Offshore Wind Turbine Monopile Monitoring Using Guided Ultrasonic Waves

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ABSTRACT

Following the rapid expansion of offshore wind farms (OWFs) within the next decade many existing OWFs, typically employing monopile supports, will come to the end of their design life. Life extension offers the potential for continued renewable electricity generation at competitive costs. The viability of continued operation can be quantified using fatigue reliability analysis, enabling risk-based decision-making for the life extension of OWFs. This contribution proposes a novel active learning framework with an ensemble of surrogate models, applied to the numerical model of an offshore wind turbine, to predict fatigue reliability. Guided waves can be employed to inspect and monitor inaccessible, submerged, and embedded sections of the wind turbine support, as they can propagate long distances along thin structures such as monopiles. This could allow for the detection of fatigue cracks and corrosion at critical weld locations below the mudline, providing important information for risk-based life extension. Experiments were conducted on a laboratory scale monopile to assess the guided wave propagation and sensitivity for the detection of critical defects. The guided wave data could be combined with wind and wave data to improve the fatigue reliability analysis based on Structural Health Monitoring (SHM).

INTRODUCTION

To meet sustainability targets for the decarbonization of electricity generation, offshore wind turbines (OWTs) play an important role for the shift towards renewable energy [1]. Most existing offshore wind farms (OWFs) have been constructed on monopile supports in shallow to medium water depths. The cyclic wind and wave loads and the harsh marine environment can lead to progressive fatigue damage, necessitating structural integrity assessment [2].

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To reduce lifecycle costs and extend the service life of OWTs, their long-term reliability needs to be verified [3]. Critical regions for fatigue failure due to the repeated stress cycles from the wind and wave loading can be at the circumferential welds below the mudline subjected to the highest bending moments. A comprehensive understanding of material behavior, environmental conditions, and loading uncertainties is required to accurately assess the remaining fatigue life [4].

Time-domain simulations of the OWT behaviour due to varying wind and wave loading are widely used for fatigue assessment, coupled with cumulative damage models such as the Palmgren-Miner rule. However, for long-term reliability assessments these approaches are computationally demanding [5]. Surrogate-based approaches have been employed to achieve more efficient fatigue reliability analysis [6]. These include artificial neural networks, polynomial chaos expansion, the response surface method, and Kriging models [7-9]. However, the employed one-shot sampling techniques with pre-determined training samples do not focus sufficiently on the most important parts of the design space with high uncertainty and close to failure boundaries, potentially compromising efficiency and accuracy [10]. Especially for the fatigue damage prediction of OWTs with varying environmental conditions, single surrogate model can be limited in correctly taking into account inherent complex and nonlinear effects [11]. Employing an ensemble of surrogate models can take advantage of their complementary strengths. Combining different surrogate models, e.g., Bayesian Support Vector Regression (BSVR) [12], Kriging [7], and Polynomial Chaos Kriging (PCK) [13], can enhance the robustness and accuracy of failure prediction. Active learning strategies can be used to focus on critical regions by iteratively selecting training samples in areas of high uncertainty. Combining ensemble of surrogate models and active learning can help to achieve accurate and efficient fatigue reliability analysis of OWTs.

Guided waves can be employed for fatigue and corrosion damage detection in a Structural Health Monitoring (SHM) approach, as they can propagate long distances along thin-walled large structures [14]. Using a similar methodology to pipeline inspection, defects in the difficult-to-access submerged and embedded monopile sections could be detected from sensor locations close to the transition piece. The guided wave SHM data could be used to update probabilistic fatigue models. This in turn would improve failure prediction accuracy and proactive maintenance strategies, enabling data driven life extension of OWFs [15]. This paper outlines a possible approach to integrate guided wave SHM with an adaptive ensemble of surrogate model to enhance fatigue life prediction of monopile-supported OWTs. The following sections provide an overview of the development of the adaptive ensemble of surrogate modelling approach for a numerical OWT model and guided wave experiments on laboratory scale welded monopile prototypes.

ADAPTIVE ENSEMBLE OF SURROGATES MODEL

An adaptive ensemble of surrogate (AEOS) model was developed, combining three surrogate models (PCK, Kriging, BSVR), as outlined in [15]. Each surrogate model is assigned a weight at each iteration step for its contribution to the overall model prediction, based on a combination of both global and local error.

A learning function allocation strategy based on reward according to performance in previous steps was employed, adjusting the selection based on performance in identifying informative samples to improve model accuracy. The learning function rewards sample selection in regions with high probability density and near to the limit state surface but prevents clustering of sample points, important to improve the computational efficiency [16, 17]. In each iteration two samples were added and failure probability calculated using Monte Carlo Simulation (MCS).

OWT MODEL FATIGUE ANALYSIS

The NREL 5 MW monopile-supported reference OWT [18] was used as a numerical model for fatigue analysis, as shown in Fig. 1. The Finite Element Analysis (FEA) used Euler-Bernoulli beam elements to represent the OWT tower and monopile [19]. Structural and soil damping were approximated as Rayleigh damping. The nacelle was assumed as a lumped mass at the top of the tower. Lateral soil springs were implemented based on *p*-*y* curves to approximate soil-structure integration along the embedded sections of the monopile. Unsteady blade element momentum (BEM) theory was used to calculate the aerodynamic forces on the wind turbine blade, and Morison's equation for the forces due to wave loading.

The derivation of the equations of motion for the coupled OWT system is described in more detail in [19]. The aerodynamic rotor forces calculated using BEM were linearized at the top at the tower as an aerodynamic damping matrix and decoupled. This reduces computational cost without compromising the accuracy of the fatigue life predictions. The numerical model was computed using the HHT-α method (extension of the Newmark-β method) with good numerical stability and efficiency, as detailed previously [19].

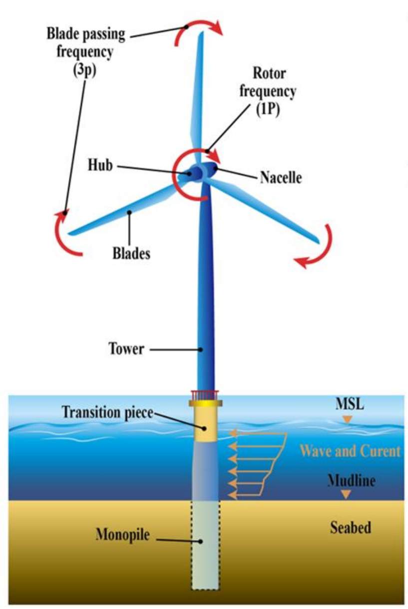

Figure 1. Schematic of considered 5 MW monopile-supported reference OWT model.

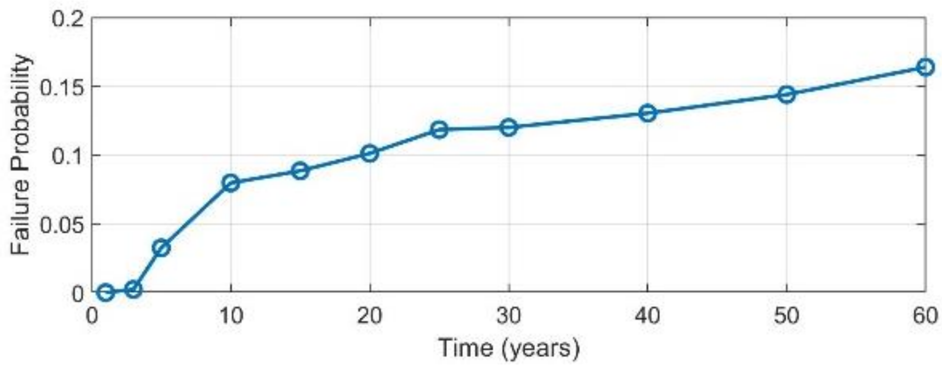

Figure 2. Predicted fatigue failure probability of OWT over time.

To calculate OWT fatigue reliability, the performance function over years of operation was calculated according to [4], for an assumed distribution of parameters [15]. The FEA model was used to calculate stress time series. Stress cycles were assessed from rainflow counting, and fatigue life estimated from *S-N* curves. The change of cumulative damage with time was evaluated using the Palmgren-Miner rule. At 20 years, calculation of the reference result using importance sampling gave a failure probability of 0.1159 with a coefficient of variation of 2.5%. This required 2753 FEA simulations and approximately 40h computational time. The developed AEOS model gave a very accurate failure prediction (0.17% error) but required only 40 minutes to compute 42 FEA simulations, providing significant computation time reduction.

Figure 2 shows the change of the predicted fatigue failure probability with time, There is a consistent increase in failure probability from almost zero initially to 0.16 at 60 years. The most significant increase happens up to year 10, with the rate of increase slowing afterwards, indicating degradation of the structural capacity at a reduced rate. The developed adaptive ensemble of surrogates (AEOS) methodology allows for the fast and accurate prediction of reliability and can be updated with monitoring data to allow for the safe life extension of OWFs.

GUIDED WAVE MONITORING OF OWT PROTOTYPE

Guided waves can propagate long distances along large and thin structures [20], such as OWT monopiles. This could allow for the monitoring of developing fatigue cracks and corrosion in the embedded sections of the monopile from permanently installed guided wave transducers below the transition piece between the monopile and tower. Combining such data with reliability analysis could help to improve the characterization of the remaining useful life (RUL) for OWF life extension.

Proof of principle experiments were conducted on scaled prototypes in the laboratory (Fig. 3) to understand the guided wave propagation across multiple welds and wall thickness changes and to estimate the sensitivity for defect monitoring. Preliminary measurements using a laboratory setup [14] were done, exciting the guided wave using a piezoelectric transducer and measuring along an axial line of the welded steel prototypes.

Figure 3. Photograph of laboratory scale monopile prototypes.

Figure 4 (left) shows a typical measured guided wave time signal and its envelope at a single monitoring location, with incident and reflected wave guided wave pulse visible. Laser measurements were conducted with a 1 mm step along the monopile prototype and the data analyzed using 2D Fast Fourier Transform (FFT) in Matlab. Figure 4 (right) shows the dispersion curve overlaid on the 2D FFT magnitude. Both the incident and a reflected guided wave pulse can be observed and analyzed to obtain reflection characteristics at different types of features.

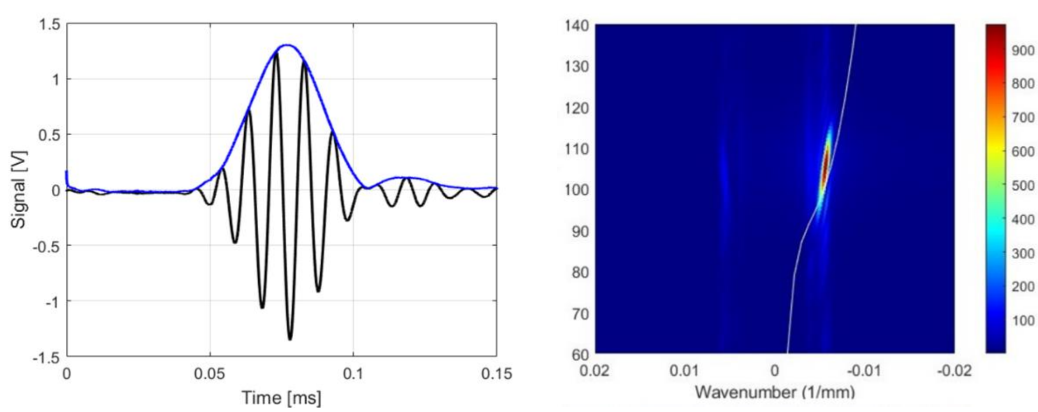

Figure 4. Left: measured guided wave time trace with envelope at one measurement location; right: 2D FFT showing incident and reflected wave with dispersion curve overlaid.

CONCLUSIONS

In the context of offshore wind farm life extension, the fatigue reliability of offshore wind turbines must be assessed. Using an adaptive ensemble of surrogate models (AEOS) the change of failure probability with time can be predicted accurately and efficiently. Guided wave monitoring of inaccessible parts of the OWT monopile, as demonstrated for a laboratory scaled prototype, could provide SHM data for integration with the probabilistic fatigue analysis to enable improved risk-informed decision-making and to guide proactive maintenance strategies.

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