for the ServoDyn module in OpenFAST, where the control commands such as generator torque, nacelle yaw rate, and blade pitch are the S-Function block inputs. For this project, the OpenFAST source code for the S-Function interface is modified to instead send inputs to ElastoDyn, where it substitutes platform displacements and velocities that were previously internally calculated. This new functionality allows for the real-time operation capabilities necessary in the desired RTHS setup. The structure of the Simulink interface with ElastoDyn largely mirrors the structure of the original interface with ServoDyn: the external inputs are set as general FAST inputs, then are sent to the module-specific inputs at the beginning of each time step. Note that the original integration with ServoDyn is still functional with this modification, but is no longer the default option; the extension tests discussed in Section 3.3.4 interfaces with ServoDyn using a shared library provided by NREL containing ROSCO, which runs a baseline wind turbine controller.

The ElastoDyn module itself was also modified so its solving procedure matches the methodology discussed in Section 3.2.1. Thus, the external platform motions are now applied directly to the local equations of motions of the hub and blades by replicating the ElastoDyn subroutines that calculate positions, velocities, and partial accelerations of the structure. These replicated subroutines are identical to the original subroutines, except continuous states defining the platform motions
Figure 3.2: Flow chart showing the modified ElastoDyn-AeroDyn coupling allowing for integration into the RTHS setup. Each box represents a different set of subroutines in the OpenFAST source code.

are replaced with the external inputs. The original subroutines calculating the structural motions run as normal using the Kane’s method approach—including the calculation of internal loads and generalized accelerations—but the six degrees of freedom of the platform are disabled. Only the outputs from the replicated subroutines are fed into AeroDyn, although the outputted aerodynamic loads from AeroDyn are fed back into both the original subroutines so other ElastoDyn states account for aerodynamic loads correctly. These loads are also implicitly captured in the platform motions actuated in the physical model, and therefore do not need to be sent to the replicated subroutines. Figure 3.2 visualizes this modified process.

Additionally, a parameter was added to the ElastoDyn input file, HybridMode,
that toggles whether ElastoDyn is used normally or in an RTHS setup with the subroutine replication with external inputs.

Disabling the internal platform degrees of freedom in ElastoDyn also eliminates the need to calculate hydrodynamics and mooring dynamics. The ElastoDyn-HydroDyn coupling is one of the most time-consuming aspects of a normal OpenFAST simulation as it requires the calculation of residuals of the inputs and outputs of both modules, which entails many calls to the rigorous ElastoDyn and HydroDyn solvers, which are both time-intensive. This reduction in solver calls more than makes up for the increase in calculation time created by the replicated ElastoDyn subroutines. This is highly beneficial for the RTHS setup, as the drastic decrease in simulation runtime is crucial for proper real time simulation, and these dynamics are physically modeled regardless.

3.2.3 Integration into Hybrid System

The initial partitioning location for the RTHS setup of this project is at the rotor; the entirety of the wind turbine structure mass is modeled physically in the wave basin, and the aerodynamic influence on the tower top is modeled numerically. The rotor, drive train, and blades are all considered rigid. This partitioning is identical to the aero-elastic coupling detailed by Hall et al [63]. If this coupling proves successful, the numerical model may be expanded to include some tower top structural dynamics, such as the drive train, generator, and/or blades. As the physical model will only contain the masses of these components and will not be geometri-
cally modeled, the structural dynamics are easily incorporated into the numerical model by enabling the component degrees of freedom in ElastoDyn. Figure 3.1 illustrates the partitioning of the RTHS setup within the modular framework of OpenFAST. As the tower structure will be geometrically modeled, the tower will always be assumed rigid. Section 3.3 explores simulating these degrees of freedom with the current ElastoDyn modifications.

Figure 3.3 summarizes the expected RTHS setup at time of writing. Qualisys Track Manager (QTM) will be used to motion capture the platform in six degrees of freedom using an array of cameras and tracker points on the physical model situated in the wave basin. These tracker points can be combined to form a rigid body of the platform with a manually set reference point. OpenFAST also considers the platform rigid with a manually set reference point, so these points can be aligned by the user. The origin of the global reference frame in QTM will be aligned with the starting location of the platform reference point as well as possible, though minor adjustments can also be specified in the ElastoDyn input file immediately prior to the start of a hybrid simulation.

As the 1/50th-scale physical experiment commences in the wave basin, QTM will export the real-time motions of the physical model to MATLAB using a plugin provided by Qualisys. These motions are then imported into the Simulink model containing the modified OpenFAST S-Function, which processes the motions as per Section 3.2.2 at full scale. In the Simulink model, the AeroDyn force outputs at the hub are extracted from the list of OpenFAST outputs at every time step, scaled down to 1/50th-scale again, and sent to a Linux system via a SCRAM-
Figure 3.3: Flow chart showing the communication between the different systems and software used in the real-time hybrid simulation setup for the OSU project.

Net+ interface. The Linux system houses the controller for a Franka-Emika Panda robotic arm, which actuates the calculated aerodynamic forces onto the physical model in real time using a 1 kHz communication bus, completing the loop.

The scaling between AeroDyn and ElastoDyn is not yet implemented at time of writing, but is straightforward to apply in the replicated subroutines in ElastoDyn and the subroutines in the OpenFAST glue code without changes to the current methodology.

As the physical model will be scaled down by 50 using Froude scaling, the periods of the ocean waves must be scaled up accordingly by $\sqrt{50}$ (about 7.07). The entire loop must therefore operate at least 7.07 faster than real time for the
RTHS setup to be successful.

3.3 Numerical Model Validation and Extension Testing

The numerical model containing the modified version of OpenFAST was validated by mimicking the RTHS setup in Simulink and comparing the numerical model outputs to results from an equivalent simulation performed using the unmodified version of OpenFAST. The smaller the error between the results, the more successful the method described in Section 3.2 is in calculating the accurate prescribed aerodynamic loads for positioning of the physical model in the wave basin at any given time.

3.3.1 Validation Test Details

The selected validation tests simulate expected resource conditions from Site 5 of NREL’s Oregon Offshore Wind Feasibility Study [67], one of the two sites of interest for the OSU project. Five resource conditions tests were previously developed for Site 5, two of which—test cases C1 and C5—are analyzed here (abbreviated TCC1 and TCC5). These tests were also performed with equivalent conditions except with turbulent winds, designated as TCC1t and TCC5t, respectively. Additionally, to observe the response of the model to more extreme wind and wave climates, the model was tested with load cases 4.3 and 4.4 as specified in the OC5 project report [46]. All turbulent wind conditions were generated using TurbSim
Table 3.1: Resource condition details of the six test cases used for validation and extension testing.

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Wind Conditions</th>
<th>Wave Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>LC43</td>
<td>Turbulent: Kaimal model, $U_{ref} = 13.05$ m/s</td>
<td>JONSWAP spectrum: $H_s = 7.1$ m, $T_p = 12.1$ s, $\gamma = 2.2$</td>
</tr>
<tr>
<td>LC44</td>
<td>Steady: $u_{x, hub} = 12.91$ m/s, $\alpha = 0.0864$</td>
<td>JONSWAP spectrum: $H_s = 10.5$ m, $T_p = 14.3$ s, $\gamma = 3.0$</td>
</tr>
<tr>
<td>TCC1</td>
<td>Steady: $u_{x, hub} = 12.4$ m/s, $\alpha = 0.0864$</td>
<td>JONSWAP spectrum: $H_s = 3.07$ m, $T_p = 9.1$ s, $\gamma = 1.0$</td>
</tr>
<tr>
<td>TCC1t</td>
<td>Turbulent: Kaimal model, $U_{ref} = 12.4$ m/s</td>
<td>JONSWAP spectrum: $H_s = 3.07$ m, $T_p = 9.1$ s, $\gamma = 1.0$</td>
</tr>
<tr>
<td>TCC5</td>
<td>Steady: $u_{x, hub} = 6.63$ m/s, $\alpha = 0.0864$</td>
<td>JONSWAP spectrum: $H_s = 2.35$ m, $T_p = 9.86$ s, $\gamma = 1.0$</td>
</tr>
<tr>
<td>TCC5t</td>
<td>Turbulent: Kaimal model, $U_{ref} = 6.63$ m/s</td>
<td>JONSWAP spectrum: $H_s = 2.35$ m, $T_p = 9.86$ s, $\gamma = 1.0$</td>
</tr>
</tbody>
</table>

[68] using the IEC-61400-1-ed3 standard [69]. The power law exponent for the steady wind cases, $\alpha$, was calculated from a previous Site 5 resource assessment conducted by the OSU project team. Full details of the load cases are provided in Table 3.1. All test cases have a set generator speed of 12.1 rotations per minute and no blade pitching.

The floating wind turbine used in the OC5 project has been selected for use in this project, and is therefore the model used in these validation tests. The tests assume a 200 meter water depth, as done in the OC5 project. This is the one
discrepancy regarding the Oregon Site 5 site conditions: Oregon Site 5 has water depths around 500 meters. However, the physical model for the project has not been constructed at time of writing, so there is no way to calibrate a comparable numerical mooring system for this deeper water depth to validate against. It is expected this validation will be replicated with a properly calibrated mooring system and water depth in the OpenFAST input files upon the completion of free decay testing with the physical model.

As discussed in Section 3.2.3, the primary focus of this validation is to confirm that the numerical model returns accurate aerodynamic loads quickly enough for an RTHS setup to be feasible, with all structural components of the wind turbine tower being considered rigid. This testing is referred to as “aero-elastic coupling” in this work. In consideration of future work for the OSU project, additional testing was carried out to evaluate the extended capabilities of the current numerical model to model some structural dynamics, and identify areas of improvement. This is detailed in Section 3.3.4.

3.3.2 Test Procedure

All validation and extension testing was conducted as follows, unless otherwise noted:

1. The test is simulated in a normal version of OpenFAST (i.e. HydroDyn, MoorDyn, and platform degrees of freedom enabled), and motion and load outputs are saved
2. For each test case\textsuperscript{1}, the platform motions and velocities in six degrees of freedom are extracted from the simulation outputs and saved in MATLAB data (.mat) files with their respective time stamps.

3. An identical test to step 1 is conducted in Simulink within the numerical model framework (i.e. HydroDyn, MoorDyn, and platform degrees of freedom disabled) using the MATLAB data files as the block inputs to the modified OpenFAST S-Function, and load outputs are saved.

4. The aerodynamic load outputs at the hub are compared between the normal OpenFAST simulations and the numerical model Simulink simulations.

All simulations are 5 minutes in length with a time step of 0.01 seconds, unless otherwise noted. The simulations are conducted at full scale. Comparisons were done by qualitatively comparing time series data and quantitatively calculating normalized root mean squared error.

3.3.3 Validation Test Results

The results of the aero-elastic coupling show almost perfect agreement between the normal OpenFAST simulation and the numerical model simulation, as shown in Figure 3.4. Errors are very small for all test cases, and are likely caused by floating point rounding errors from the MATLAB data files.

\textsuperscript{1}For extension testing, the motions and velocities extracted in this step are from OpenFAST simulations without any structural degrees of freedom enabled, even if they are enabled in the extension test. This is because these motions are meant to emulate the motion of the physical model caused by the loading in the wave basin, where tower top motions are not being captured.
Time testing was conducted by repeating the numerical model simulation of TCC5 with various time steps to determine the bounds feasible for simulating in real time with sufficient fidelity. This testing was performed on the Windows machine at the wave basin expected to be used for the RTHS setup, possessing an Intel Core i9-9900K CPU overclocked to 5 GHz, a Samsung 970 EVO Plus solid state drive, and 64 GB of memory. The time testing results are presented in Table 3.2. In general, it was found that the numerical model runs efficiently enough (7.07× real time or better) for time steps of 0.009 seconds to 0.015 seconds to be used in the simulation while maintaining good fidelity and stability.

The accuracy and speed of these tests validates the numerical model devised using the method in Section 3.2. While coupled validation must be performed upon completion of the physical model to account for other sources of error, the
Table 3.2: Numerical model time testing results. For real-time simulation with the 1:50 Froude-scaled physical model, the numerical model must run at least 7.07 times faster than real-time.

<table>
<thead>
<tr>
<th>Sim Time Step</th>
<th>Time to Sim (seconds)</th>
<th>× Real Time</th>
<th>Simulation Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.005</td>
<td>73.755</td>
<td>4.068x</td>
<td></td>
</tr>
<tr>
<td>0.006</td>
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<tr>
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<td>14.782x</td>
<td>Simulation outputs lose most transient details</td>
</tr>
<tr>
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<td>16.218</td>
<td>18.507x</td>
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</tr>
<tr>
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<td>24.601x</td>
<td>Simulation warning: Skew wake correction error</td>
</tr>
<tr>
<td>0.04</td>
<td>11.003</td>
<td>27.261x</td>
<td>Unstable simulation outputs</td>
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</table>

The current numerical model is expected to be capable of operation in the future RTHS setup with the current methodology.

3.3.4 Extension Test Results

The OSU RTHS project team has discussed several areas on interest to explore if the initial RTHS setup with aero-elastic coupling succeeds. This section assesses
the suitability of the current numerical modeling method in accomplishing these stretch goals, including (1) numerically modeling tower top structural components, and (2) enabling a control system to vary the blade pitch and generator torque in the numerical model.

3.3.4.1 Incorporating Structural Degrees of Freedom

Tower top structural degrees of freedom are easily enabled in ElastoDyn, including the drivetrain/generator (shortened to just “drivetrain” here, as the implementation of their degrees of freedom are very similar) and the blade flap and edge bending modes. This is done here to analyze how the numerical model handles tower top structural components using the same testing procedure as Section 3.3.3. Overall results are shown in Figure 3.5. Results are mixed, though it is clear that the assumption discussed in Section 3.2.1 (inertial loading impacts on the platform are negligible) does not hold for many of the test cases. The aerodynamic loading matches very well for TCC5 with the drivetrain degree of freedom enabled, matches decently for LC43 and TCC1t, and matches poorly for all other test cases. Interestingly, the tests with turbulent wind perform well when considering only the blade degrees of freedom, though the errors for most of the tests with steady wind are even higher than for the drivetrain degrees of freedom. None of the tests performed well for the combined drivetrain and blades tests, although TCC5 is not as drastic as the others. Across all tests, the measurements in the $x$ direction match fairly well; the most glaring issues are consistent overestimates in loading in the $y$
and z directions. This is illustrated in the time history examples in Figure 3.6.

LC44 and TCC1—the worst performing tests—both have strong steady winds that generate large oscillatory pitch motions not present in the other tests. This pitch oscillation is largely a structural inertial response, and since the wind loading is relatively small in the $y$ and $z$ directions, the relative influence of inertial couplings on platform motions is no longer insignificant. The relative effects of active loading versus inertial loading also explain why TCC5t performs worse than LC43 despite similar wind loading, as LC43 has a much more active wave climate than TCC5t. Naturally, the inertial loading in general increases as more degrees of freedom are considered, hence why the combined drivetrain and blade tests perform the worst.

The large errors presents an area of improvement of the current numerical modeling method if the project team wishes to eventually model aspects of the tower top numerically. However, at least two potential solutions exist that only require fairly minor changes to the current OpenFAST modifications and methodology. These are discussed in Section 3.4.

3.3.4.2 Incorporating Wind Turbine Controls

The potential introduction of tower top structural degrees of freedom also presents the opportunity to incorporate a wind turbine control system to the numerical model. The OpenFAST modifications, to my previous knowledge, did not interfere with ElastoDyn or AeroDyn couplings to the control system module, ServoDyn.
Figure 3.5: Normalized root mean square error of the extension testing with tower top degrees of freedom enabled.
Figure 3.6: Sample time history results from extension testing, showing a mix of very good agreement (top), decent agreement (center), and poor agreement with excessive overestimation (bottom).
Figure 3.7: Sample validation results of incorporating ServoDyn into the numerical model, showing reduced and smoother wind loading with pitch control introduced.

However, this had not been verified, so this section presents work to demonstrate that the module functions as expected in the numerical model.

To verify the stability of the module in the numerical model, resource conditions for LC43 were used, but with the structure rotated 20 degrees out of line with the wind to ensure high angle of attack on the blades. Two tests were performed, one with the pitch control and generator torque control enabled in ServoDyn, and one with ServoDyn disabled. A sample from the results of these tests is shown in Figure 3.7. The addition of the pitch control reduces the angle of attack on the blades, noticeably reducing and stabilizing the $x$ direction aerodynamic force acting on the structure, verifying that ServoDyn can be incorporated into the current numerical model without issue.
3.4 Conclusion

This work presents a method for modifying OpenFAST for integration as a numerical model in an RTHS setup in order to correct similitude issues between Reynolds and Froude scaling for floating offshore wind scale model testing. The model sends tower top aerodynamic loads to a robotic arm actuating a physical turbine model in a wave basin, with the physical platform motions inputted back into the numerical model. The OpenFAST source code was modified to allow the existing Simulink interface to accept these external inputs in real time during an OpenFAST simulation. The structural dynamics solver in OpenFAST has also been modified to send platform motions measured in the wave basin directly to the aerodynamics solver while removing consideration of the platform degrees of freedom in the Kane’s method structural dynamics solver. This eliminates the issue of decoupling platform inertial and active forces needed for Kane’s method, as well as removing the need for the hydrodynamics module. The method was validated using the wind turbine model and resource conditions expected to be tested with the fully constructed RTHS system by comparing Simulink outputs to parallel simulations ran in normal OpenFAST and checking for error. The validation testing found excellent agreement of aerodynamic loading when considering platform degrees of freedom with a fully rigid physical structure, and operates stably at time steps warranting its coupling to a 1:50 Froude-scaled physical model.

Extension testing was performed to gauge the validity of using the method with some tower top degrees of freedom enabled. Results were mixed, with test cases
with oscillating pitch motions performing particularly poorly due to the violation of a methodological assumption where inertial loading on the platform from the rest of the structure is considered small. This is an area of improvement in future work. The recommended method to reduce this error is to rework the Kane’s method procedure in ElastoDyn using kinematics for the platform degrees of freedom instead of the partial loads. This would allow for the unmeasurable forces discussed in Section 3.2.1 to be implicitly captured in the kinematics of the platform without disrupting the calculations of other degrees of freedom. This method will be pursued in immediate future work. Other possible methods to reduce error include adding a platform added mass term into ElastoDyn that approximates the expected inertial loading on the platform for a given test, mitigating the effects of unaccounted inertial effects in the Kane’s method solver. Alternatively, the tower top motions from the physical model could be sent to ElastoDyn in a similar manner to the platform motions, granting more accurate position vectors when calculating loading for tower top degrees of freedom.

Another future addition to the numerical model is the incorporation of a tuned mass damper via ServoDyn, as that functionality currently has dependencies on ElastoDyn not accounted for using the current methodology. Later work regarding the overall RTHS model includes the re-validation of the numerical model at the properly modeled water depth following the calibration of the physical model, testing the model with other sources of latency and error in the full RTHS setup, determining the error in the RTHS setup due to lack of direct influence of the wind on the waves, and re-writing the OpenFAST source code modifications to adhere
to modular framework developer guidelines as specified by NREL, as my version of the modified source code occasionally violates the framework. Regression testing for the new OpenFAST features must also be introduced.
Chapter 4: General Conclusion

This body of work presents the following novel contributions to the state of the art in the floating offshore wind research community:

- Chapter 2 contributes a novel optimization algorithm used to minimize costs associated with failure, presenting a method to relate the tradeoffs between cost and reliability for floating offshore wind systems. The method is applied to a case study of a large floating wind farm using shared anchors, incorporating another relevant topic of ongoing research in the offshore wind community. A preliminary cost model associated with the costs of failure is also consolidated from values in existing literature, and the sensitivity of the cost model to different costs is explored to help account for uncertainty.

- Chapter 3 contributes the methodology and validation of a numerical modeling approach contributing to a novel real time hybrid simulation setup. New functionality is added to the popular wind turbine simulation software, OpenFAST, allowing for a real time interface with a scale model physical test in a wave basin where wind turbine forces and motions are exchanged. I also detail the interface between the numerical model with the rest of the novel hybrid setup. Further testing analyzes the capabilities of the method to account for structural dynamics, and I identify future work that would
enable this functionality in the real time hybrid simulation setup if project goals were to expand.

Overall, the contributions presented here address and improve upon shortcomings with existing computational modeling approaches in the floating offshore wind research community. In turn, these improved modeling approaches will enable researchers and developers to be more effective in reducing costs and uncertainty in future floating offshore wind developments, facilitating the emergence of the technology as a competitive addition to the renewable energy sector.
Bibliography


[21] Choi, Y. J., 2007, “Reliability Assessment of Foundations for Offshore Mooring Systems under Extreme Environments,” PhD dissertation, The University of Texas at Austin, Austin, TX, accessed 2020-09-17, https://repositories.lib.utexas.edu/bitstream/handle/2152/3169/choiy89567.pdf?sequence=2&sa=U&ei=8qZSU5amGYq8QHM4oHgBw&ved=0CDcQFjAF&usg=AFQjCNFzyq5FP0gVXq0S5h3z-RYqzru4mA


