A Novel Numerical Approach for Fatigue Load Emulation of Offshore Wind Turbines Using Machine Learning

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ABSTRACT

During their lifetime, offshore wind turbines are subjected to complex loading conditions. Understanding the loading history of the support structure of these structures and the long-term implications on the structural integrity renders structural health monitoring (SHM) imperative. In that direction, it is common practice in the wind turbine industry to use only a few physical sensors in a small number of intelligent turbines per fleet to directly measure the load levels in the support structure, implying SHM insights limited to only the instrumented turbines. This often leaves stakeholders with insufficient information on a farm level, not facilitating important decisions regarding project lifetime or adjustments to the trade-off between energy harvest and fatigue damage accumulation through upgraded controller behavior. To bridge this gap, machine learning models have been used as surrogate models with the purpose of virtually sensing fatigue loads through a process known as load emulation. However, previous applications have used site-specific, position-specific training data to develop the machine learning models. As such, the resulting surrogate model decreases in performance when asked to extrapolate to a different site, or even to a different position of the same wind farm. This research presents a novel methodology for constructing a single machine learning load emulation object that is useful for emulating fatigue loads in a generic concept, applicable to any wind turbine within a wide, pre-defined solution space without loss in accuracy. The methodology introduces the use of simplified structural models which preserve key degrees of freedom of the geometric and dynamic properties to represent potential offshore wind sites that cover the desired solution space. These structural models are used to run 10-minute, hydro-servo-aeroelastic numerical simulations and the results are used to train the machine learning model. Load emulation is performed at the foundation-tower interface level. Finally, the surrogate model is validated by comparing the emulated loads from the novel simplified approach against the detailed loads from the numerical assessment of site-specific turbine models at two offshore sites in the North Sea.

INTRODUCTION

The ongoing growth of the offshore wind energy industry has brought forth an increased demand for structural health monitoring (SHM) campaigns that can provide stakeholders with the necessary information to aid important decisions regarding existing wind farms. Among the SHM activities, the fatigue life analysis is of special interest since fatigue loads are often a design driver and thus the project's lifetime is determined by the fatigue loading. Monitoring the utilization of a wind turbine (i.e. the accumulated fatigue load relative to the estimated fatigue loading capacity during design) can open the possibility for project lifetime extension or for more aggressive power harvesting, or alert the need for curtailment [1].

In spite of these potential advantages, offshore wind turbines often lack the necessary instruments to perform an appropriate fatigue load analysis at a farm-wide level. The existing industry practice entails the instrumentation of only a small fraction of wind turbines per farm with SHM measurement systems [2]. Moreover, existing SHM measurement systems are often sparse, making the reliability of the system fragile to a single sensor failure. This practice has been a consequence of the high cost of installation of sensors in the offshore environment [3].

Because of this, there is a high interest from industry and academia for the virtual sensing of fatigue loads. A promising field of research is the use of data-driven machine learning models that estimate short-term damage equivalent loads of 10-minute periods. The advantage of using 10-minute blocks is that they are less labor and memory intense than time series and can be used for long-term monitoring purposes. Neural networks and other machine learning models have been shown to be suitable load emulators for blade [4], jacket foundation [5], monopile foundation [6], and tower loads [7, 8].

Nevertheless, until now the application of machine learning for fatigue load monitoring has been site-specific: training models based on measurements or simulations from only one turbine [9]. While this method produces models which accurately estimate fatigue loads of the learned turbine, the model performance decreases when it is applied to a neighboring turbine. This limitation has precluded the application of virtual sensing for farm-wide SMH purposes.

Herein, a novel approach for training machine learning models that can be applied to any turbine of the same type (i.e. turbines of the same rotor diameter, controller, and foundation type), across different wind farms, is presented. First, the structural models are simplified by identifying the key degrees of freedom which control the dynamic behavior and loading of the wind turbine. After this, the degrees of freedom are used to create a set of hypothetical models by defining different combinations of values for each degree of freedom. Using a hydro-servo-aeroelastic simulation software, a broad set of 10-minute simulations are performed on the models which represent a large variety of potential climate conditions. The results form a training database for the machine learning models, which are later tested on simulation results from site-specific, detailed structural models of a real site.

SIMPLIFIED STRUCTURAL MODELS

A typical structural model of an offshore wind-turbine is the result of a complex, iterative design process which takes into account the site-specific conditions of the location it represents. These include the wind-wave climate, the soil conditions, and water depth, among other factors. In particular, monopile foundation designs may differ greatly for turbines of the same type at different sites. In order to perform 10-minute simulations on

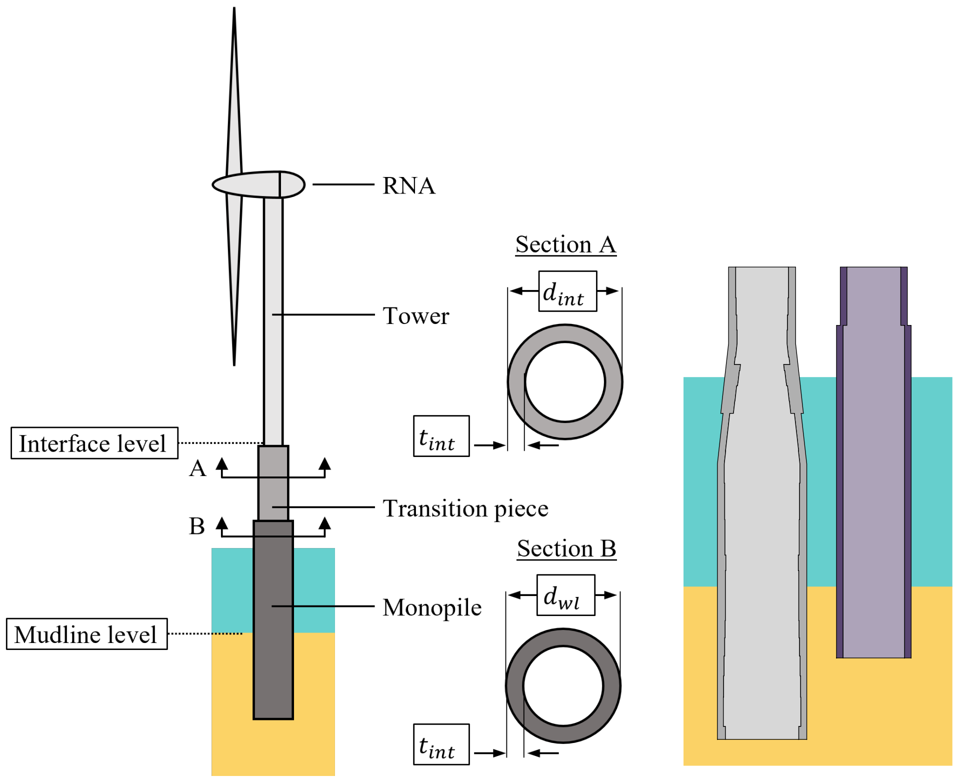

Figure 1. (left) Geometric degrees of freedom (indicated with a box) of an offshore wind turbine with a simplified foundation and (right) comparison between the geometry of a detailed foundation and that of a dynamically-equivalent simplified foundation created based on identical geometric degrees of freedom.

a wide variety of potential sites, it is necessary to substitute the traditional iterative design which yields a representative structural model in favor of a faster and more flexible model generation process.

In the proposed method, the structural model is simplified by defining a set of degrees of freedom which are known to play key roles in determining the fatigue loads of the offshore turbine. The monopile foundation geometry is then defined only in terms of the degrees of freedom, allowing for the quick generation of simplified structural models which can be used for performing 10-minute simulations.

The selected degrees of freedom are illustrated in Figure 1(left). Note that the interface level and mudline level of the bottom-fixed turbine are defined relative to the lowest astronomical tide (LAT). In addition to basic geometric definitions of the foundation, three dynamic properties are considered as degrees of freedom. These are the first eigenfrequency in the fore-aft direction f_1, the structural damping ratio of the first mode ζ_1, as well as a key hydrodynamic parameter referred to as α_{LAT}. This last parameter corresponds to the normalized modal amplitude associated with the first vibration mode at the water level and is known to play a key role in hydrodynamic loading as it is indicative of the energy transmitted to the structure by the waves.

These three dynamic properties are treated as degrees of freedom despite the fact that they are typically a consequence of the geometric definition of the model. This is done for two reasons. Firstly, decoupling the geometric degrees of freedom from the dynamic degrees of freedom helps reduce the modeling error that is introduced by the simplification process. Secondly, treating these dynamic properties as independent from the geometric definition of the model allows for different dynamic properties to be considered based on the same generic geometry. This enables the model to capture the effects of other variables which are not considered as explicit degrees of freedom and variables that carry a large degree of uncertainty in practice (e.g. soil stiffness, soil damping, and structural damping).

The decoupling of dynamic and geometric properties is made possible by a structural tuning algorithm, in which stiffness factors are used to alter the stiffness matrix while at the same time the pile penetration depth is modified to achieve the target f_1 and α_{LAT} combination. At a high level, the resulting model reflects the appropriate contributions of soil, foundation, and tower stiffnesses to the overall stiffness. Separately, the target damping ratio can be achieved by modifying the Rayleigh damping coefficients. In Figure 1(right), a comparison between a detailed foundation design and a dynamically-equivalent simplified foundation is shown. The simplified foundation is created by first adopting the geometric degrees of freedom defined in this section, followed by the structural tuning algorithm, with the dynamic properties of the detailed structure as a target.

Having defined the structural model parametrically based on the degrees of freedom, new simplified models can be generated to represent hypothetical site-specific designs by assigning values to each degree of freedom. A set of 82 simplified structural models was created by sampling each degree of freedom from a pre-defined interval which covers the variability of designs across multiple wind farms of the same turbine type. To conduct the sampling, a quasi-Monte Carlo sampling method based on the Sobol sequence [10] was used due to the space-filling advantages that low discrepancy sequences offer.

DATABASE OF SIMULATIONS

To create a training database for the machine learning model, environmental conditions are assigned to each of the structural models to define the simulation conditions. For this, key environmental degrees of freedom are selected and a probability distribution is assigned to each. The wind environment is modeled with a Weibull distribution representative of sites in the North Sea. For this case, the turbulence intensity is defined as a direct function of the wind speed using the IEC 61400-3 Turbulence Class C. The wave environment is represented in the form of 10-minute significant wave height (H_s) and peak spectral period (T_p). Their values were determined based on wind-wave correlation equations derived from multiple sites in the North Sea. Wind directions from 0 to 360 degrees and wind-wave misalignments from -90 to 90 degrees are considered with uniform distributions. Having defined the wave environment parameters, an in-house wave generation engine is used to create the wave load time series based on the model geometry and wave statistics using the Morison equation and the JONSWAP spectrum [11].

Using this method, 30,000 10-minute simulations were created distributed across the 82 structural models. The relevant result channels are then post-processed into basic 10-minute statistics (minimum, maximum, average, and standard deviation). This follows the current industry practice of data-logging SCADA signals and therefore represents a realistic representation of the data that would be available in real turbines. The standard set of channels include power, pitch angle, rotor speed, wind speed, and nacelle

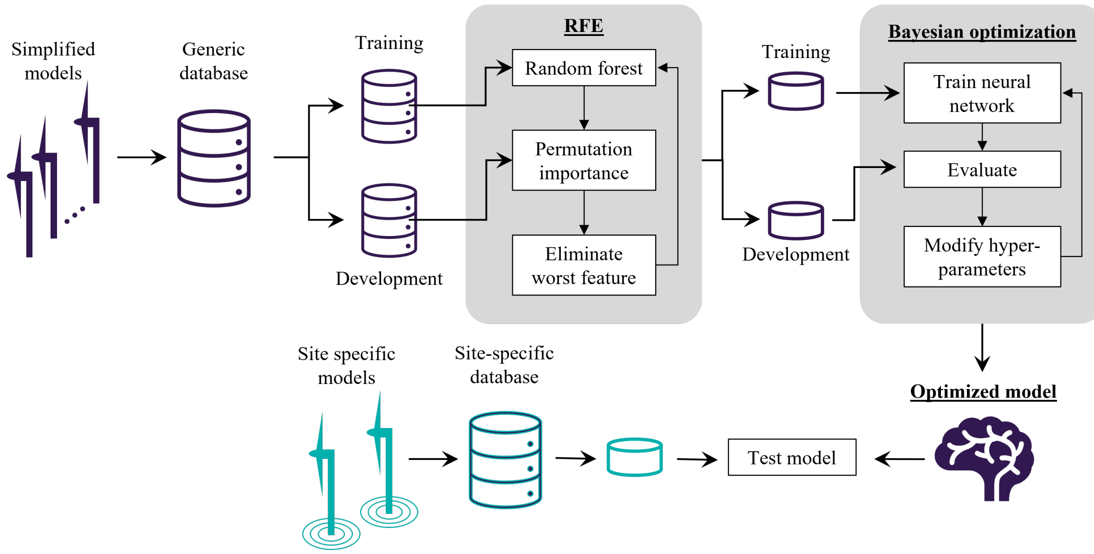

Figure 2. Flowchart of the machine learning methodology.

accelerations. On top of the set of standard signals, dynamic properties (frequency, α, and damping ratio), geometric properties (mudline level, interface level, and external diameter at the water level), and wave statistics are provided as inputs to the model. The bending moment at the interface level (i.e. the target variable) is post-processed into a short-term, damage-equivalent load by means of rainflow counting the fatigue loading cycles and applying Miner's rule with a Wöhler slope of 3.5 [12].

MACHINE LEARNING METHODOLOGY

Having created a database of simulations of a wide range of hypothetical site-specific wind turbine designs and environmental conditions, a machine learning model is trained on this data. A flowchart detailing the entire training, development, and testing process is shown in Figure 2. Prior to training the model, recursive feature elimination (RFE) is performed to eliminate redundant and unnecessary inputs. The RFE is implemented using random forest regression models and the feature importance is measured by the permutation importance [13]. After each round, the least important feature is removed from the dataset. By applying RFE, the number of inputs was decreased by 55%, from 47 to 21 inputs.

Using the selected inputs, a feed-forward neural network was implemented using Tensorflow. The hyper-parameters (e.g. network architecture and learning rate) are selected by means of Bayesian optimization using a Gaussian process. ReLU functions are used for the activation of all hidden layers. The loss function was chosen following a physics informed machine learning approach which includes the influence of the Wöhler slope [14]. During the Bayesian optimization, the neural network is trained for 100 epochs. This was observed in early stages to be sufficient for convergence of the model. Early stopping was considered with a patience of 10 epochs on the validation loss. The optimized model consists of 4 hidden layers with 256 units per layer.

RESULTS

Upon optimizing the neural network, the model is tested on data obtained from similar hydro-servo-aeroelastic 10-minute simulations, however this time the structural models correspond to two real sites, one in the Belgian North Sea (Site 1) and another in the German North Sea (Site 2). The SCADA-like signals of the simulations, wave statistics, and geometric parameters are provided to the neural network for prediction of fatigue loading at the interface level. The model predictions are then compared to the fatigue loading observed during the detailed, site-specific simulation. The results of this comparison are shown in Figure 3. Here, the normalized interface STEL load is plotted against the wind speed. It is seen that the scatter clouds for the neural network model and the detailed simulations closely match each other on both sites. Moreover, the wind speed binned average of the STEL load is nearly identical across the entire wind speed range.

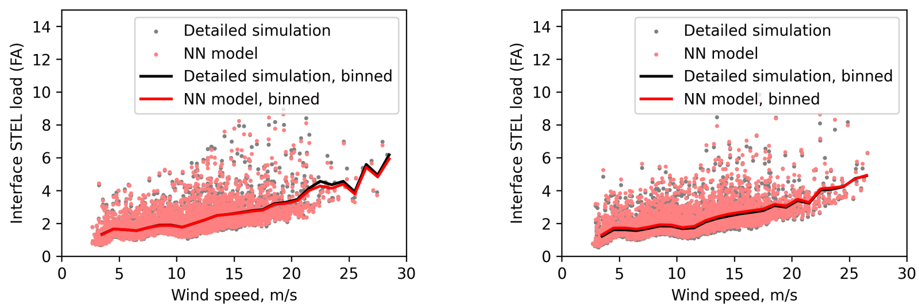

Figure 3. Comparison of the short term equivalent loads obtained through detailed simulation and machine learning load emulation for Site 1 (left), and Site 2 (right).

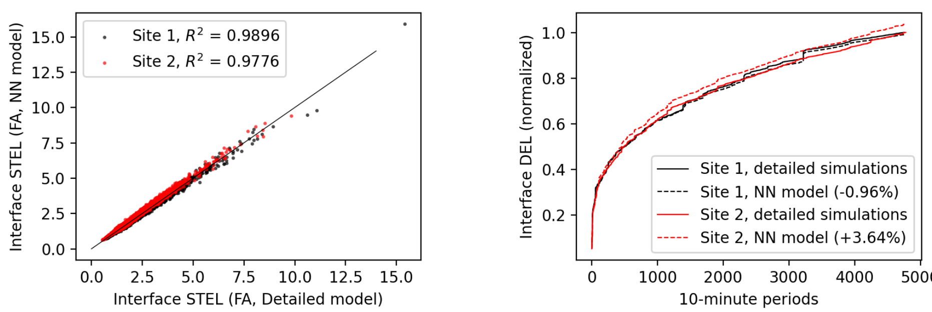

Figure 4. (left) Comparison of 10-minute STELs predicted by the NN model vs the true value obtained from detailed simulation, and (right) comparison of the long-term accumulation of fatigue loading.

In Figure 4(left), the predicted values $\hat{y}$ are plotted against the true values y. Note that the axis values are only indicative of relative scale, as both axes have been normalized by the same arbitrary value. It is seen that, for both sites, the neural network model accurately predicts the STEL. Site 1 shows slightly better performance than Site 2, with a coefficient of determination of 0.9896 and a mean absolute percentage error of 3.24%, opposite to 0.9776 and 5.30% respectively for Site 2. For Site 2, there is a slight tendency of the surrogate model to over-predict, as the scatter cloud lies slightly above the $y = \hat{y}$

line. For Site 1, the scatter cloud lies just below the $y = \hat{y}$ line indicating a small bias for under-prediction.

This behavior is better observed in Figure 4(right), where the aggregation of fatigue loading obtained from the load emulator and the simulations of a (shuffled) set of 10-minute samples is compared. It is seen that for Site 1, the neural network model estimates the long-term, damage-equivalent load within 1%, while Site 2 overestimates by just 3.64%. Recalling that the two sites have different foundation geometry, dynamic properties, and environmental conditions, these results show that the trained load emulator is capable of predicting fatigue loads across a wide range of sites and wind farms of the same turbine type.

CONCLUDING REMARKS

In this paper, a methodology for constructing physics based machine learning load emulators based on simulations for the site-independent virtual sensing of fatigue loads was presented. By the novel approach of training the machine learning model on a database of SCADA-like inputs from multiple structural models obtained through a parametrically defined generation process, the resulting trained model is capable of predicting 10-minute equivalent fatigue loads of new sites with high accuracy. In particular, when tested on simulations of two detailed, site-specific designs in the North Sea, the machine learning model predicted the short-term fatigue load with an average error of 5%. When the short-term loads are aggregated over time, the predicted fatigue load was 0.96% lower (Site 1) and 3.64% higher (Site 2) than the load obtained from simulations. The results show the great potential of this methodology for farm-wide fatigue load emulation and structural health monitoring.

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