Physics-informed machine learning for rapid fatigue assessments in offshore wind farms

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Introduction

Offshore wind turbine lifespan is dependent on the fatigue of parts and structural components including the monopile due to repeated cyclic loading from wind and waves. Fatigue failure predictions are fundamental during design of wind farms, although rapid assessment of cumulative fatigue throughout the lifespan is limited. Advancements in the temporal accuracy and speed in estimating monopile fatigue aid tactical operation and maintenance decision, and can support life extension assessments [1].

Monopile fatigue can be evaluated through aero-hydro-servo-elastic numerical modelling simulations encompassing many variables, with the environmental hydro-dynamic and meteorological conditions being principle variables. Due to the complex nature of real-world conditions, numerical modelling can require a degree of simplification. For example, higher-order wave kinematics are noted within industry standards [2] due to resonance effects, yet are commonly omitted in the majority of academic research. This can result in an underestimation of structural loading and fatigue [3, 4], notably when the turbine is parked [3], although when operational the aerodynamic loading is of greater importance. Furthermore, in-situ environmental measurements are commonly 'lumped' to reduce the number of representative loading cases (wind-wave scenarios) thus minimising the computational demand [5, 6, 7, 8]. Lumped data and corresponding probabilities need to maintain representation of the equivalent damage load associated with the full dataset as best as possible. Data lumping provides a reasonable approach to reducing computation time while obtaining an reasonable indication of fatigue, yet the simplifications produce a degree of error [8], and omit wave frequencies close to the structures eigenfrequencies that are critical for resonance effects.

Meta-models and statistical regression have been employed to reduce simulation demands while maintaining accuracy [9,10,11]. The simplification of environmental conditions proves successful in determining bulk fatigue loads, yet offer limited benefit when evaluating short time-frame and continuous temporal fatigue information. Recently, structural monitoring of turbines has implemented machine learning (see review by Stetco et al. [12]), including the use of artificial neural networks to evaluate offshore wind turbine

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foundation damage using data-driven approaches [13]. While data-driven approaches are advantageous, turbine specific accelerometer data is not always available.

This project set out to develop a novel approach that integrates physics-based modelling and machine learning to predict monopile damage based on basic met-ocean data.

Project Aims and Objectives

The aim of this project was to quickly and accurately forecast offshore wind turbine fatigue at wind farm scale, including nonlinear wave loading-induced resonance. We set out to address this through three main objectives:

Objective 1: Create a library and meta-model for customised nonlinear time series of environmental conditions, making fully nonlinear wave kinematics industry-accessible.

Objective 2: Assess accumulated fatigue sensitivity to a range of environmental and operational conditions, identifying critical cases that would inform and improve efficiency of the fatigue risk model.

Objective 3: Develop a predictive physics-informed machine learner for lifetime fatigue risk on wind farm scale. The proposed objectives will facilitate future research and joint industry projects to address the wind farm scale effects and their integration in efficient lifetime fatigue models.

Summary of Work Conducted

This section reports achievements across all three work packages: Environmental conditions (WP1), Fatigue Sensitivity (WP2) and Risk Forecast Model (W3).

WP1: Environmental conditions

Non-linear wave kinematics were simulated in a fully non-linear fashion using the Higher-Order Boundary Element Method (HOBEM) library. This process was facilitated by the University of Hull's HPC system Viper, using six different seeds for simulation in line with industry standards (IEC 61400-3). The resulting dataset covered a total of 381 different sea states with significantly varying wave heights and peak period in 30 meters deep water. The parameters for this simulation were defined based on the span of conditions recorded within the FINO-1 offshore dataset [2]. This is illustrated in Figure 1 on the right. Twenty-five wind conditions were also simulated using TurbSIM, to provide turbulent flow fields based on mean hub height velocities spanning from 0 to 25 ms^{-1}.

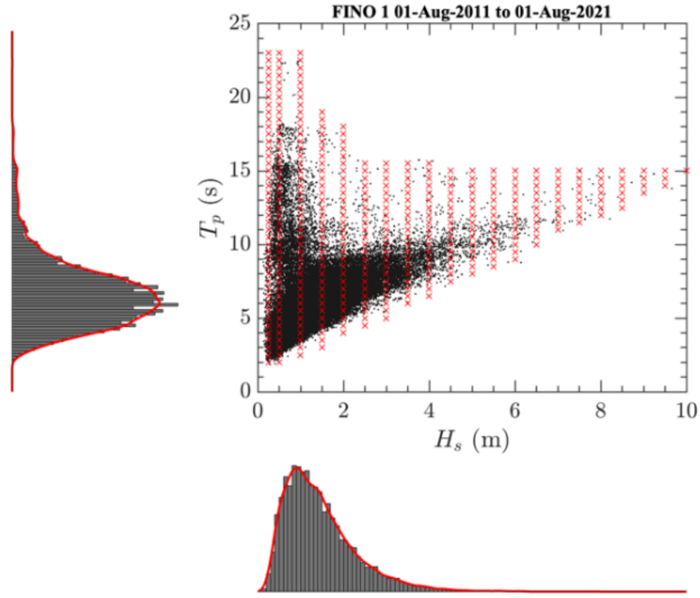

Fig 1: Fino-1 North Sea hourly wave conditions from August 2011 to August 2021. Red crosses indicate the simulated sea states using HOBEM to define the environmental conditions library.

WP2: Fatigue Sensitivity

Numerical simulations were conducted in this WP using the aero-hydro-elastic-servo simulation software FAST(v7) [14] to obtain the monopile mudline fore-aft bending moment (My) for the reference NREL-5MW wind turbine [15] with OC3 monopile foundations [18] in 30 m water depth. The monopile was modelled as rigidly fixed to the seabed, and two turbine operational conditions were simulated, power-producing (operational) or parked, whereby the appropriate blade pitch and rotor speed were applied [15]. As per IEC 61400-3 design standards [16] six 10-minute numerical simulations were conducted with different wind and wave seeds for each combination of sea state (n. 381), wind speed (n. 25), and operational condition (n. 2), resulting in the output of My for 114,300 environmental-operational scenario time series. This is conducted for both linear and fully non-linear wave kinematics. An example time series of M_y for a given scenario is presented in Figure 1a, for which rainflow counting techniques and Miner's rule are applied to determine the associated fatigue and damage equivalent load. Time-domain simulations of M_y are used to determine the associated monopile damage fraction for each environmental-operational condition using a time-domain approach [17].

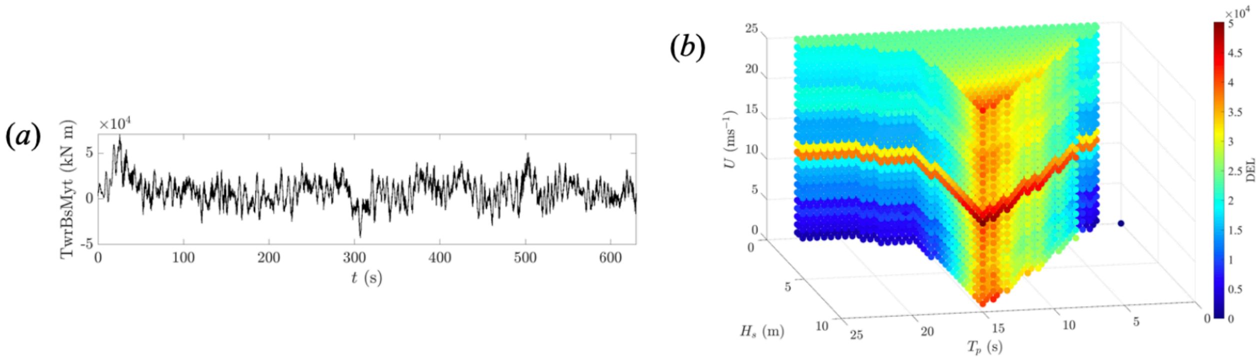

Fig 2: *(a) Example tower fore-aft mudline bending moment output from areo-hydro-elastic-servo simulator (FASTv7), damage is subsequently estimated using rainflow-counting methods. (b) Monopile Damage Equivalent Load (DEL) for simulations based on the NREL-5MW monopile wind turbine during operational conditions.*

WP3: Risk Forecast Model

Based on the outputted fatigue damage datasets for each environmental and operational condition, a machine learning meta-model was then developed based on Convolutional Neural Networks (CNN), in the first instance. This process requires some trial and error to determine the most appropriate layers and parameters required to obtain the lowest validation error. A simplified representation of the model architecture is depicted in Figure 3a. The model test results are presented in Figure 3b, and demonstrate the capability of the model to provide a reasonable prediction across the full range of Damage Equivalent Loads simulated. The model was subsequently retrained based on the direct stress outputs, as opposed to equivalent loads, enabling forthcoming capacity to implement lifetime damage estimations.

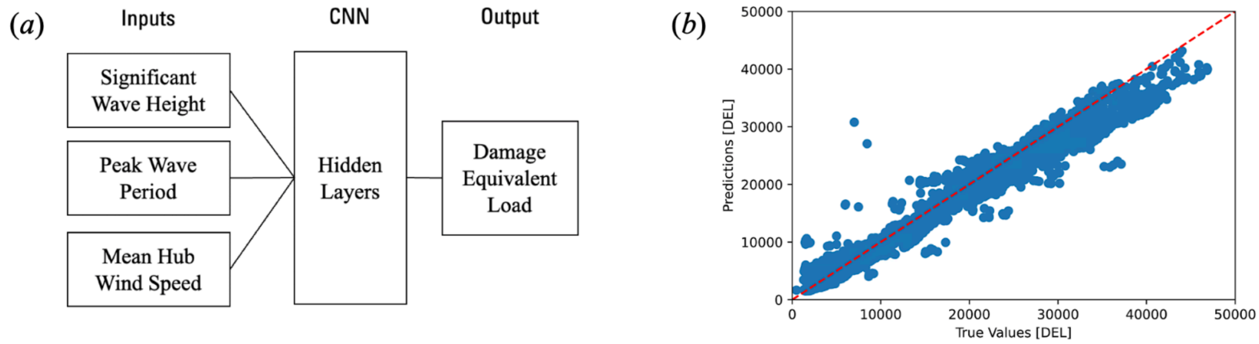

Fig 3: *(a) Convolutional Neural Network (CNN) model architecture for monopile Damage Equivalent Load (DEL) prediction for various ECs and OCs. (b) Test data results for the machine learning model, true simulated DEL values against machine-learnt DEL predictions.*

The deep learning model used was a CNN with a single convolutional and max pooling layer, using 64 filters and a kernel size of 7, two dense layers (with 64 and 32 units), a ReLU activation and an Adam optimiser with mean-squared error loss function. Dropout was applied on our max pooling layer (0.2) and the first dense layer (0.1). The model was trained over 100 epochs with a batch size of 64. The training inputs and outputs were normalised and implemented with a random train-test split of 80%-20%.

Project Results

We generated results in three areas: (i) the assessment of short-term monopile damage including the influence of wave nonlinearities; (ii) accumulated damage using a traditional lumping method; and (iii) the development of a machine learning-based meta-model.

Assessment of short-term damage — We can see from Figure 4a that when the turbine is parked, the effect of wind speed is negligible and the influence of wave properties dominate. Here, larger significant wave heights correspond with the greatest damage. This is indicated by the distribution of the red scatter plot being skewed significantly

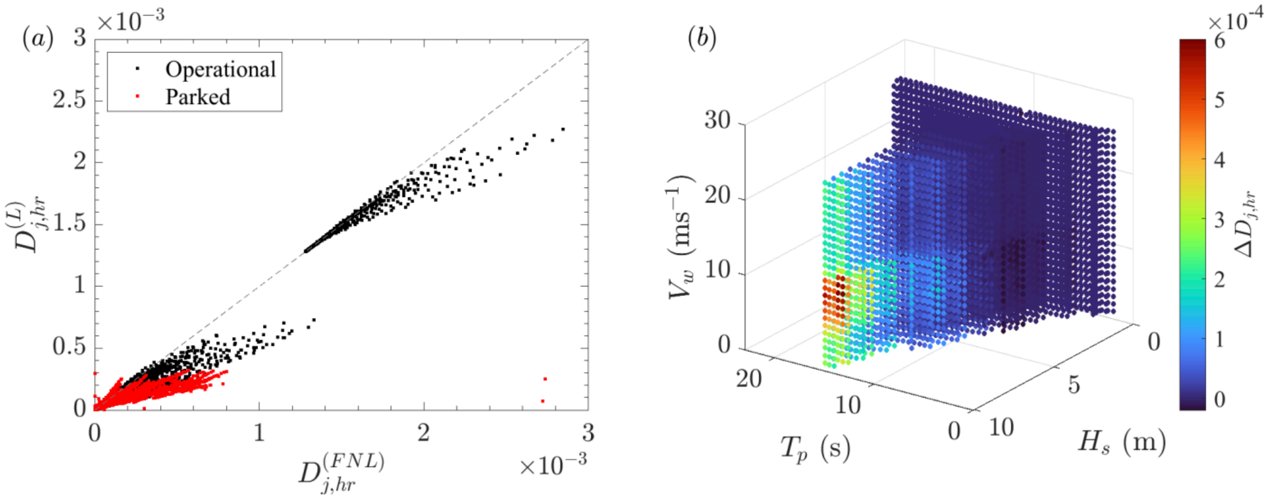

Fig 4: (a) Comparison of environmental condition hourly damage fractions $D_{j,hr}$ for fully non-linear (FNL) and linear (L) wave kinematics for operational (black) and parked (red) conditions, and (b) the difference in hourly damage $\Delta D_{j,hr}$ between FNL and L wave kinematics when the turbine in operational, plotted over wind speed (V_w), wave period (T_p) and wave height (H_s).

towards larger FNL values. Similar (although less severe) behaviour is also seen in operational conditions. This identified the conditions that are wind- rather than wave-dominant. A deeper insight into the operational conditions is given in Figure 4b, showing the distribution of the difference between damage from fully nonlinear and linear waves. Here it can be seen that the importance of wave nonlinearities increases at larger magnitude peak wave heights. Although, when the turbine is operational, there is an additional dependence on the wind speed, with the largest damage difference occurring at the turbine rated wind speed and slightly lower (Figure 2b).

Accumulated damage — Here our results shows showed that the accumulated damage over an example year is remarkably close when comparing the use of linear and fully non-linear waves kinematics, with a difference of only 0.71%. Inspection of the loading cases revealed differences of up to 7%. It was previously shown that that the inclusion of fully non-linear wave kinematics is most critical at larger significant wave heights, yet lumped load cases did include significant wave heights over 5 m. Given the conditions associated with higher magnitude damage are not discretely included in lumping methods, we hypothesised that this may result in an underestimation of accumulated damage. These findings motivated the use of fully non-linear waves in the application of the previously introduced CNN meta-model (WP3) and the use of hourly data to provide more accurate temporal damage estimations.

Machine learning meta-model — The cumulative damage throughout the example year determined by the meta-model demonstrated good agreement with the data lumping approach. This supports the traditional data lumping approaches for an operational turbine, yet the effects of downtime and parked turbines on accumulated damage values requires further evaluation. Fundamentally, the results offer a promising new approach to obtaining high temporal frequency updates on monopile damage through the use of a meta-model.

Summary of Dissemination and External Engagement

We held two stakeholder workshops during the project, on for kick-off in August 2021 and one to update the partners and consult on ongoing issues at mid-term.

Individual conversations on project requirements took place with partner Eleven-I in the scope of the Aura CDT Conference in Hull in September 2021; and further engagement took place to further explore suitable approaches to conduct physical modelling experiments that will support cross-comparison on numerical simulation results in January 2022.

Communication with partner TECOSIM has been continuous and intensified during the final three months with the aim of exploring suitable approaches for cross-comparison of fatigue results.

Project progress was presented at the Supergen 4th Annual Assembly, with the project receiving 1st prize in the poster competition.

A paper summarising project results was accepted for oral presentation and publication at the European Workshop on Structural Health Monitoring (EWSHM).

We also ran a Hackathon on AI for Sustainability in March 2022, funded through a NERC Discipline Hopping grant, and features this projects as one of three for participants to work on. The event was attended by about 30 undergraduate and postgraduate students, who collaborated to developed a set off additional machine learning baselines.

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