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MOORING OPTIMIZATION USING ML TECHNIQUES

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ABSTRACT

The mooring optimization process for a FOWT is a complex study that involves a large number of simulations. All possible designs of the optimization process should be assessed and the operational and survival constrains verified for acceptance or disregard the solution. These constraints are mainly the design bases of the mooring lines, but also the FOWT operational and survival conditions, which are mooring system dependant as it is the governing component for surge, sway and yaw stiffness. Machine Learning (ML) algorithms are used to predict the simulations results by training the model from a set of defined simulations, allowing for a significant reduction of the computational cost of the large number of required simulations. The methodology's main advantage is the high velocity once the model is trained. However, some uncertainties can arise from the exactness of the predicted values.

The aim of the paper is to design an optimized mooring system for the WindCrete platform for a Gran Canary Island with a 200 m sea depth for ULS. To overcome the difficulties of the optimization process two ML models are developed. The first one, the static ML model, is based on the static response of the mooring system that allows to reduce the solution space of the optimization problem. The second one, the dynamic ML model, is based on the dynamic response of the FOWT and allows to assess the constraints applied to the objective function as penalties. The objective function is defined as the total mass of the mooring system. The variables of the optimization problem are the main line and delta line lengths, the radius to anchor and the chain diameters.

The first ML model is set-up to predict the static mean line tension at rated wind speed, the vertical force on anchor at rated wind speed and the initial Yaw period of the FOWT. These parameters allow to discard a large number of possible solutions that do not fit with the following design bases: the maximum line tension and no vertical force on anchor. Moreover, a maximum yaw natural period threshold is set-up based on design experience. This is needed due to the lack of damping in yaw direction of Spar platforms. The static ML model is used to create an initial sample of feasible solutions to train the dynamic ML model. Also, during the optimization process is used as a classification model to exclude non-feasible solutions to ensure the performance of the second ML model.

The second ML model is based on the dynamic response of the WindCrete platform and the mooring system using OpenFast simulation tool. The model is set-up to predict the maximum line tension, vertical force on anchor, maximum surge position and maximum pitch which are used as constraints parameters to be applied at the optimization function as penalties.

The results show a good approximation of both ML models with a high potential to be applied in determining design load cases, including fatigue assessment in the optimization design process.

Keywords: Place any keywords here

ABBREVIATIONS

ANN	Artificial Neural Network
DE	Differential Evolution Scheme
DLC	Design Load Case
FOWT	Floating Offshore Wind Turbine
LC	Load Case
MBL	Mooring Breaking Load
ML	Machine Learning
MLP	Feedforward Multilayer Perceptron
MSL	Mean Sea Level
O&G	Oil and Gas
PF	Potential Flow
RF	Random Forest
SF	Safety Factor
ULS	Ultimate Limit State

1. INTRODUCTION

Mooring systems have become one of the subsystems which impacts on the reliability of a FOWT and constitute a non-negligible part of its cost. Thus, cost consideration as part of the conceptual design is very important in order to improve the competitiveness of the technology. The mooring system design is often a trade-off between various considerations including platform offset limitations, yaw stiffness in spar type platforms, maximum line tension, span life and the overall cost[1].

Time domain dynamic mooring line models are needed to capture the dynamic behaviour of the mooring lines and, therefore, play an important role in the design process, as inertial and hydrodynamic terms influence on the total tension on the line. In order to assess the behaviour of any component of a FOWT, a large number of long simulations are required for several operating and survival conditions. These requirements imply a large number of simulations with a high computational cost to assess the design loads and operational requirements such as motions and accelerations. Moreover, an optimization process will require the evaluation of any candidate solution required by the optimization problem. Therefore, the application of an optimization process for any FOWT component will require very large numbers of simulations.

Optimization methods can be grouped in two: 1) gradient methods that use Jacobians or Hessians, and 2) heuristic methods that employ algorithms with a defined behaviour and strategy to find the result through multiple iterations and comparisons.

The use of gradient-based methods is effective and traditionally used. Iterative methods main advantage is that require a reduced number of iterations [2], in particular when the partial derivatives of cost function are known. However, for non-convex and highly constrained problems will need a large number of iterative calculations. Moreover, gradient search tries to find improved solutions near the initial data. Therefore, it may be useful to run the optimization with different initial data or variable ranges. Fylling and Berthelsen [3] presented an integrated design tool for the optimization of a moored spar buoy type support structures for wind turbines. More recently, L.Li et al. [1] use a Kriging model to replace the real time-domain dynamic simulations and apply the Sequential Quadratic Programming to minimize the objective function.

Heuristic models allow a direct optimization of the objective function. The simplicity and practicality of these models make them an attractive and popular tool in the optimization framework. These methods, require the evaluation of the objective function in a sufficient number of iterations. In general, these do not establish a robust convergence criterion, as depend on a predetermined number of iterations. However, these models are less likely to fall into local minima than the gradient-based methods. To find a global solution for hard problems within an acceptable period of time, heuristic methods might guarantee a solution[4], however finding an exact global solution under these conditions is not assured.

In the field of mooring system optimization, meta-heuristic methods have been employed for offshore oil platforms [5], [6], and for floating offshore wind turbines (FOWT) [7], [8],[9]. Within the O&G industry the objective function to be minimized is the motion of the platform, as is the main constraint to ensure the operation reliability of the risers. Whereas, the objective function for FOWT is usually the cost of the mooring system or a related parameter as the total weight for only chain systems. Moreover, penalty functions are included in the objective function to include the design constraints within the met-heuristic models.

During the optimization process, the searching algorithm normally requires a large number of function evaluations to assess the constraint parameters. The straight forward approach is to evaluate the objective function at each iteration. However, heuristic models imply a large number of valuations which increase significantly the computational cost. To overcome this difficulty, subrogate models based on Machine Learning (ML) technics are used to estimate of the response of the evaluated mooring-FOWT system. The estimated response is based on previously assessed simulations, allowing to reduce the computational costs dramatically [1], [7], [10], [11], [12], [13], [14], [15].

Subrogate models are built using machine learning technique in order to reduce the computational costs of the optimization evaluation process through a functional approximation architecture[7]. Machine learning techniques, such as Artificial Neural networks (ANN) have been used to predict the analysis outputs in the context of optimal design of structural systems, and in some other areas of structural engineering applications [16], [17]. ANN are powerful machine learning algorithms. That have also been applied in generating the response surfaces for system approximation [18].

The basic idea of ANNs is that we can represent multivariate functions through a hierarchy of features with high complexity. The most typical example of an ANN is a feedforward multilayer perceptron (MLP). A highly attractive property of MLP is that under mild assumptions on the underlying function being approximated, MPLs are universal approximators [16].

In the field of mooring design optimization using subrogate models L.Li et al. [1] apply an integrated optimization methodology to design a single-point mooring system for a vessel-shaped offshore fish farm. The methodology applies both simplified and advanced analysis methods, that employs metamodel-based evaluations when searching for the optimal solutions. Moreover, the integrated optimization method applies a simplified analysis to screen the design space. It is found that the screening analysis is advantageous to reduce the initial sample size before the time-consuming dynamic analysis

Ajit C. Pillai et al.[7] explore the optimization of the geometry of a mooring system of a FOWT to reduce mooring line cost and fatigue damage. The variables used to optimize the problem are the anchor horizontal position, line segments lengths, line sections and anchor horizontal angle. Moreover, the optimization problem accounts for a maximum horizontal distance of the anchor, line length constraints related to water depth, MBL of the line segments and portion of the line resting on the seabed. A random forest (RF) ML algorithm was used in order to speed up the optimization process evaluations. In the implementation, the input features to the machine learning technique are the decision variables of the optimization problem and the output features are the objective functions, the cumulative fatigue damage and the cost of the line. Moreover, the optimization model uses a RF classifier to determine the constraint satisfaction component of the problem.

These results of [7] indicate that the use of this hybrid surrogate model achieves high accuracy results for both constraint satisfaction and the output feature values. This implementation of a trained random forest to replace the time-intensive time domain simulations generally used in the design process reduces the average time required to evaluate a single mooring design (including time spent retraining the surrogate) from 692.2 to 6.1 s. Representing a time reduction approximately of 114 times. Subrogate models are proposed to represent the unknown relations between the interested dynamic responses and design variables.

In this paper, a new approach of mooring system optimization is presented. The model seeks to optimize the mooring system for the WindCrete platform in Gran Canaria location. The optimization problem is based on the Differential Evolution optimization heuristic scheme. The objective function to optimize is the mooring system weight plus a series of penalty functions related to mooring constraints to reduce an un-constraint optimization problem. In order to reduce the computational cost, three ML models were set up to estimate the platform response for constraint verification. The first ML model is a classification ANN-MLP model based on the static solution to filter feasible solutions within the solution range. The second and third ML models are regression ANN-MLP models that predict the constraints for DLC 16 using two wind speeds (rated wind speed and cut-off wind speed) based on OpenFast [19] simulations.

The paper is structured as follows: first the properties of the FOWT, the mooring system and site location are described. Second, the optimization problem is described in terms of the objective functions, cost function and penalty terms. Third the classification ANN model is described and its main characteristics presented. Forth, the regression ANN models and its main characteristics are presented. Finally, the results of the optimization problem are presented.

2. WINDCRETE PLATFORM AND MOORING SYSTEM OVERVIEW

The platform used in this study is the WindCrete [20] designed to support the IEA-15MW reference wind turbine [21]. A sketch of the WindCrete platform is shown in ***Figure 1***. The structure is a monolithic prestressed concrete platform with a tower of 129.5 m tall, from the MSL, and a draft of 155 m [22]. The hub height is at 135 m above the MSL, allowing a 15 m clearance between the blades and the mean sea level. The tower starts at the MSL and has a base diameter of 13.2 m and a top diameter of 6.5 m at the yaw bearing. The thickness of the tower is set constant of 0.4m. The substructure consists on three pieces with a constant thickness of 0.5m: the tapered transition piece, the cylindrical buoy and the bottom hemi-sphere. The transition piece is a 10 m tapper element with a top diameter of 13.2 m and a bottom diameter of 18.6 m where the cylindrical section is connected. The cylinder buoy allows the placement of the ballast and gives the needed buoyancy. The cylinder has a length of 135.7 m and a diameter of 18.6 m. The 9.3 m radius hemi-sphere at the bottom distributes the hydrostatic pressures in a compression field around the base. The ballast added to achieve the needed Pitch/Roll stiffness has a weigh 25.07 kTons and consists on an aggregate with a specific weight of 25 kN/m3 located at the bottom of the cylinder.

The main geometric properties of the platform are summarized in **Table 1**. The inertia terms are assessed from the CM and include the RNA. The hydrostatic stiffness values also account for the weight [23].

Table 1. WindCrete main properties

Displaced volume [m^3]	4.054e+04
Draft [m]	155
Concrete mass [kg]	1.474e+07
Ballast [kg]	2.507e+07
Wind turbine mass [kg]	8.211e+05
CM [m]	-93.72
CB [m]	-77.29
Total Mass [kg]	4.063e+07
I_{44} [kg·m^2]	1.986e+11
I_{55} [kg·m^2]	1.987e+11
I_{66} [kg·m^2]	1.947e+09
C_{33} [N/m]	1.376e+06
C_{44} [N·m/rad]	6.713e+09
C_{55} [N·m/rad]	6.713e+09

The mooring system consists of three catenary lines (line #) spaced 120º apart with a delta line connection to the buoy to provide yaw stiffness to the system, as shown in **Figure 2**. For simplicity, all lines and anchors are symmetrically distributed and composed with two different chain diameters for the main and delta lines respectability. The inputs to describe the mooring configuration are the anchor radius (r_{anch}) and the lengths and diameters for each line type ($l_{main}, l_{delta}, d_{main}, d_{delta}$).

Table 2: Reference mooring system properties

Radius to anchor [m]	600
Chain line length [m]	565
Delta line length [m]	50
Chain nominal diameter [mm]	160
Chain apparent diameter [mm]	301
Chain wet weight [N/m]	4.8e+03
Chain Axial stiffness [N]	2.3e+9

The mooring system predesign for WindCrete 15 MW at Gran Canaria [24] will be used as a reference mooring system to compare with the optimization solution. The properties of reference mooring system are shown in ***Table 2***. It has to be noted, that the mooring system was designed using a static approach, where the limiting constraints were a natural yaw period of the system of 11s, and that the maximum tension on the lines assessed as a the most tensioned line for a mean surge due to rated wind speed plus a dynamic offset of 3 meters. Also, no vertical force on the anchor must be verifies in the same condition.

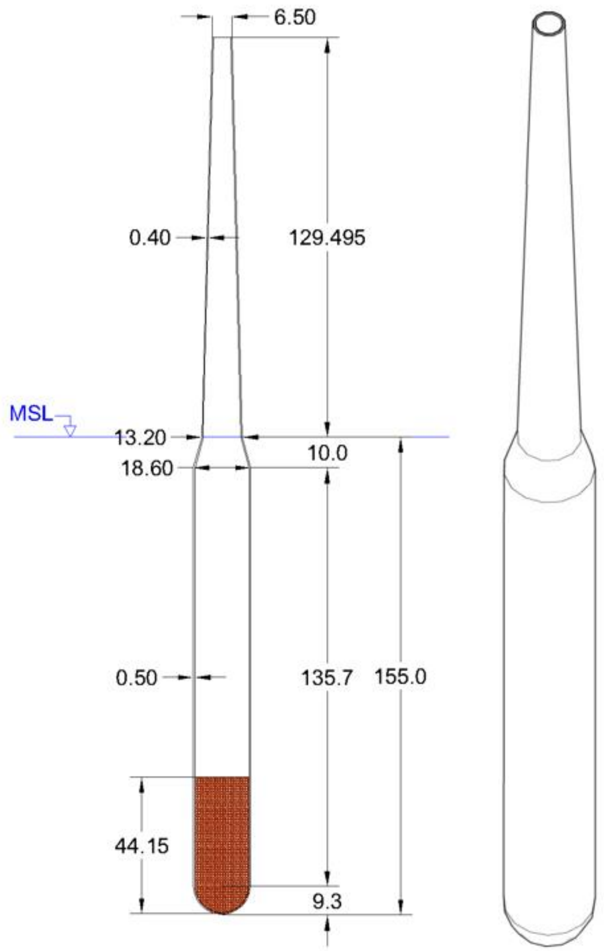

Figure 1: WindCrete sketch with main dimensions

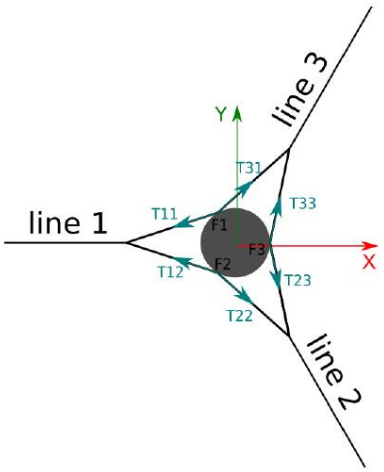

Figure 2. WindCrete mooring system disposition

3. SITE LOCATION

The location for the WindCrete is based on the southeast part of Gran Canaria in the Canary Islands [24], as show in **Figure 3**. The Southeast part of the Canary Islands is set to 200 m depth and it will be considered constant for the mooring system optimization design process.

The wind data is provided by the SIMAR point 4038006 from the Spanish port authority on the coordinate’s latitude 15o19’48” W, longitude 27o45’00” N. **Table 3** shows the wind speed profile for the mean wind speed and for the extreme wind at 1 year and 50 years return period.

Figure 3. WindCrete Gran Canaria location

Table 4 shows the extreme wave characterization based on the data provided by the same SIMAR point. The characterization is shown for return periods of 1, 10, 20 and 50 years.

Table 3. Normal and extreme wind speed profile at different heights**.**

	Normal mean wind profile	**Extreme wind profile Tr=50 yr.**	**Extreme wind profile Tr=1 yr.**
Height [m]	**Wind Speed [m/s]**		
10	9.83	29.77	16.00
20	10.48	32.35	17.39
50	11.33	36.11	19.41
100	11.98	39.24	21.09
119	12.14	40.07	21.54
150	12.36	41.20	22.14

Table 4. Wave data for SIMAR point 4038006 [24]

Return period (years)	**Hs (m)**	**Tp (s)**
50	5.11	9.0 - 11.0
20	4.69	9.0 – 11.0
10	4.40	9.0 – 11.0
1	3.35	8.0 – 10.0

4. OPTIMIZATION PROBLEM

The optimization problem is defined by the minimization of the objective function Eq. (1) subjected to certain restrictions expressed as inequalities, Eq. (2), where $X = (x_1, x_2, \dots, x_N)$ are the decision variables. As stated in Section 2 the decision variables in this problem are the anchor radius (r_{Anch}) and the lengths and diameters for each line type (l_{main}, l_{delta}, d_{main}, d_{delta}).

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$$f(X) = f(x_1, x_2, \dots, x_N) \quad (1)$$

$$g_j(x_1, x_2, \dots, x_N) \le 0 \quad (2)$$

Moreover, in order to limit the solution space, the decision variables are constrained by imposing a feasible solution range based on previous experiences. The **Table 5** shows the lower and upper limit range of the variables. In order to ensure all feasible solutions, multiple non-feasible solutions will be present because of the limits for the radius to anchor and the length of the main line. As an example, a combination of the minimum radius to anchor and the maximum main line length will lead to a total slack mooring line as the sea depth from the fairlead is 110 m.

Table 5: Decision variable range limits

Variable	Lower Limit	Upper Limit
r_{Anch} **[m]**	680	800
l_{main} **[m]**	680	800
l_{delta} **[m]**	30	80
d_{main} **[mm]**	30	200
d_{delta} **[mm]**	30	200

The objective function, Eq (3), is defined as the summation of the cost function of the mooring system and the penalty functions to include the constraints within the objective function.

$$f_{obj} = f_{cost} + f_{penalty} \quad (3)$$

The cost function, Eq. (4) is defined as the total weight of the mooring system normalized by the weight of a reference mooring line with a length of three times the depth and a chain diameter of 100mm.

$$f_{cost} = \frac{l_{main} \cdot \omega_{main} + 2 \cdot l_{delta} \cdot \omega_{delta}}{3 \cdot depth \cdot \omega_{100mm}} \quad (4)$$

Where:
ω is the mass per meter length of the desired chain

The constraints of the problem are applied through the penalty function that increases the value of objective function if the constraints are not fulfilled in order to transform a constraint problem into an unconstrained one. This method was selected due to the impossibility to apply direct equations of the constraints into the metaheuristic optimization model. In this case, the constraints are assessed through the postprocessing of the simulations. The constraints applied to the problem are the following, which are based on operational limits and mooring design criteria based on DNV-ST-0119:

- Surge motion < 15 m $\rightarrow g_1 = \frac{r_1}{15} - 1 \le 0$
- Pitch rotation < 5.5 deg $\rightarrow g_2 = \frac{r_5}{5.5} - 1 \le 0$
- Yaw rotation < 15 deg $\rightarrow g_3 = \frac{r_6}{15} - 1 \le 0$
- $T_d = 1.3\, T_{mean} + 1.75 T_{dyn} < 0.95 MBL$
  $g_4 = 1.3\, T_{mean} + 1.75 T_{dyn} - 0.95 MBL \le 0$
- $F_{V,anchor} = 0\, N$ $\rightarrow g_5 = F_{V,acnhor} \le 0$

These constrains are applied to the problem by including its penalty term $(f_{p,surge}; f_{p,pitch,}; f_{p,T}; f_{p,FV})$ for surge, pitch maximum tension, and vertical force on anchor respectively at Eq (5)

$$f_{penalty} = f_{p,surge} + f_{p,pitch,} + f_{p,T} + f_{p,FV} \quad (5)$$

The penalty terms for each constraint are assessed by Eq. (6), where $q_j(X)$ denotes the magnitude of violation of the j_{th} constraint in Eq. (7). The function $\theta\left(q_j(X)\right)$ shown in Eq. (8), is a continuous multi-stage assignment function, and $\gamma\left(q_j(X)\right)$ is the power of the violated function, shown in Eq.(9).

$$f_p = \theta\left(q_j(X)\right) q_j(X)^{\gamma\left(q_j(X)\right)} \quad (6)$$

$$q_i(X) = \max\{0, g_j(X)\} \quad (7)$$

$$\theta\left(q_j(X)\right) = \begin{cases} 10, & if\ q_j(X) < 0.001 \\ 20, & if\ q_j(X) < 0.1 \\ 100, & if\ q_j(X) < 1 \\ 300, & otherwise \end{cases} \quad (8)$$

$$\gamma\left(q_j(X)\right) = \begin{cases} 1 & if \quad q_j(X) \le 1 \\ 2 & if \quad q_j(X) > 1 \end{cases} \quad (9)$$

The optimization problem is solved using a Differential Evolution (DE) optimization scheme. The DE is a metaheuristic method that optimizes a problem by creating new candidate solutions by combining old ones and keeping the best candidate solutions.

5. STATIC CLASSIFICATION MODEL

The solution space of the decision variables has to be enough wide to ensure all feasible anchor positions, line lengths, and chain diameters combinations. However, a large portion of the combinations are non-feasible solutions only based on static violation of the constraints.

The classification model is set-up in order to verify the feasibility of the possible solutions. This model is used in two phases of the work. First, the classification is used to get feasible solutions for training and validating sets of decision variables for the regression ANN. Second, the classification model is used within the optimization problem in order to discard function evaluations for decision variables out of the training range that can lead to wrong solutions within the subrogated model.

The static classification model classifies the decision variables set are or not feasible solutions based on the following constraints:

- $T_6 < 15s$
- $F_{V,anchor} < 0$ at mean surge location at rated wind
- $T < MBL$ at mean surge location at rated wind

The first constraint limit is the yaw natural period (T_6) that should be below 15 seconds. This constraint is based on previous experiences, where at least a yaw natural period of 12s was needed for the spar WindCrete 15MW platform to balance the low damping produced in yaw direction [23]. The second and third constraint are the vertical force on anchor $\left(F_{V,anchor}\right)$ and maximum line tension (T). These values have to lower than 0 and Mooring Breaking Load respectively at mean surge location for rated wind.

5.1 Static model

The static model is based on the catenary equations of the mooring lines. The catenary equation can be solved accounting for the axial stiffness of the line by the Eq. (10).

$$\begin{aligned} x - x_0 &= \frac{T_H}{\omega}\left[ln\left(\frac{1}{cos(\phi)} + tan(\phi)\right) - ln\left(\frac{1}{cos(\phi_0)} + tan(\phi_0)\right)\right] + \frac{T_H}{EA}l \\ z - z_0 &= \frac{T_H}{\omega}\left[\frac{1}{cos(\phi)} - \frac{1}{cos(\phi_0)}\right] + \frac{1}{2}\frac{\omega}{EA}l^2 \end{aligned} \tag{10}$$

Where x, z are the in plane horizontal and vertical positions, T_H is the horizontal component of the line tension, ω is the wet weight per meter length of the line, ϕ is the angel between the vertical and horizontal tension, l is the length of the line and EA is the axial stiffness of the line.

The constraints are assessed by applying the catenary equations to the mooring system for an imposed surge excursion and for an imposed yaw platform rotation. From the surge excursion, an interpolation process is performed to get the mean position for the rated wind speed, and further interpolation is used to obtain the vertical force on anchor and the tension. **Figure 4** shows the mooring system response, the line tension and the vertical force on anchor response and the interpolation points. From the platform yaw rotation, the yaw stiffness of the mooring system is obtained. The yaw natural period is assessed by Eq. (10). **Figure 4** b shows the yaw response of the mooring system.

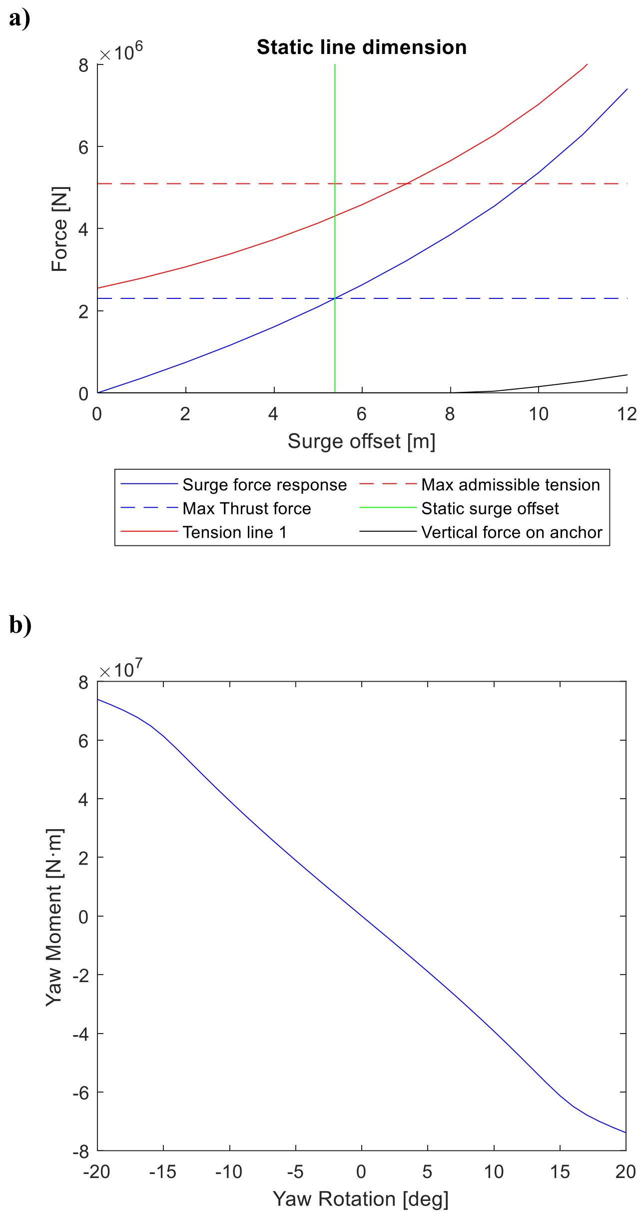

Figure 4: Static model approach

$$T_6 = 2\pi\sqrt{\frac{I_{66}}{K_6}} \tag{11}$$

5.1 Classification model implementation

30,000 sets of decision variables where analysed in order to train the classification model based on an ANN. In this set 116 feasible solutions were found through the static analysis, only a 0.3%. ***Table 6*** shows the confusion matrix obtained from the training results of the classification ANN following the 60/40 validation criterion. Then, 60% of the data is used for training the model, while the remaining 40% is used for the validation stage. The index ROC-AUC obtained in the validation subset is 0.957.

Table 6: Confusion matrix of the classification model

True Not Feasible:11 946	False Not Feasible:7
False Feasible: 4	True Feasible: 43

The classification model allowed to create the feasible set of mooring line parameters to be simulated in OpenFast. From a set of 200.000 population, 1000 feasible solutions were obtained in order to train the ML regression model.

Figure 5 shows the graphs of the cumulative distribution function of the initial sample of training set of the classification model, and the feasible solutions to be tested in OpenFast. It can be seen that the initial sampling has a random distribution. However, the feasible solution set, has a much narrow distribution due to the imposed constraints.

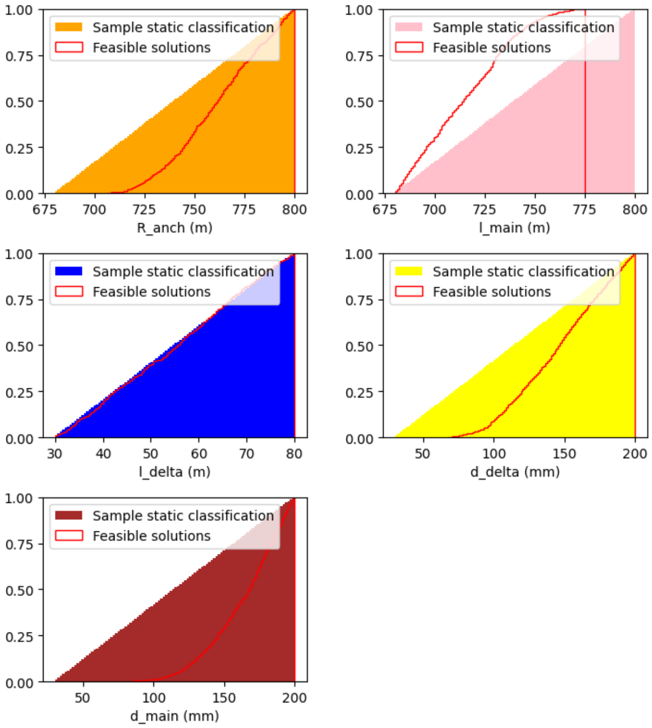

Figure 5: Cumulative distribution comparison of the initial set of population and the subset that fits with the classification ANN

6. SUBROGATED MODELS FOR DLC1.6

The subrogate models used for predicting the constraint values for each set of design variables evaluations are based on two different LC of DLC1.6. The DLC1.6 aims to analyse the wind turbine in operation conditions combined with a severe sea state. UPC [25] found that this DLC is the most demanding for mooring design verification. The chosen LC are defined for a V_{hub} of 10.5 m/s at rated conditions and for a V_{hub} 25m/s at cut-out conditions. These wind speeds are chosen because generates the large thrust for the rated wind speed and the large yaw torque when misalignment is produced due to yaw motion for the cut-off wind speed. The sea state used is for a return period of 50 years with a Hs of 5.11m and a Tp of 10s. The wind speeds time series were generated by TurbSim software. The sea wave surface used for the all the simulations was the same and also the wind time series were the same for each wind speed value. This approach helps to reduce the computation effort as the wind is already created, and reduces the results dispersion to better implementation the ML model.

Once the simulations are assessed, a postprocess analysis is performed to obtain the constrain values using a python code. These values are the maximum of the surge position, the maximum of the pitch rotation, the maximum yaw rotation, the maximum main line and delta line tensions and the maximum vertical force on the anchor. The models are trained with a set of 1000 different mooring systems designs that fit with the static classification model. The simulations are performed with OpenFast WindCrete models [23] with a duration of 5400s plus 600s for avoiding transient effects. The wind turbine is modelled using the dynamic blade element momentum theory. The hydrodynamics of the platform are assessed by PF theory adding distributed drag terms at the spar. Moreover, 2nd order wave forces are assessed for the difference frequency range from Wamit Quadratic Transfer Function. The mooring lines are simulated using MoorDyn module and the hydrodynamic parameters used are shown in **Table 7**. More details of OpenFast WindCrete Files can be obtained at [26]. In order to increase the reliability of the simulations, the mass and inertia of the substructure is updated at each simulation to balance the difference of buoyancy produced for the difference on initial vertical force on the fairleads.

Table 7: Mooring line hydrodynamic properties

Parameter	Can	Cat	Cdn	Cdt
Value	1	0.5	1.33	0.64

The models are ANN with three hidden layers of 120, 120, and 60 neurons. The ANN used is based on the Sckit-learn library [27]. **Figure 6** shows the bias-variance analysis of the R^2 parameter for different ratios of training validation sets. The results show that a training/validation ratio of 60/40 presents an R^2 of 0.98 for the validation model that verifies the good performance of the model. Considering a R^2 of 1 means that the model can predict perfectly the problem. Then, it can be stated that a training/validation set of 500 cases can be enough to generate a regression ANN ML model with an accuracy over 95% using a ratio of 60/40.

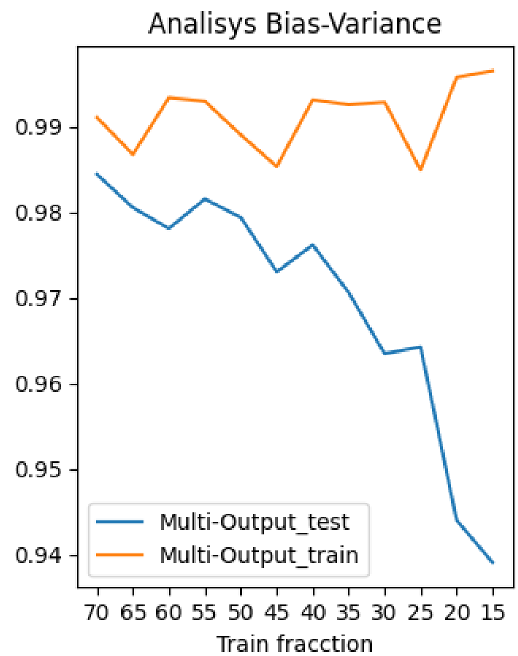

Figure 6. Bias-Variance analysis for the R2 index

The models used for the optimization problem are trained with the 60% of the simulated data and the 40% is used for the verification process. The input data for training the models are the decision variables presented in Section 4 and the outputs are the maximum values of the required constraints, the maximum surge, the maximum pitch, the maximum yaw, the maximum tension on the main line and the maximum tension on the delta line.

6.1 Model results and analysis

The ***Figure*** *7* shows the cumulative distribution of the results predicted by the regression ANN model comparing with the data obtained with the OpenFast results. The results show the good performance of the model to predict all the studied parameters.

7. MOORING SYSTEM DESIGN AND VALIDATION

The optimized solution using the DE algorithm and the three metamodels: the classification model, and the regression ANN models for DLC 16 $V_{hub} = 10.5\ and\ 25\ m/s$ is shown in ***Table 8***. The optimization problem took 58 iterations with an initial population of 50 cases. This means, that a total of 2900 evaluations for each regression ANN were performed, 5800 in total. Then, the total time used is almost 3 times lower than if fully time domain analysis with OpenFast were performed during the optimization process.

Table 8: DE optimization solution

r_{anch}	l_{main}	l_{delta}	d_{main}	d_{delta}
750 m	682.7 m	75 m	128 mm	107 mm
+25%	+21%	+50%	-20%	-33%

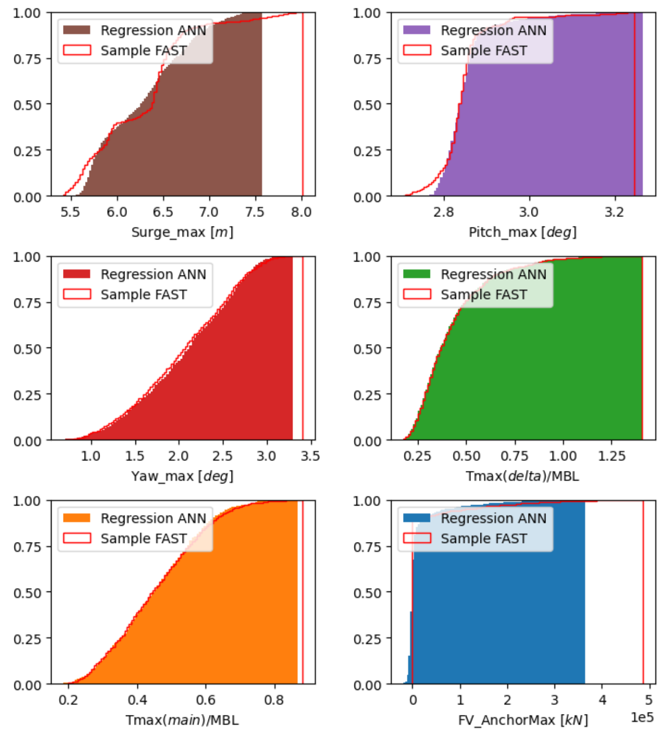

Figure 7: Cumulative distribution for the studied output variables of the OpenFast model and regression ANN model

The optimized solution has a larger radius to anchor than the reference mooring system. This leads to larger line lengths but also a reduction of the chain diameters to get a lighter mooring system. Also, it is worth to note that the delta length is increased up to 75m. A more in deep analysis of this results may lead to new configurations of delta line arrangements, as for example the validation against DLC 61 and 62..

The optimized solution is then analyzed by simulating the response of the WindCrete 15MW for the design LC used, LC16 for V_{ref} of 10.5m/s and 25m/s in OpenFast. The ***Table 9*** shows the constraints of the simulation results of the studied cases. The results show the good performance of the regression ML models because the simulation of the optimization solution fulfill the constrain criteria. They also show that the maximum yaw rotation is produced for the larger wind speed as expected. However, maximum line tension is found in both LC depending on the analyzed line segment. The MBL for the chain diameters of the main line and delta line are $1.52 \cdot 10^4$kN and $1.15 \cdot 10^4$kN respectively. Then, the maximum design tensions fulfill the requirements of the design.

The total cost of the mooring system in terms of mass is 851 Tons. The initial reference mooring system has a mass of 1,122 Tons, which mean a reduction of 25% of the total mass of the mooring system.

Table 9: Summary of the design constraints of DLC simulations

Property	Value	V_{ref}
Max Surge [m]	11.32	10.5
Max Pitch [deg]	4.94	10.5
Max Yaw [deg]	1.93	25
Td Main Line [kN]	7.50E+03	25
Td Delta Line [kN]	5.90E+03	10.5
Max Vertical Force Anchor [kN]	0.00E+00	10.5/25

8. CONCLUSIONS

The paper presents a methodology to perform mooring system optimization using a classification ANN model and two regression ANN models to predict the response of the FOWT constraints.

The classification ANN model is trained from the static response of the mooring system. This model is used in order to create feasible solutions based on static mooring tension, vertical force on anchor, and platform surge at rated wind speed. Then, a 1000 population of feasible solutions are created to be simulated using OpenFast. Moreover, the classification model is used during the optimization process to discard non-feasible solutions. This methodology allows to discard sets of design variables that can be miss-predicted by the regression ANN, as they are out of the training space.

The responses from the simulations are used as the training values of the regression ANN models. The models show enough accuracy to predict the desired values. Moreover, the initial amount of data could be reduced in a factor of 2.

The optimization problem performed 5800 evaluations of the response of the mooring system, that should be performed by OpenFast simulations. This leads to a time reduction of 65%, which was one of the main objectives of using ML techniques.

The optimized solutions lead to a cost reduction of 44% from the initial reference mooring system. Design requirements were verified by OpenFast simulations of the optimized mooring system. All the results fit with the initial design basis.

Future work will include more DLC as 6.1 and 6.2 including some wind misalignment. Also, fatigue analysis prediction could be implemented to get a more reliable mooring system optimal design.

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