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A Machine Learning Approach to Wind Turbine Fragility Analysis: An IEA-15MW Case Study

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ABSTRACT: The objective of this research is to showcase the capacity of Artificial Neural Network (ANN) in modeling intricate non-linear systems. The authors have replaced the BEM theory with ANN to compute the aerodynamic forces acting on wind turbine blades, resulting in a significant reduction in computational time required to compute the wind turbine response. A fragility analysis is performed on the IEA-15MW wind turbine, focusing on the serviceability limit state of foundation tilt. The results demonstrate the importance of considering Soil-Structure Interaction (SSI) in wind turbine design.

1. INTRODUCTION

In the face of growing global warming and energy security concerns, nations worldwide are increasingly turning to renewable energy sources to meet their energy demands. Wind power, in particular, has experienced substantial growth in scale and power generation over the past few decades, with offshore wind turbines playing a pivotal role in driving this expansion. Offshore turbines offer several advantages over onshore turbines, including the ability to be installed on a large scale without disrupting urban environments, access to higher wind speeds and lower turbulence, and, as a result, improved power production. Engineers are designing larger turbines with higher hub heights and longer blades to generate more power to meet the growing demand for renewable energy and lower energy costs. However, as wind turbines increase in size, they become more flexible and vulnerable to the harsh dynamic load environment they experience. This, combined with their low stiffness, makes them dynamically sensitive, which can lead to reduced performance, increased maintenance costs, and even failure. Engineers are exploring new designs and materials to address these challenges, including advanced carbon fibre composites and developing sensors and control systems to monitor and optimize turbine performance in real-time.

The new generation wind turbines face challenges such as higher loads, higher vibration levels and more fatigue damage. In recent years, many failures in wind turbines have been observed (Lin et al., 2016; Ribrant and Bertling, 2007). For a wind turbine transmission system, critical components like the generator, gearbox and blades have the highest failure rates (Tavner et al., 2007). Failure of these components in a wind turbine can result in significant downtime, reduce efficiency, and cause potential safety hazards. Furthermore, different geographical locations and climatic conditions for the same wind turbine can be subjected to different loading configurations, leading to different reliability levels (Tavner et al., 2007). Calibrated partial safety factors can achieve a consistent level of reliability for the structural components in various load conditions. However, not all uncertainties can be captured by partial safety factors. Presently, no explicit target reliability levels are given for the partial safety factors in IEC 61400-3: 2009 (Commission et al., 2009) for Offshore Wind Turbines (OWTs). Consistent operation reliability should be promised to ensure that the wind turbines can be regarded as a reliable energy generation source. Also, implementing a partial safety factor approach for the design of wind turbines may lead to a cost-ineffective design. The probabilistic design of wind turbines addressing the uncertainties in system parameters and reliability evaluation by considering the site-specific condition can ensure more reliable performance.

The probabilistic design of wind turbines entails the evaluation of the structural response at various environmental conditions and uncertain parameters. However, as the dimensionality of the parameter space increases, the amount of data required to represent the problem grows exponentially, leading to a substantial increase in computation time. This challenge, known as the "curse of dimensionality," has hindered the probabilistic design of wind turbines. Researchers have turned to surrogate modelling (Slot et al., 2020; Dimitrov et al., 2018; Li and Caracoglia, 2019) to reduce the computational time involved in response prediction. Surrogate models provide an efficient alternative to complex models, allowing accurate predictions of outputs over a range of input parameters. Gaussian Process Regression models (Slot et al., 2020), Polynomial Chaos Expansion (Dimitrov et al., 2018), and Response Surface methods (Seo et al., 2022) are the most widely used surrogate modelling techniques in wind turbine design. The authors in this study aim to use a more robust Artificial Neural Network (ANN) to reduce the computational time involved in response prediction. In evaluating the response of a wind turbine, a significant computational effort is spent on computing the aerodynamic forces for turbulent inflow conditions. The aerodynamic forces are calculated using the Blade Element Momentum (BEM) theory, which involves an iterative process to predict the angle of attack at each airfoil section used to compute the aerodynamic forces. For a wind turbine, assuming the aerodynamic properties of an airfoil are constant, an ANN algorithm can be trained to replace the BEM theory and improve computational efficiency.

This study aims to conduct a fragility analysis of the IEA-15MW reference wind turbine, which is currently the largest standalone wind turbine. The authors developed a numerical model of the wind turbine using Kane's Dynamics approach (Kane and Levinson, 1985) and validated it against OpenFast, a widely used wind turbine modelling tool. The researchers chose foundation tilt as the limit state for evaluation to underscore the importance of soil-structure interaction, which is often neglected in wind turbine design. Additionally, the study will evaluate the computational advantages gained by replacing Blade Element Momentum (BEM) with Artificial Neural Network (ANN). This methodology can be applied to conduct a more detailed probabilistic analysis for any selected limit state.

2. IEA-15MW WIND TURBINE

The IEA 15MW wind turbine is a reference model for the next generation of offshore wind turbines designed to achieve maximum energy capture. It is a 3-bladed upwind rotor prototype model developed by the International Energy Agency (IEA) and is intended to serve as a benchmark for the design and performance evaluation of future offshore wind turbines. The IEA 15MW wind turbine has a rotor diameter of 240 meters and a hub height of 150 meters, making it the largest standalone wind turbine in the world Gaertner et al. (2020). The key parameters of this wind turbine are included in the table 1, while a detailed description of this model can be found in the official document (Gaertner et al., 2020).

This wind turbine model is designed for both fixed-base and floating configurations. For the fixed-base design, the wind turbine is supported on a monopile with a base diameter of 10m and

Parameter	Value
Power rating	15 MW
Hub height	150 m
Blade length	117 m
Cut-in wind speed	3 m/s
Rated wind speed	10.59 m/s
Cut-out wind speed	25 m/s
Minimum rotor speed	5 rpm
Maximum rotor speed	7.56 rpm

Table 1: Key parameters of the IEA-15MW wind turbine

a thickness of 55mm. The monopile supports the wind turbine loads by mobilising the lateral pressure of the surrounding soil. Proper modelling of the interaction between monopile and soil is crucial for accurate load estimation and life-cycle analysis of a wind turbine. During the design process of the 15MW wind turbine, the effect of soil structure interaction on the performance of the wind turbine is not taken into account. The importance of soil structure interaction is presented in the next section.

3. Soil Structure Interaction

Wind turbines are considered to be dynamically sensitive structures because they are subject to loads that vary with time and can cause significant structural response. The complex and variable nature of wind as an environmental factor and the mechanical properties of the wind turbines themselves means that they are subjected to a wide range of loading conditions that can cause dynamic effects such as vibrations, fatigue, and damage to the structure. As a result, the design of wind turbines requires careful consideration of their dynamic response to environmental loads to ensure their safe and reliable operation. This is particularly concerning for monopile-based wind turbines as they are subjected to a broad range of excitation frequencies due to the environmental loads. To avoid resonance, the wind turbine is to be designed such that its natural frequency should not fall in the range of external excitation frequencies. However, since the natural frequency of a wind turbine is a function of the stiffness offered by the soil strata, change in soil parameters can significantly affect the natural frequency and subsequently the load experienced by the structure (Page et al., 2019). Especially for the variable speed rotor design, there is a very narrow spectrum of "safe natural frequencies" where the wind turbine has to operate to avoid resonance. Therefore, accurate foundation modelling is crucial for accurate life cycle analysis of a wind turbine. Many authors have studied the effect of considering soil-structure interaction on various aspects of wind turbine operations, fatigue life (Damgaard et al., 2015), controller operations (Fitzgerald and Basu, 2016), and damping characteristics (Shirzadeh et al., 2013) are some of them. All these studies conclude that considering the soil-structure interaction effect significantly alters the wind turbine response. From an economic standpoint, foundation manufacturing and installation alone contributes to around 30% of the overall development cost of a wind turbine. Proper modelling and coupled optimisation of the complete structure can help to reduce this cost and subsequently lower the cost of energy

In this study, flexibility at the foundation is modelled by a linear 4x4 stiffness matrix. The effect of axial deformation and twisting of the foundation is not considered. Since the monopile foundation offers a large axial stiffness and the dominant loads are in the lateral direction, the axial rigidity assumption is justified. Also, during normal operation, a wind turbine structure does not induce significant twisting moments at the foundation level so the twisting of the foundation is ignored. The constant stiffness offered by soil in the lateral and rotational direction is calculated using the following methodology presented in the PLAXIS MoDeTo manual. The development of the numerical model used for analysis in this study is presented in the next section.

4. Numerical model of the IEA-15MW Wind Turbine

A multi-body dynamic model of the offshore WT is developed using Kane's method (Kane and Levinson, 1985). Kane's method reduces the labour needed to derive the equations of motion, and these equations are easier to model in a computer programme than earlier classical approaches, such as the Euler-Lagrange method and D'Alembert's principle. The equilibrium equations for a simple holonomic multi-body system using Kane's approach can be stated as :

$$F_r + F_r^* = 0 \tag{1}$$

where F_r stands for the Generalized active forces and F_r^* represent the Inertia force. These forces can be expressed in terms of the kinematic quantities as

$$F_r = \sum_{i=1}^{n} {}^{E}v_r^{X_i} \cdot F^{X_i} + {}^{E}\omega_r^{N_i} \cdot M^{N_i} \tag{2}$$

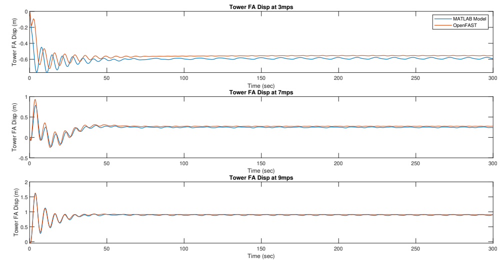
$$F_r^* = -\sum_{i=1}^{n} {}^{E}v_r^{X_i} (m^{N_i}\, {}^{E}a^{X_i}) - {}^{E}\omega_r^{N_i} \cdot {}^{E}\dot{H}^{N_i} \tag{3}$$

where, F^{X_i} is a force vector acting on the centre of mass of point X_i and M^{N_i} is the moment vector acting on the rigid body of N_i. ${}^{E}v_r^{X_i}$ and ${}^{E}\omega_r^{N_i}$ are the partial linear and partial angular velocity of the point X_i and rigid body N_i, respectively. ${}^{E}\dot{H}^{N_i}$ is the time derivative of the angular momentum of rigid body N_i about its centre of mass X_i in the inertial frame, given by the following equation

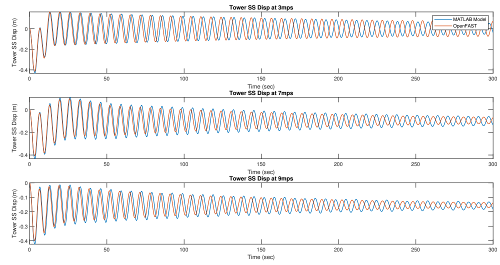
$${}^{E}\dot{H}^{N_i} = \bar{\bar{I}}^{N_i} \cdot {}^{E}\alpha^{N_i} + {}^{E}\omega^{N_i} \times \bar{\bar{I}}^{N_i} \cdot {}^{E}\omega^{N_i} \tag{4}$$

To describe the motion of the offshore wind turbine, a total of 22 degrees of freedom are considered in this study. These DOFs represent platform motion (6DOF), tower deformations (4DOF), and blade deformations (9DOF), along with the Nacelle yaw, Generator azimuth angle and the torsional bending of the drive train. Kinematics of the system are expressed through these DOFs and the equations of motion are derived using Kane's approach. The detailed derivation of the equations of motion is beyond the scope of this work. Interested readers can refer to (Sarkar and Fitzgerald, 2021) for more information.

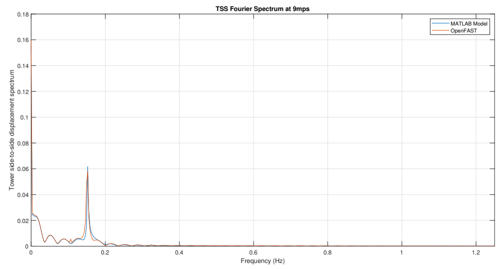
The wind turbine model is benchmarked against the commonly used modelling platform OpenFAST Jason Jonkman (2019), so that further studies can be reliably performed on this model. The model verification results are presented in Figure 1 and Figure 2. The response predicted by the Matlab model is found to be in agreement with the response predicted by the OpenFAST, this establishes the accuracy of the derived model. The wind turbine response at different wind velocities is considered to ensure that the model agreement is consistent across different wind velocities.



(a) Tower FA deformation response



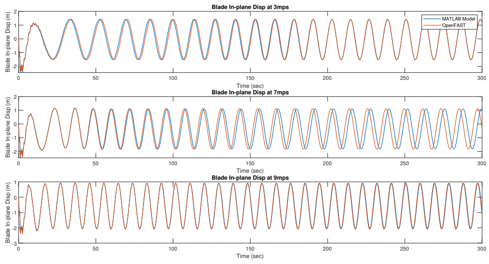
(b) Tower SS deformation response



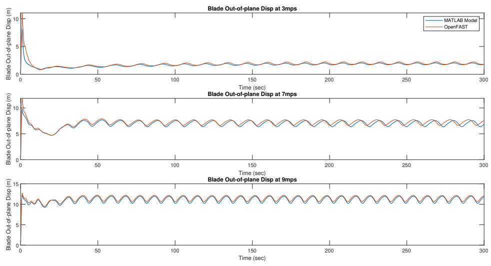
(c) Fourier spectrum of Tower SS response

Figure 1: Model Verification: Comparison of tower response

The current numerical model employs BEM theory to calculate aerodynamic loads. However, a profiler analysis revealed that a considerable amount of computational time is spent on solving the BEM equations. To overcome this limitation, a more efficient machine learning model can be used to replace BEM theory and accelerate the prediction of responses. This approach can facilitate the execution of more simulations necessary for probabilistic analysis. The authors provide a short



(a) Blade in-plane deformations



(b) Blade out of plane deformations

Figure 2: Model Verification: Comparison of blade response

overview of BEM theory in the subsequent section, followed by a description of the methodology used to train the ANN model.

5. Blade Element Momentum Theory

The aerodynamic forces acting on a wind turbine blade are a function of the wind speed, density of air, airfoil dimensions, shape of the blade, angle of attack, and induction factors. The BEM theory is used to compute the induction factors and the angle of attack for the given inflow and the airfoil parameters, which are subsequently used for calculating the aerodynamic forces. The BEM theory combines two different theories: The Blade Element Theory and The Momentum Theory as these theories on their own cannot estimate the aerodynamic forces. The aerodynamic forces acting on a blade are a function of airfoil geometry and the inflow parameters. The Blade Element Theory expresses the aerodynamic forces as the function of airfoil geometry. Using this approach, the equations for the Torque (dQ) and the Thrust (dT) acting at an airfoil section are given as,

$$dT = \frac{1}{2} B\rho U_{rel}^2 \left(C_l cos\phi + C_d sin\phi\right) cdr \qquad (5)$$

$$dQ = \frac{1}{2} B\rho U_{rel}^2 \left(C_l sin\phi - C_d cos\phi\right) crdr \qquad (6)$$

Where B represents the number of wind turbine blades, ρ is the air density, U_{rel} is the relative wind velocity, ϕ is the angle of the relative wind, c is the chord length of the airfoil, and C_l and C_d are the lift and the drag coefficient, respectively. The Momentum theory, however, expresses the Torque (dQ) and the Thrust (dT) as the function of inflow wind parameters. This theory refers to a control volume that extends upstream and downstream of the wind turbine and applies the conservation of angular and linear momentum principle within the control volume such that the change in linear momentum gives rise to the thrust, and the change in angular momentum causes the torque. The equation for the differential torque (dQ) and the differential thrust (dT) obtained from the momentum theory are:

$$dT = \rho U^2 4a(1-a)\pi r dr \qquad (7)$$

$$dQ = \rho U 4a'(1-a)\Omega\pi r^3 dr \qquad (8)$$

Where a and a' represent the axial and tangential induction factors which are the measure of induced linear and tangential wind velocity at the rotor plane, and Ω represent the angular velocity of the wind turbine blades. The remaining symbols carry the usual meanings. Although these theories give the equations for the torque (dQ) and the thrust (dT), none of the theories can compute the forces individually as these theories do not capture the entire dynamics of wind turbine operation independently. The Blade Element Momentum (BEM) theory combines the information from these theories by equating the torque (dQ) and the thrust (dT) estimates of these two theories. The BEM theory expresses the Lift Coefficient (C_l) as the function of the inflow parameters and the operating condition as:

$$C_l = 4sin\phi \frac{cos\phi - \lambda_r sin\phi}{\sigma'(sin\phi + \lambda_r cos\phi)} \qquad (9)$$

This equation is the BEM theory's prediction of the feasible C_l vs α curve for a wind turbine operating at a tip speed ratio (λ_r). However, the lift and drag coefficients for an airfoil is a function of the angle of attack α and the Reynold's numbers. Using this function and BEM theories prediction, the angle of attack (α) can be calculated which can then be used to compute the aerodynamic forces. The BEM theory equations can be solved graphically or numerically using an iterative approach. An efficient method presented in (Ning et al., 2015) is used to solve the BEM equations in this study. The BEM equation is solved along the wind turbine blade for each airfoil cross-section to compute the aerodynamic forces at the particular section; these forces are summed up to get the total aerodynamic force on each wind turbine blade.

6. Artificial Neural Networks

Artificial Neural Networks (ANNs) are a type of machine learning algorithm that are inspired by the Nobel prize work of Hubel and Wiesel (Hubel and Wiesel, 1963, 1962). ANNs are widely used for data classification and regression. ANNs are trained to accurately map the input data x_j to output data y_j, using M-fully connected layers. The training process involves finding the layer parameters (weights and biases) which minimizes the loss-function. The mathematical formulation of ANNs can be described as

$$\underset{A_j}{\text{argmin}} \left(f_M(A_M, ..., f_2(A_2, f_1(A_{1,x})...) + \lambda g(A_j) \right) \tag{10}$$

where A_k denote the parameters of neural network connecting k^{th} layer to $(k+1)^{th}$ layer, $g(A_j)$ is regularization function, λ is regularization strength. This optimization problem is often solved using stochastic gradient descent and back propagation algorithms. Many good texts explaining the fundamentals of neural networks and their application are available (Brunton and Kutz, 2022; Kutz et al., 2016).

In this study, the ANN model is trained to replace the BEM algorithm. TurbSim (Jonkman, 2006) is used to generate the turbulent wind speed time history and the response is evaluated using the numerical model of the 15MW wind turbine. For each turbulent realisation, the angle of attack at each blade node is recorded. The input features are selected such that these parameters should be measurable during actual wind turbine operation. The

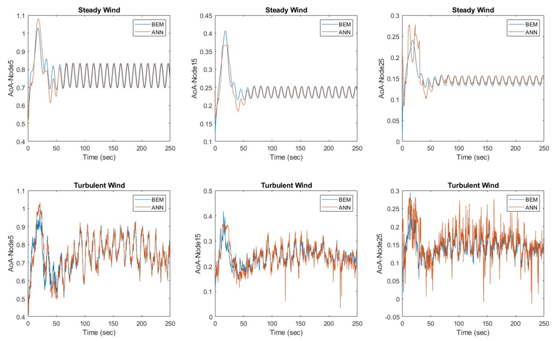
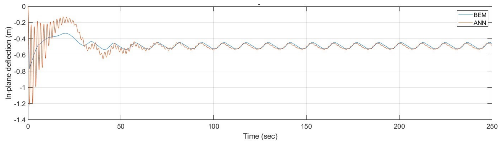
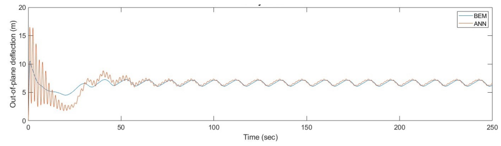


Figure 3: ANN Model Verification: Comparison of Angle of attack

four parameters selected to predict the angle of attack at each blade node are the wind velocity at blade node in x and y direction, the rotor speed, and the rotor azimuth angle. The objective function is selected as a linear combination of squared errors and weights. Using weights to objective function serves as the regularization technique which results in an efficient network which can generalize the data and avoid over-fitting. An optimization routine is first executed such that an optimum balance between accuracy and speed is achieved at the minimum number of neurons per layer. The details of Bayesian optimization routine can be found in (MacKay, 1992; Foresee and Hagan, 1997). The ANN training process is performed using the Statistics and Machine Learning toolbox in Matlab. A 3-layer NN is found to predict the angle of attack with a high accuracy. A R-squared value of more than 0.98 for the test data is achieved at all the blade nodes. The prediction accuracy of ANN model is validated in both steady and turbulent cases. The performance of ANN model at three blade nodes is presented in figure 3. The comparison time history response of wind turbine estimated using BEM and ANN algorithm is presented in figure 4. By replacing the BEM algorithm by ANN model, the overall computational time is reduced by 30%. A far better speed-up can be achieved when using the ANN-model in standalone mode for computing the aerodynamic forces alone.



(a) Blade in-plane deformations



(b) Blade out of plane deformations

Figure 4: ANN Model Verification: Comparison of blade response

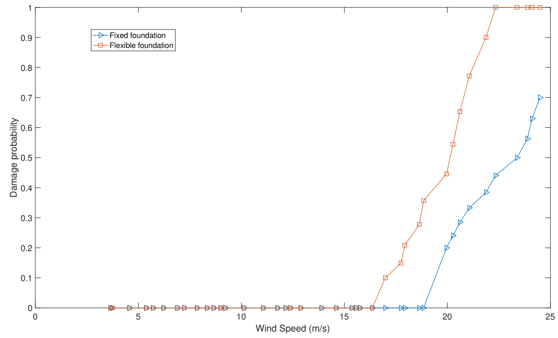


Figure 5: Effect of SSI on serviceability LS of IEA-15MW wind turbine

7. Fragility Analysis

This study focuses on investigating the effect of soil-structure interaction (SSI) on the serviceability limit state of the IEA-15MW wind turbine. The limit state chosen for this study is the rotation at the tower-base, which must be less than 0.5°, including the construction error which ranges from 0.2° to 0.25°, according to DNV guidelines (DNV, 2014; Zuo et al., 2020). The fragility analysis is conducted for wind speeds ranging from cut-in to cut-out wind speeds with a constant turbulence intensity of 10%. The study evaluates wind turbine response for both fixed base and flexible base conditions, where the soil stiffness is computed for a Dense sand with a representative shear modulus of 320GPa. The obtained fragility curves for the serviceability limit state of the IEA-15MW wind turbine in case of fixed base and with consideration of SSI are presented in figure 5. The results show that SSI has a significant impact on the behavior of wind turbines. The methodology used in this study can be further extended to analyze multiple limit states and random variables

8. CONCLUSION

In this research, the effectiveness of Artificial Neural Network (ANN) in modeling a complex non-linear system is demonstrated. The authors provide a brief introduction to the Blade Element Momentum (BEM) theory and emphasize the need for an efficient evaluation of aerodynamic forces in the context of probabilistic design. The use of ANN has resulted in a considerable reduction in computational time. The authors conduct a fragility analysis of an IEA-15MW wind turbine, focusing on the serviceability limit state of foundation tilt. The results of the fragility analysis underscore the importance of considering Soil-Structure Interaction (SSI) in the design process of wind turbines. The primary objective of this study is to showcase the potential of ANN, which could be extended further to carry out a more comprehensive analysis, including multiple limit states and additional random variables.

9. Acknowledgements

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