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Published in:
Floating Wind; Systems Design and Multi-Fidelity/Multi-Disciplinary Modelling; Future Wind; Smaller Wind Turbines

Link to article, DOI:
10.1088/1742-6596/2265/4/042048

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

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To cite this article: Michael K. McWilliam *et al* 2022 *J. Phys.: Conf. Ser.* **2265** 042048

A surrogate model of offshore wind farm support structures for wind farm design and financial valuation

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Abstract. In the preliminary phases of offshore wind farm development, very little information on project design are available for supporting financial valuation and site design. In this work, we develop a surrogate model for offshore wind support structure mass for input to techno-economic analysis that is based on a small set of input parameters. Using reference turbines and a broad set of met-ocean conditions, a large design spaced is developed from which a sampling of conditions is used to estimate the dimensions and mass of monopile support structures. The results are parameterized using statistical methods to create a functional model of costs relative to high-level site and technical inputs. To preserve the transparency of the model input-output relationships, a statistical surrogate model is used based on quadratic functions of the inputs. Overall, the rated power and rotor diameter of the turbine has the greatest influence on the mass, followed by the specific power. The water depth was the next most important environmental parameter, followed by wave period. The full surrogate model captures 98.5% of the variance of the monopile mass as a function of the above inputs. We present results related to monopile foundations, but the methodology is flexible and can be applied also in the case of other types of support structures.

1. Introduction

Offshore wind development continues to grow at an exponential rate. At the same time, the levelized cost of energy (LCOE) for offshore wind farms continues to fall. This is driven by a number of factors - for example, economies of scale associated with upscaling wind turbines to larger rated powers [1]. The increasingly competitive economics of offshore wind coupled with decarbonization initiatives are driving further offshore wind development in a large number of regions around the world. As offshore wind goes global, new project sites will face additional challenges in terms of next generation very large turbine, harsher wind and wave conditions, deeper sea depths and more complex soil conditions, various extreme weather events, and more [2]. Fig. 1 shows a set of wind and wave conditions for current global offshore wind projects under development.

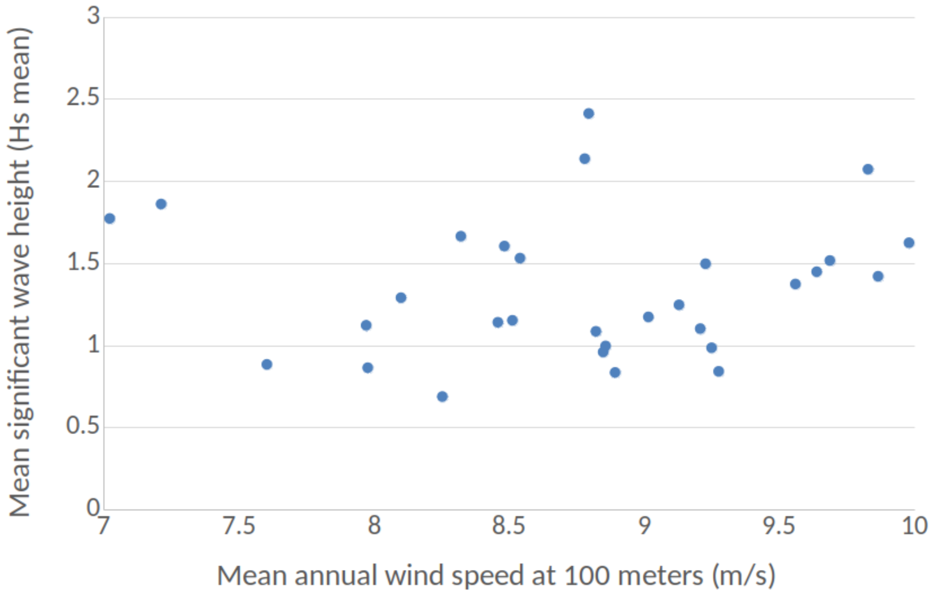


Figure 1: Global wind and wave conditions for offshore wind project locations.

In order to support project development for financial valuation and site design, it is important to be able to assess the influence of changing technological and environmental conditions on project performance and cost metrics. Unfortunately, in the bidding and even in the early design stage of a project, very little information on project design are available for estimating performance and cost metrics.

For early-stage financial valuation, techno-economic analysis tools using high-level inputs are used to assess project profitability and support investment decisions. Such analysis tools are often empirical - relying on data from past projects and extrapolating when necessary as technological (e.g. turbine size) and site conditions (e.g. water depth) change [3]. More recently, models that use both empirical data as well as underlying design studies have been developed to support analysis with next generation technologies and across a broader range of site conditions [4]. One focal point for such work is on the support structures as their sizing and costs are sensitive to turbine upscaling and site conditions - and these costs are a significant portion of overall project capital expenditures [5]. For example, [4] looked at the effect of varying turbine sizes from 3 to 10 MW, hub heights from 100 to 200 m, and sea depths from 20 to 60 m for monopile and jacket sizing. Typically, these models have used a very small set of input characteristics due to the large effort associated with the design studies. Furthermore, past work used simplified curve fits of the outputs of interest (mass and cost) to 2-3 design inputs. The low dimensionality is attractive to support quick and intuitive analysis, but it neglects the complexity associated with the broad range of conditions as the current offshore wind industry faces.

From a wind farm design perspective, optimization of the layout for LCOE requires addressing major performance (e.g. annual energy production - AEP) and cost (e.g. support structures and collection system) elements [6]. In [7] it was showed that the integrated optimization of a wind farm layout with sub-optimization of the support structures and collection system improved the LCOE over sequential optimization. However, sub-optimization of the support structure and collection system lead to non-trivial computational cost. Simplified models for each system would allow for faster optimizations - especially as the size of wind farms and the number of projects under development grow.

The need for both accuracy and speed to support both early-stage financial valuation and site design is an ideal application for surrogate models. This paper presents the development of a techno-economic tool for estimating the mass of monopile support structures for offshore wind turbines in order to support financial valuation and holistic wind farm design. The model is based on a wide range of turbines and environmental conditions (i.e. wind and wave conditions). The data for the surrogate was generated by optimizing a range of designs over all the different conditions. The development of the monopile size database required the use of high performance computing capabilities while the resulting surrogate models can be implemented as simple functions in a programmed model or in a spreadsheet calculation tool.

This paper starts by explaining the methodology in section 2. Then in section 3 the paper shows selected results from both the support structure optimization and the surrogate model construction. The paper concludes with a short discussion in section 4 and conclusions in section 5.

2. Methodology

2.1. Generation of the data set

The data for the techno-economic model is originally based on three reference wind turbines: the 3.4 MW [8] onshore reference wind turbine, and the 10 MW [8] and 15 MW [9] reference offshore wind turbines. To obtain coverage over a wide range of rated powers and specific powers, a series of rotor scaling optimizations using the NREL WISDEM software [10], based on minimizing the LCOE, were executed to scale each of the turbines to specified rated powers and specific powers. The details of this optimization are given in a forthcoming journal paper [11]. Not all the rotor optimizations succeeded at higher rated powers for all of the reference turbines. To improve the coverage of the design space for the monopile optimization analyses, it was necessary to run 2 sets of redundant rotor scaling optimizations, the different sets differed by executing the optimization at different starting points within the design space.

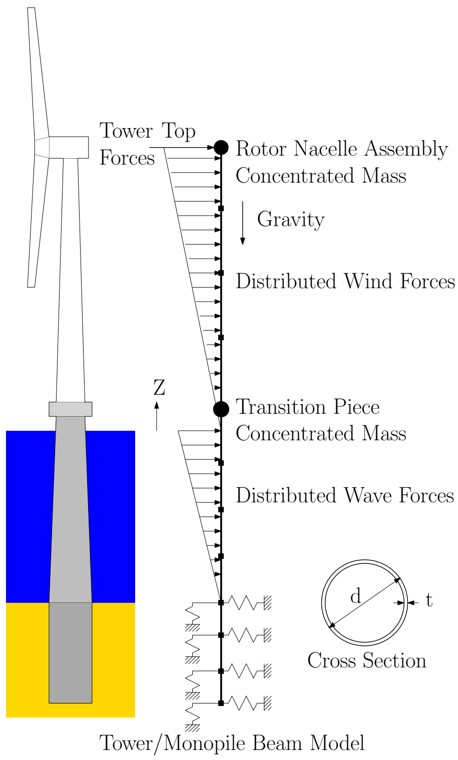


Figure 2: Schematic of the model

For each of the successful rotor optimization results, multiple support structure designs were optimized for varied site conditions. Each of these optimizations are based on the problem formulation (1). The objective is to minimize the total support structure mass (M_{tot}), by varying the tower diameter (d_t), tower wall thickness (d_w), monopile diameter (d_m) and monopile wall thickness (t_m). The support structure design is constrained by the yield strength (σ_y), panel buckling (n_s) and global buckling (n_g). Furthermore, to reflect manufacturing limitations, there is a constraint of the diameter to thickness ratio ($\frac{d}{t}$) and the taper (κ).

$$
\begin{aligned}
\underset{\boldsymbol{d}_t, \boldsymbol{t}_t, \boldsymbol{d}_m, \boldsymbol{t}_m}{\text{minimize}} \quad & M_{tot} \\
\text{subject to:} \quad & 3.87\,m < d_t, d_m < 10\,m \\
& 0.004\,m < t_t, t_m < 0.4\,m \\
& \sigma < \sigma_y \\
& n_{s,g} < 1.0 \\
& 120 < \frac{d_t}{t_t}, \frac{d_m}{t_m} \\
& 0.2 < \kappa
\end{aligned}
\tag{1}
$$

To reduce the computational complexity, there are two load cases (DLCs) considered in this design problem: DLC 1.6, Maximum rotor thrust (*i.e.*, rated wind conditions) and maximum wave loading (50-yr); DLC 6.1, Wind turbine idling during an extreme 50-yr wind and wave event. While this is an unrealistic simplification, it was deemed adequate to support the sizing of the structure for supporting the intended use case of early-phase financial evaluation and site design.

As with the wind turbine design, the optimization analyses of the monoopiles were solved using WISDEM [10]. The support structure analysis is based on steady state analysis of the turbine and then using the forces at the extremes on the top of the support structure. Additionally aerodynamic drag forces are applied to the tower. The Morison equation is used to apply hydrodynamic forces to the mono-pile. The Airy wave theory is used to model the ocean waves. Finally the soil is modelled as a set of springs according to the model of Arya [12]. The structural analysis is based on an FEM frame model [13]. The results of which were used to calculate the von-mises stress (σ), and both shell and global buckling according to [14] and [15] respectively. Further details of the support structure optimization can be obtained from McWilliam *et. al.* [16]. The support structure analysis and optimization methods used in this work has already been bench-marked against industrial designs by Damiani *et. al.* [17]. The comparison showed good agreement over a wide range of sea depths.

For a given turbine, the different support structure optimizations differed according to a range of environmental conditions. In order to define appropriate ranges for the water depth, significant wave height and period, and average wind speed, we analyzed all offshore wind farms across Europe. In particular, we first obtained the details of the wind farm layouts from the database of Sea Impact [18]. Then, we collected the relevant wind, wave, and bathymetry data for the wind farms from the ERA5 database [19]. To avoid the curse of dimensionality, the pile-depth was set equal to the water depth. In addition to exploring different environmental conditions, the DOE also looked at the effect of the hub-height. Due to the very large range of rotor diameters, hub height variation was modeled as a ratio (r_h) to rotor diameter ($i.e.$ $H_{hub} = r_h D$).

The domain sampled for the DOE is listed below:

- Rated Power: 3-20 MW in increments of 1MW
- Specific Power: 250, 300 and 350W/m^2
- Initial turbine for rotor scaling: 3.4MW, 10MW, 15MW
- Redundant rotor scaling set: set 1 and 2
- Hub-height ratio: 0.55-0.88

- Transition piece height: 10-16m
- Water-depth/pile depth: 10-31m
- Significant wave height: 1.5-5.5m
- Significant wave period: 1-11s
- Average wind speed: 5-13m/s

The sampling within the first four variables was according to all the rotor scaling optimizations that converged successfully ($N_r = 186$). Then the remaining dimensions were sampled according to Smolyak sparse grids using Dakota [20] with grid level 3 ($N_s = 545$). Together, these DOE's combine to give 101,370 unique support structure optimizations, where a total of 101,096 successfully converged and were subsequently used to train the surrogate model. The optimization analyses were run in parallel, on the Sophia HPC cluster of the Technical University of Denmark.

2.2. Description of the surrogate construction methods

A variety of surrogate modelling techniques, including machine learning based methods, were initially considered. A key requirement of the resulting surrogate model was transparency of the input-output relationships and a statistical approach was selected as a result. Several different functional forms were investigated for the development of the statistical surrogate model of the support structure mass, e.g. polynomial, logarithmic, exponential, and arctan forms. From this study, the Quadratic Least Squares was chosen as adding additional, more complex and/or higher order terms increased the cost of training and evaluation with only minimal improvement in the model fit. The data set was divided into 6 batches for the different sets of optimization (2) and for each set of optimization starting from the different reference turbines (3). Terms were added and removed in order to finalize a set of input variable combinations and final surrogate model fit with a suitable coefficient of determination.

3. Results

In this section we first present trends between some of the input variables and the structural mass. Subsequently, we present the results concerning the surrogate model developed based on the above mentioned dataset.

3.1. Key trends from the optimization results

We now present the results obtained from the optimization analyses used for generating the dataset. Fig. 3, Fig. 4, and Fig. 5 show the variation of the wind turbine total mass for varying wind turbine rated power. In the figures, the line plot follows the mean values of the dataset, whereas the shaded bands represent standard deviation of the dataset around the mean vale.

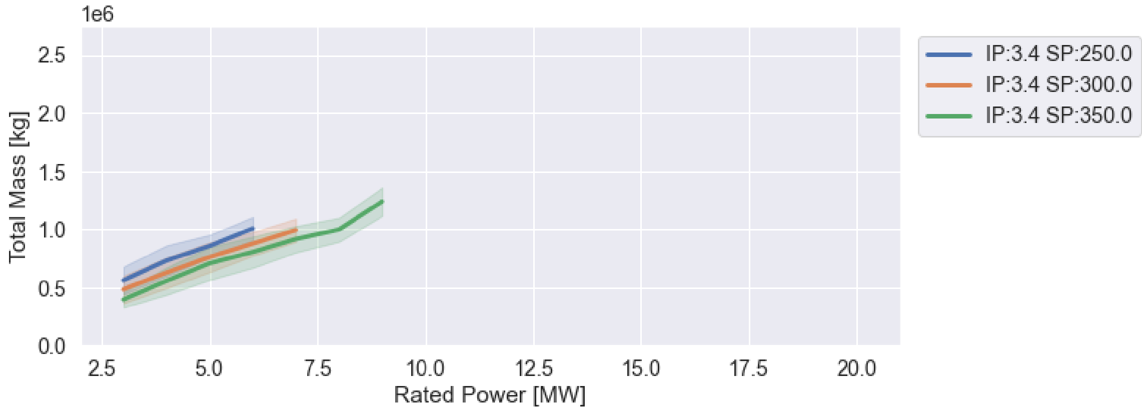


Figure 3: Total mass for varying wind turbine rated power. The wind turbines used for the shown dataset are obtained from scaling of the IEA 3.4 MW reference wind turbine

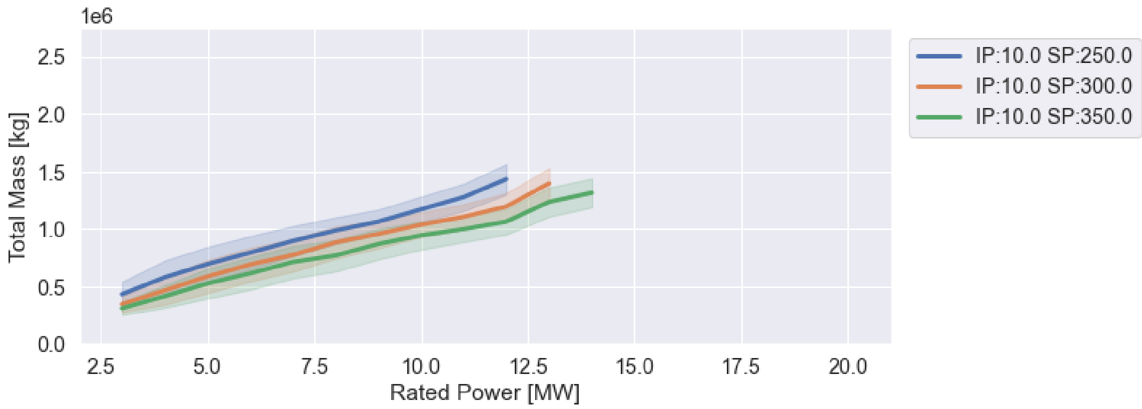


Figure 4: Total mass for varying wind turbine rated power. The wind turbines used for the shown dataset are obtained from scaling of the IEA 10 MW reference wind turbine

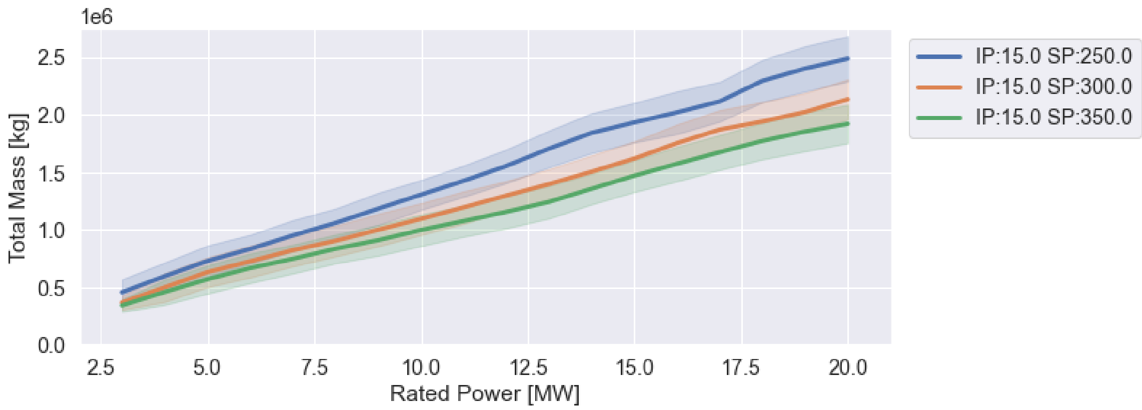


Figure 5: Total mass for varying wind turbine rated power. The wind turbines used for the shown dataset are obtained from scaling of the IEA 15 MW reference wind turbine

In particular, Fig. 3 shows the results obtained from wind turbines scaled starting from the IEA 3.4 MW reference wind turbine, i.e. $IP = 3.4$, for the three values considered of specific power SP. Similarly, Fig. 4 and Fig. 5 show the results obtained starting from the IEA 10 MW and IEA 15 MW reference wind turbines. It is possible to observe that only for $IP = 15$ MW the dataset is fully populated. For $IP = 3.4$ MW and $IP = 10$ MW there are mass values associated only to a subset of wind turbine rate powers. This is due to the sampling scheme adopted, which selects a subset of sampling points non homogeneously distributed over the dataset domain.

The data clearly shows that the rated power had the greatest influence on the total mass. An exception was the influence of water-depth/pile-depth shown in figure 6. As expected, this shows a significant increasing mass with increasing depth.

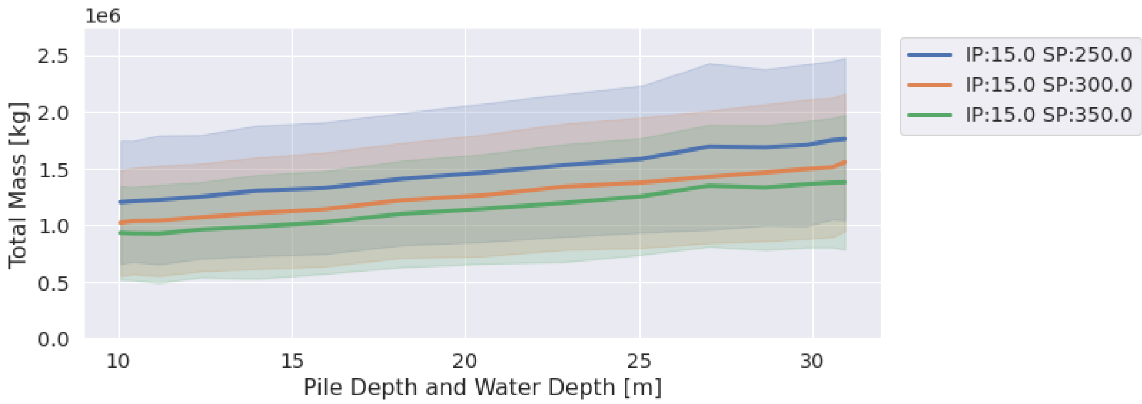


Figure 6: Total mass for varying Pile-depth and Water-depth together. The wind turbines used for the shown dataset are obtained from scaling of the IEA 15 MW reference wind turbine

3.2. Surrogate construction results

The fit of surrogate models to each of the 6 batches of monopile optimization data sets behave similarly and in this section we will highlight the one with set-ID 1 and initial power of 15MW. In figure 7 the QLS-approximated mass can be seen as a function of the mass from the simulation and the fit has a correlation coefficient of $R^2 = 0.986$. The simulation mass is the mass obtained from the Wisdem optimization described in section 2.1.

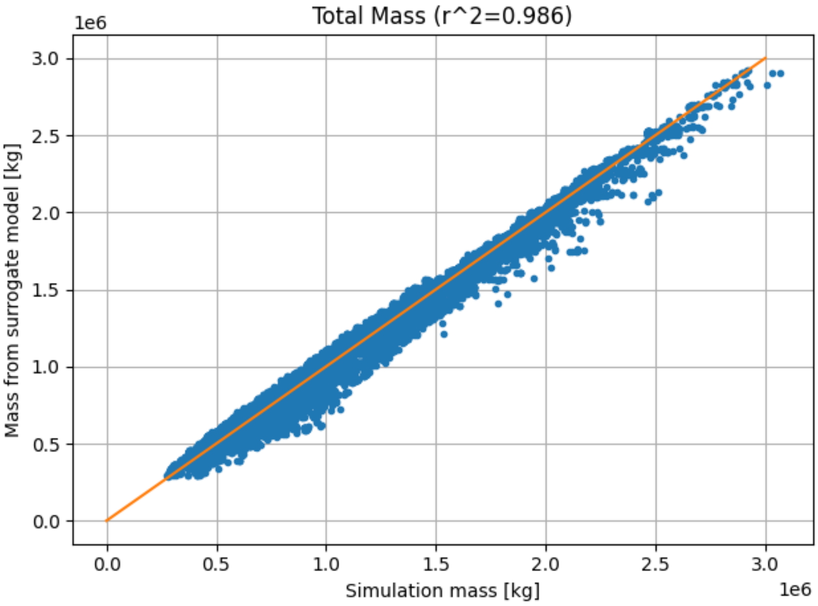


Figure 7: Total mass approximated with QLS as a function of total mass from the simulation data

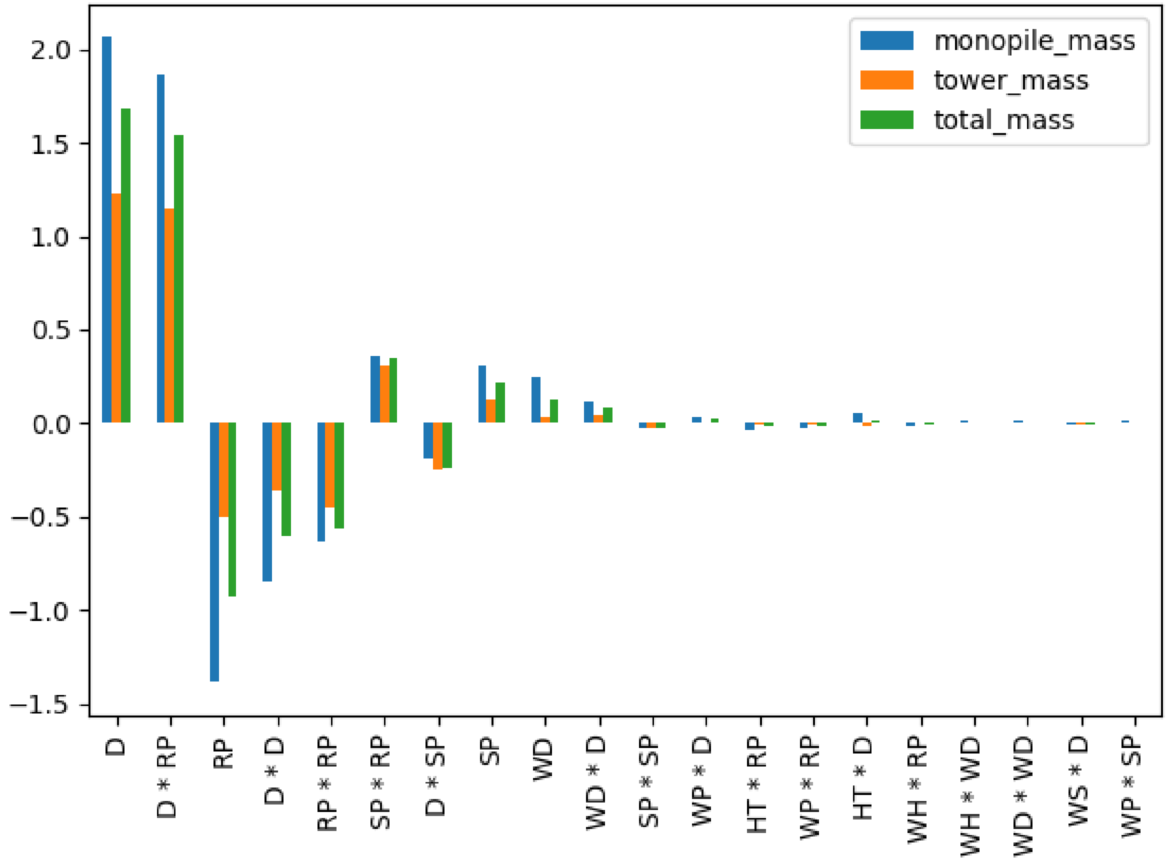


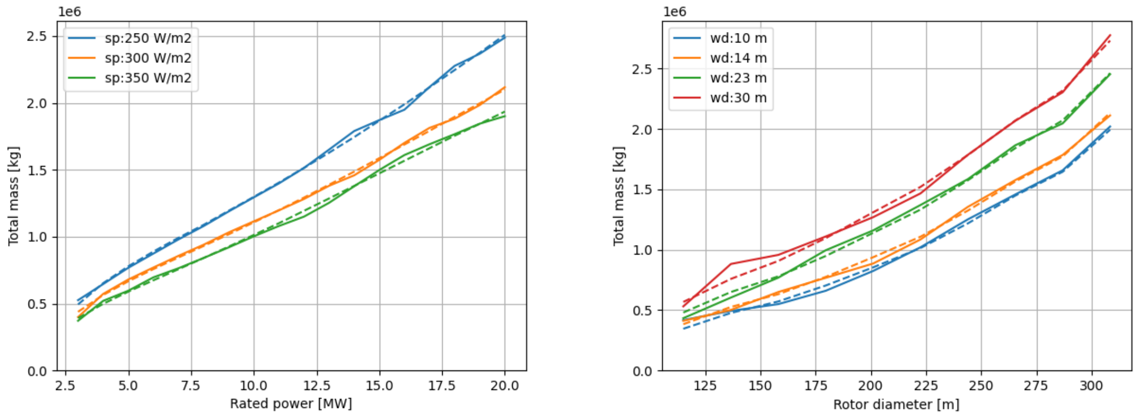
Figure 8: Dependency of the total mass on the 20 most influential terms from Quadratic Least Squares approximation. D is rotor diameter, RP is rated power, SP is specific power, WD is water depth, WP is wave period, HT is height of transition piece, WH is wave height and WS is wind speed.

The input dataset has been scaled with a min-max scaler to -1 - 1 and the output to -0.7 - 0.7. From figure 8 it is evident that the rotor diameter and the rated power are the most influential factors on the total weight of the support structure. Water depth, hub height, transition piece height and met-ocean parameters are of smaller importance.

Once trained the surrogate model can be used to predict the mass of the support structure. In Fig. 9 mean values for the simulated and predicted total mass plotted as a function of rated power and rotor diameter. The curves show very good agreement between the surrogate model and the simulation data and the main tendencies are reflected.

4. Discussion

Given the application of supporting early-stage project valuation and design where very little information on a project is known, this model represents a step forward by bring physic bases optimization to the analysis. Furthermore, the breadth of coverage of 101,096 designs distributed over 9 dimensions, gives a much more comprehensive model compared to prior work - addressing a wide range of site and technical conditions as are pertinent to the evolving global offshore wind sector. Such wide coverage would not be practical with higher fidelity optimization and analysis. This enables decisions makers to assess a wide range of different projects with this model.



(a) Mean total mass as a function of number of rated- and specific power

(b) Mean total mass as a function of rotor diameter and water depth

Figure 9: Mean total mass as function of selection of driving input parameters. Dashed lines are surrogate values and continuous lines are simulation results.

However, there are some important limitations that must be considered when using this model. First, the underlying optimization that was used to generate the data set does not contain the same level of rigour that would be required to both design the turbines and the support structures. Both the rotor and support structure optimization was based on steady state analysis. Thus, the effect of fatigue damage and other unsteady loads cannot be included in the optimization. Another important consideration for future development would be to quantify the uncertainty of a model like this. For example, The model could be compared with existing installations and data as well.

5. Conclusions

This paper has successfully demonstrated how a surrogate model could be constructed for support structure mass. This is an important parameter in determining the potential cost of an offshore wind farm. The key contribution of this work both the very large coverage over a range of turbine designs and environmental conditions and the application of physics based optimization in training the surrogate. The model was based on a wide range of parameters, 9 dimensions in total. Due to the large range of rated powers considered in this model, rated power and rotor diameter became by far the most important parameter in predicting the total mass. The next most important parameter was the specific power. This suggests that the turbine selection matters more for support structure costs than the actual environmental conditions. The most important environmental factor in the costs was the water depth followed by the wave conditions. As the surrogate is a statistical model, it is also fully transparent to the user. Such a model can easily be embedded in spreadsheet programs and easily support decision makers at the very early stages of a project.

Acknowledgments

We would like to acknowledge both Garret Barter and Pietro Bortolotti from NREL for their support in using WISDEM for the turbine and monopile optimization work.

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