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DYNAMIC CHARACTERIZATION OF OFFSHORE WIND TURBINES SUPPORTED ON A JACKET USING ARTIFICIAL NEURAL NETWORKS

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Abstract. The dynamic characterization of an offshore wind turbine (OWT) and its foundation is an important task within the design stage of the support structure. The system fundamental frequency should not coincide with that of the loads that affect it, otherwise resonance phenomena can conclude with the collapse of the structure or its deterioration due to fatigue. Assuming a linear behaviour, the system fundamental frequency can be computed by solving the eigenvalue problem after defining the stiffness and mass global matrices. This procedure can become computationally expensive if soil-structure interaction (SSI) phenomena is taken into account. For this reason, a surrogate model based on Artificial Neural Networks (ANN) is proposed for estimating the fundamental frequency of the wind turbine assembly, jacket support structure and pile foundation considering SSI effects.

A dataset is generated to train the ANN. This synthetic data collects the characteristics of the OWT-jacket-foundation and its fundamental frequency, which is obtained by a finite element substructuring model. The SSI is reproduced through impedance functions computed through a previously developed continuum model. Comparing the predictions of the ANN with the results obtained by the structural model, it is observed that this type of regression allows to reproduce in a sufficiently precise way the dependence of the fundamental frequency with respect to the variables that define the system. Thus the use of Machine Learning techniques, such as ANNs, makes it possible to take into account the system behaviour obtained by rigorous models in large-scale calculations that it would be unfeasible otherwise.

1 INTRODUCTION

The growing interest in taking advantage of the wind conditions at sea generates the need to increase the economic profitability of offshore wind turbines (OWTs) in increasingly deeper waters. From this perspective, the optimization of the support structures of these devices represents a significant cost reduction, because they represent a considerable part of the total cost of the projects [1]. In the design stage of the OWTs, it must be verified, among other requirements, that the fundamental frequency of the system does not coincide with the speed of rotation of the rotor or with the frequencies of the environmental loads [2]. By this, resonance phenomena that can cause the collapse of the structure or its deterioration due to fatigue are avoided.

Obtaining the dynamic characterization of the OWT on a jacket can suppose a considerable computational cost, which further increases if the soil-structure interaction (SSI) phenomena are taken into account. Therefore, including this calculation in an optimization process greatly increases its computation time. The recent advantages in machine learning techniques have allowed different authors [e.g., 3, 4, 5] to build surrogate models that are capable to reproduce results of complex numerical models in a sufficiently accurate way, but in a significantly reduced amount of time.

In this work, the use of artificial neural networks (ANNs) is proposed as a surrogate model for the dynamic characterization of jacket-supported offshore wind turbines through the fundamental frequency of the system, considering the soil-structure interaction.

2 Methodology

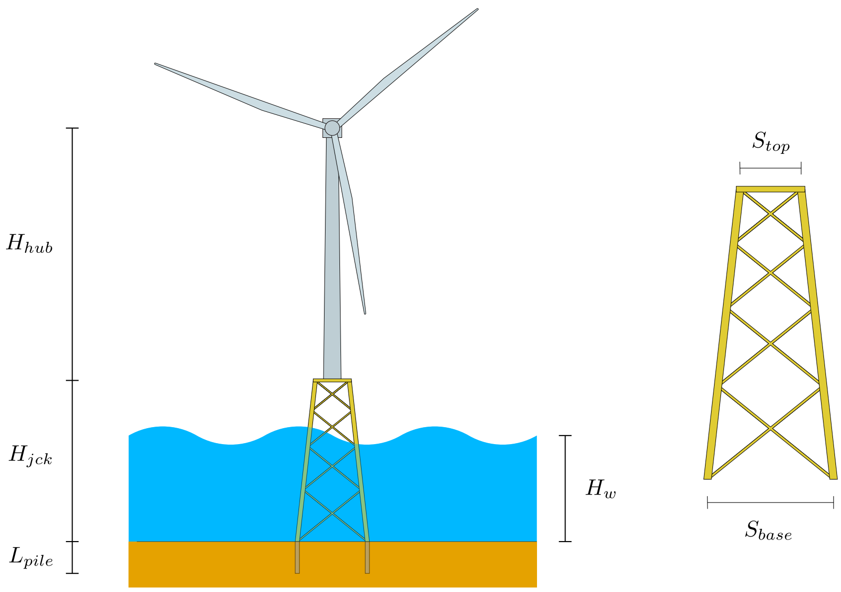

Figure 1: Representation of the structural system. An offshore wind turbine on a jacket with a pile foundation.

A surrogate model based on ANNs requires for its training a dataset that contains already solved cases of the target task. According to the objective of this work, that dataset must include as input variables those required for defining the structural system (figure 1), while the output variable would be the fundamental frequency. Regarding the first group, in this work the variables considered must be able to define the wind turbine, the site conditions and the jacket substructure. Lower and upper bounds are established for each of these input variables, whose values are randomly generated through a uniform distribution. The list of selected variables and their lower and upper boundaries are shown in the tables 1 (site conditions), 2 (wind turbine) and 3 (jacket structure). The tower of the wind turbine and all tubular members of the jacket structure are assumed to be made of steel so the following material properties are considered: density of 7850 kg/m^3, Young's modulus of 210 GPa, Poisson's ratio of 0.3 and hysteretic damping coefficient of 0.5%.

Table 1: Site conditions variables definition.

Variable	Lower bound	Upper bound
Soil shear wave propagation velocity (c_s)	60 m/s	600 m/s
Soil Poisson's ratio (ν_s)	Eq. 1a	Eq. 1b
Soil density (ρ_s)	Eq. 2a	Eq. 2b
Water depth (H_w)	25 m	60 m

$$\nu_{s,\text{lower limit}} = 0.4 + (0.25 - 0.4) \cdot \frac{c_s\,(m/s) - 60}{600 - 60} \tag{1a}$$

$$\nu_{s,\text{upper limit}} = 0.499 + (0.35 - 0.499) \cdot \frac{c_s\,(m/s) - 60}{600 - 60} \tag{1b}$$

$$\rho_{s,\text{lower limit}} = 1600 + (2000 - 1600) \cdot \frac{c_s\,(m/s) - 60}{600 - 60}\,\left(kg/m^3\right) \tag{2a}$$

$$\rho_{s,\text{upper limit}} = 2000 + (2500 - 2000) \cdot \frac{c_s\,(m/s) - 60}{600 - 60}\,\left(kg/m^3\right) \tag{2b}$$

Table 2: Wind turbine variables definition.

Variable	Lower bound	Upper bound
Tower height (H_{hub})	80 m	145 m
Tower bottom diameter (D_{bottom})	$H_{hub}/16$	$H_{hub}/13$
Tower bottom thickness (T_{bottom})	$D_{bottom}/250$	$D_{bottom}/200$
Tower top diameter (D_{top})	$D_{bottom}/1.65$	$D_{bottom}/1.45$
Tower top thickness (T_{top})	$D_{top}/290$	$D_{top}/190$
Rotor mass (M_{RNA})	$H_{hub}^2 \cdot 35\ (kg/m^2)$	$H_{hub}^2 \cdot 60\ (kg/m^2)$
Rotor inertia about roll axis ($I_{RNA,roll}$)	$0.1^2 \cdot H_{hub}^2 \cdot M_{RNA}$	$0.15^2 \cdot H_{hub}^2 \cdot M_{RNA}$
Rotor inertia about yaw axis ($I_{RNA,yaw}$)	$0.6 \cdot I_{RNA,roll}$	$0.75 \cdot I_{RNA,roll}$

Table 3: Jacket substructure variables definition.

Variable	Lower bound	Upper bound
Height (H_{jck})	$1.1 \cdot H_w$	$1.6 \cdot H_w$
Number of legs (n_{leg})	3	5
Top leg spacing (S_{top})	D_{bottom}	$2.5 \cdot D_{bottom}$
Base leg spacing (S_{base})	Eq. 3, $\alpha_{leg} \sim U\,(60°, 90°)$	
Number of bracing levels (n_{br})	Eq. 4, $\beta = 70°$	Eq. 4, $\beta = 30°$
Leg and pile diameter (D_{leg})	0.5 m	3.5 m
Leg and pile thickness (T_{leg})	$D_{leg}/64$	$\min\{D_{leg}/16, 0.1\text{ m}\}$
Bracing diameter (D_{br})	$D_{leg}/5$	D_{leg}
Bracing thickness (T_{br})	$D_{br}/64$	$\min\{D_{br}/16, 0.1\text{ m}\}$
Pile length (L_{pile})	5 m	40 m

$$S_{base} = S_{top} + \frac{2H_{jck}\sin(\pi/n_{leg})}{\tan(\alpha_{leg})} \tag{3}$$

$$n_{br} = \begin{cases} \dfrac{H_{jck}}{S_{base}\ \tan(\beta)} & \text{if } S_{base} = S_{top} \\[2ex] \dfrac{\log\left(S_{top}/S_{base}\right)}{\log\left(1 - \dfrac{2\tan(\beta)}{\sqrt{\left(\dfrac{2H_{jck}}{S_{base}-S_{top}}\right)^2 + \dfrac{1}{\sin^2\left(\pi/N_{leg}\right)} - 1 + \tan(\beta)}}\right)} & \text{if } S_{base} > S_{top} \end{cases} \tag{4}$$

Once the variables that define the problem have been generated, the fundamental frequency for each case must be obtained. For this purpose, a structural finite element model of the jacket substructure and the wind turbine tower is used. The inertia contribution of the rotor-nacelle assembly is included as a puntual mass at the top of the tower.The soil-structure interaction is introduced through the foundation impedance functions. They are obtained with a previously developed model [6] based on the integral formulation of pile-soil interaction with Greens function of the layered halfspace, that rigorously reproduce the linear response of an embedded pile or group of piles. The water-structure interaction is taken into account through the inertial effects that it induces, in accordance with DNVGL-RP-C205 [7]. Finally, a punctual hysterical damper is introduced at the top of the tower to consider the aeroelastic damping. To do this, according to the data compiled by Chen [8], a value of 6% in fore-aft direction and 0.755% in the side-side direction is assigned, with respect to the equivalent stiffness of the tower over a infinitely-rigid base.

Once the structural model is defined through the stiffness and mass matrices, the fundamental frequency is obtained by solving the eigenvalue problem iteratively. Note that the iterative procedure is required due to the variation of the foundation impedance functions with frequency.

On the other hand, the ANN used as a surrogate model is a fully connected neural network with 22 inputs (indicated in the tables 1, 2 and 3), one output (the fundamental frequency) and a variable number of hidden layers and of neurons per hidden layer, allowing a reduced study of the possible architectures. The Rectified Linear Unit (ReLU) is used as activation function and the mean squared error (MSE) as objective function, analysing the convergence of the validation set to avoid overfitting. An example of the neural network is shown in figure 2.

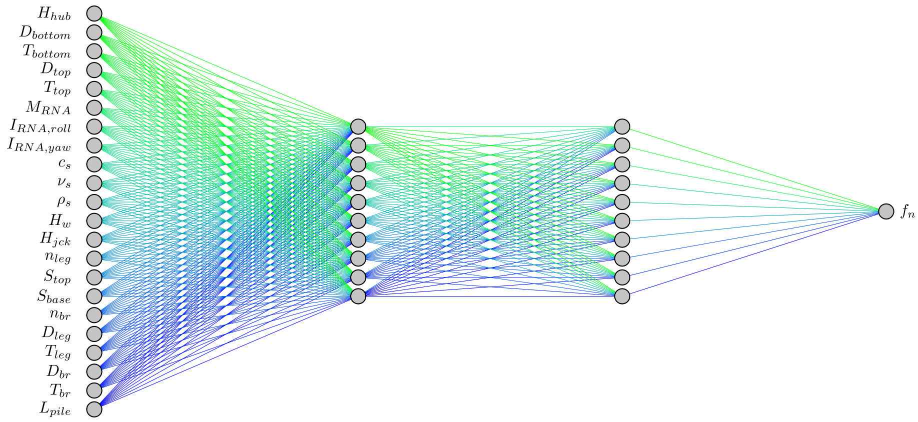

Figure 2: Representation of the ANN. Example of arquitecture with 2 hidden layers of 10 neurons each.

3 Results

To build the proposed surrogate model, different neural networks are trained in order to do a small study of the architectures. The number of hidden layers is varied from 1 to 4, and 10, 25, 50, 75, 100, 125 or 150 neurons per layer are considered. Also, due to the randomness in the initialization, 20 independent networks are created for each of the mentioned combinations. A generated dataset of 100,000 cases is randomly divided into sets of train (70%), validation (15%) and test (15%) in order to train the different networks.

The comparison between the different generated networks is done by evaluating the test sets and computing the relative error in absolute value ($|E_r|$) of each prediction. As a representative value of the model error, the 99th percentile of the distribution of errors is considered. Figure 3 shows the performance of each of the trained artificial neural networks against their number of parameters, grouped by number of hidden layers and neurons per hidden layer. An important variability in performance is observed for each of the combinations studied due to the random initialization of the process. However, the expected general trend is observed: increasing the number of total parameters, increases the performance of the model. Nevertheless, for networks with more than 10,000 parameters, the performance improvement is greatly reduced for this problem. For the best performing generated networks, 99% of their predictions are expected to have relative errors of less than 4% with respect to the finite element model.

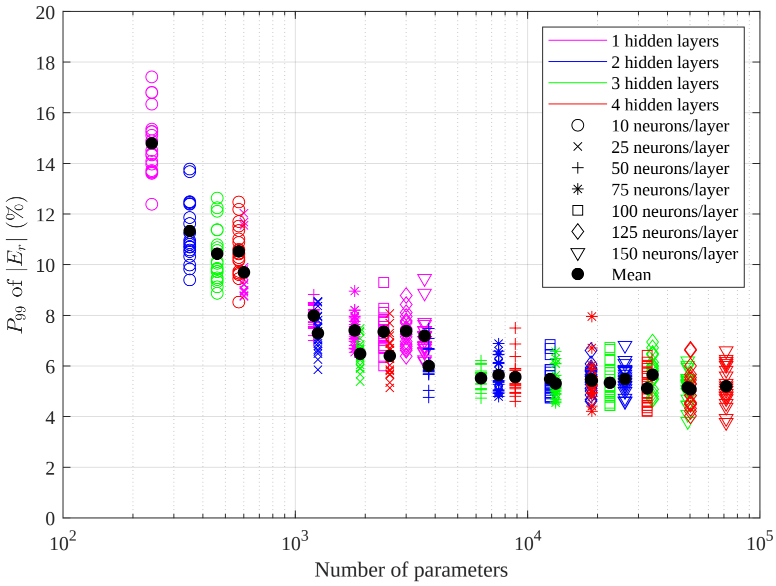

Figure 3: Performance of the obtained artificial neural networks against the number of parameters.

In order to obtain a more robust model, it is proposed to build an ensemble model using the different ANNs trained for each combination together, so that statistical markers such as the mean and standard deviation of the individual predictions of each network can be extracted. After generating a new dataset of 10,000 cases, the predictions produced by the individual neural networks and the ensemble models built from them are analyzed. The figure 4 shows the performance of the individual networks and compares it with that of the ensemble models. Note that the ensemble models have a higher number of parameters since it corresponds to the sum of the parameters of the individuals networks. However, the ensemble models achieve slightly better performances.

4 Conclusions

This work shows the ability of artificial neural networks to reproduce the dynamic characterization of an offshore wind turbine supported on a jacket with pile foundation through the fundamental frequency of the system. Architectures capable of reaching a prediction accuracy such that 99% of the cases present relative errors of less than 4% are achieved, which validates its usefulness as a surrogate model. It should be noted that the randomness in the initialization process can produce a significant variation in performance, so a minimum statistical analysis must be conducted to determine the capabilities of the model. Furthermore, as in most regression models, the performance of the surrogate model strongly depends on the number of parameters.

On the other hand, the alternative of building an ensemble model from different independent

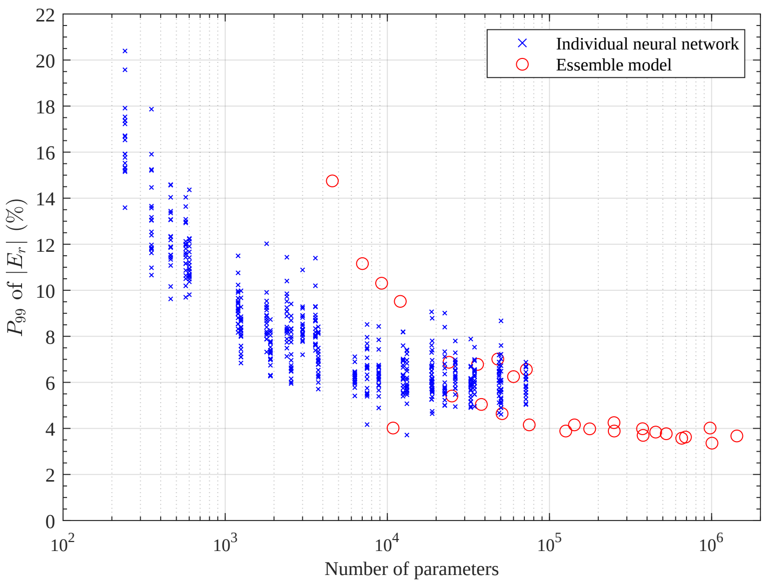

Figure 4: Performance of the individual ANNs and ensemble models against the number of parameters.

networks increases the size of the model and the training costs. However, it makes it possible to achieve slightly higher performances, as well as incorporating uncertainty measures into the prediction.

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