# Rapid assessment of offshore monopile fatigue using machine learning

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Abstract. Offshore wind turbine monopiles require structural health monitoring throughout their lifespan, yet direct structural measurements are limited. This paper combines numerical modeling and machine learning to present an approach to obtain rapid estimations of monopile fatigue using hourly metocean conditions. Aero-hydro-servo-elastic numerical simulations for a reference turbine provide the meta-model training dataset that encompasses wind-wave conditions applicable to the North Sea. Analysis reveals conditions whereby higher-order fully non-linear wave kinematics produce larger damage values compared to linear waves. This increase in damage is absent when implementing a simple probabilistic data lumping method. The prototype meta-model is developed based on convolutional neural networks to determine the monopile damage from measured wind-wave conditions at high temporal frequency. The proof-of-concept meta-model provides a step-change that demonstrates a promising approach to estimate monopile fatigue accumulation at high temporal resolution with scope for development to specific real-world offshore wind farms where validation data is available.

Keywords: Offshore wind  $\cdot$  Monopile fatigue  $\cdot$  Damage fraction  $\cdot$  Non-linear waves  $\cdot$  Machine learning.

# 1 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 [28].

Monopile fatigue can be evaluated through aero-hydro-servo-elastic numerical modeling simulations encompassing many variables, with the environmental hydrodynamic and meteorological conditions being principle variables. Due to the complex nature of real-world conditions, numerical modeling 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 [14, 27], notably when the turbine is parked [14], 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. This data sampling can be conducted through various principle techniques, Kühn [13] presented an iterative damage-equivalent approach based on probability occurrence, Seidel [23] implemented a frequency domain approach, while recent advances include consideration of the turbine dynamics through damage-equivalent contour lines [19, 12]. 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 [12], 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 [30, 17, 5]. 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. [24]), including the use of artificial neural networks to evaluate offshore wind turbine foundation damage using data-driven approaches [18]. While data-driven approaches are advantageous, turbine specific accelerometer data is not always available, thus physics based modeling and machine learning is explored herein to develop an approach towards predicting monopile damage based on basic metocean data.

This paper presents a proof-of-concept application of deep learning to enable rapid estimation of short-term monopile damage and the accumulated damage throughout the lifespan. An exemplar metocean dataset is used to evaluate the influence of fully non-linear (FNL) versus linear (L) wave kinematics on damage accumulation using a traditional data lumping method, followed by comparison with the meta-model estimations. The presented meta-model shows promise in accurately representing the numerically simulated fatigue, although cross-validation of the damage values against direct measurements is required to compliment and evaluate the simulated damage accuracy.



Fig. 1. Processes and outputs associated with development of the meta-model.

# 2 Methods

Numerical simulations of a reference turbine provide monopile fatigue damage values for an extensive range of aero- and hydro- dynamic stochastic representations, forming the meta-model training data. The workflow is presented in Figure 1.

#### 2.1 Areo-hydro-sevo-elastic simulations

Firstly, the input environmental kinematic datasets were generated. Kinematic flowfields of fully non-linear waves were simulated using Higher-Order Boundary Element Method (HOBEM) [15] for 381 sea states with peak periods ( $T_p = [2, 23]$  s) and significant wave heights ( $H_s = [0.25, 10]$  m) in 30 m deep waters, encompassing measured conditions at the North Sea FINO1 research platform [4] between August 2011-2021. Simulation of sea states that extend into breaking wave regime were smoothed, thus the simulated  $H_s$  is recalculated. Complimentary linear wave kinematic simulations provide comparative insight. Turbulent wind flow fields are simulated using TurbSIM [8], with mean hub height wind speed ( $V_h = [0, 25]$  ms<sup>-1</sup>) according to Kaimal model with turbulence intensity A, as per IEC 61400-3 design standards [7].

Numerical simulations were conducted using the aero-hydro-elastic-servo simulation software FAST(v7) [11] to obtain the monopile mulline fore-aft bending moment  $(M_y)$  for the reference NREL-5MW wind turbine [9] with OC3 monopile foundations [10] in 30 m water depth. The monopile was modeled as rigidly fixed to the

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seabed, and two turbine operational conditions were simulated, power-producing (operational) or parked, whereby the appropriate blade pitch and rotor speed were applied [9]. The wind and waves were co-directional and mean currents neglected given that the loading is predominately wave driven [20]. Additional damage load case simulations including start-up, shut-down, and fault conditions required for design standard [7] are not considered herein during the initial meta-model development.

As per IEC 61400-3 design standards [7] 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  $M_y$  for 114,300 environmental-operational scenario time series. This is conducted for both linear and fully non-linear wave kinematics. An initial additional transient 30second run-in period was simulated but excluded from analysis. The 6×10min series are appended to one-another to establish a 1-hour long series prior to fatigue calculations [6]. This approach follows recommended design requirements for stochastic realisations [7] and mitigates any potential modeling bias effects due to a specific singular signal seeding, while increasing the statistical convergence [16, 25, 29].

#### 2.2 Damage and fatigue calculations

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 [21]. The  $M_y$  time-series is converted to the approximate direct stress,  $\sigma = (M_y^2)^{0.5}/S$ , given the section modulus of a hollow cylinder,  $S = \pi (d_o^4 - d_i^4)/(32d_o)$ , and  $d_o$  and  $d_i$  are the cylinder outer and inner diameters respectively. This simplified approach is conservative due to assessment of one axis and omission of directional dependence [5], justified by the simulated uni-directional environmental loading.

The varying amplitude of stress time-series recorded for each environmentaloperational scenario, denoted as j, are evaluated using rainflow cycle-counting techniques and linear damage accumulation based on the Palmgren-Miner rule [21], resulting in the associated damage fraction:

$$D_j = \sum_{i=1}^{N_c} \frac{n_i}{N_i} \tag{1}$$

whereby  $N_c$  is the total number of stress amplitude bins,  $n_i$  is the number of cycles recorded in a given stress range bin (i), and  $N_i$  is the cycle limit of fatigue failure for the given stress range bin based on a given S-N curve. An S-N curve for transverse welds with detail of 71 MPa including the appropriate thickness reduction factor as per guidelines are implemented [3], which is suitable for monopile welds [5]. Fatigue failure occurs when the damage fraction summation over time reaches unity.

The damage fraction associated with an hour long time-series  $D_{j,hr}$  for each environmental-operational scenario is obtained by appending six 10-minute simula-

tions. To provide clarity on the explicit methods in design standards [7], comparable values are obtained when taking the average of the six 10-minuet simulations and multiplying this value by six  $D_{j,(6\times10\text{min})}$ ; whereby assessment of data within this study shows a near 1:1 relationship of  $D_{j,hr} = 1.013D_{j,(6\times10\text{min})}$  valid for (0, 0.0028).

It is noted the reported damage fraction values in this study are disproportionately large due to extrapolation of a monopile diameter designed for 20 m water depth to 30 m [26]. Further, resonance effects associated with the generator motion and the second fore-aft tower bending mode increase the cyclic loading. Nevertheless, the approach supports the development of the model and assessment of damage accumulation due to the influence of fully non-linear waves over a shorter duration.

# 3 Results

This section presents the initial results of this ongoing development of a meta-model for monopile fatigue estimating. The results focus on the assessment of the short-term damage including the influence of wave nonlinearities ( $\S3.1$ ), accumulated damage using a traditional lumping method ( $\S3.2$ ), the development of the machine learning based meta-model ( $\S3.3$ ) and initial results of its application ( $\S3.4$ ).

#### 3.1 Short-term damage

Figure 2a presents the damage fraction based on the simulated datasets for linear and fully non-linear waves under comparable wind-wave properties, for both parked and operational turbine conditions. When the turbine is parked, the effect of wind speed is negligible and the influence of wave properties dominate, whereby larger significant wave heights correspond with the greatest damage. This is indicated by the distribution of the red scatter plot being skewed significantly towards larger FNL values. Similar, although less severe, behaviour is also seen in operational conditions. The larger magnitude cluster of damage values in Figure 2a show a significant peak in the overall damage value occurring in the region of 1.3 to  $3 \times 10^{-3}$  corresponds to the values around the rate wind speed, regardless of wave conditions. This identified the conditions that are wind- rather than wave-dominant.

A deeper insight into the operational conditions is given in Figure 2b, showing the distribution of the difference between damage from fully nonlinear and linear waves,  $\Delta D_{j,hr} = D_{j,hr}^{(FNL)} - D_{j,hr}^{(L)}$ , for operational conditions across the wind speed, wave period, and wave height. Here it can be seen that the importance of wave nonlinearities increases at larger magnitude peak wave heights. This is also valid for the parked turbine conditions (not shown). 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).



**Fig. 2.** (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  $(H_s)$ .

While the relatively calm environmental conditions result in comparable values regardless of the simulation wave kinematics, fully non-linear wave kinematics result in greater damage as wave conditions become increasingly rough, even more so for parked turbine, congruent with previous research [14, 22, 27]. These results indicate that linear wave kinematics will result in an underestimation of accumulated damage over time, and therefore the wave kinematic data simulated with fully non-linear model is implemented in the development of the meta-model described in this paper.

#### 3.2 Accumulated damage

The accumulated damage between linear and fully non-linear waves is compared using measured environmental data over 1-year period (31-Aug-2019 to -2020) from research platform FINO1. Wave and wind data was re-sampled to produce corresponding hourly averages, and lumped based on Kühn [13] following preservation of wave height given that wave height was determined as the leading characteristic in §3.1. A worked example is given in [1]. Data above 26 ms<sup>-1</sup> is omitted herein due to insufficient measurements to accurately determine representative loading conditions.

The data lumped into 13 load cases is presented in Table 1, along with their probability. Additional numerical simulations as per methods in §2 provide the corresponding damage fraction values given in Table 1. The turbine is considered operational when wind speeds are within the cut-in  $(3 \text{ ms}^{-1})$  and cut-out  $(25 \text{ ms}^{-1})$  limits of the reference turbine, thus fault and maintenance downtime effects are absent.

Load	$V_h$	$H_s$	$T_p$	%/year	$D_{j,year}^{(FNL)}$	$D_{j,year}^{\left(L ight)}$	%diff.
Case							
1	2	1.04	4.68	9.05	$5.91 \times 10^{-3}$	$6.22 \times 10^{-3}$	5.09
2	4	1.20	5.15	17.51	$1.44 \times 10^{-2}$	$1.51 \times 10^{-2}$	5.24
3	6	1.42	5.82	18.80	$7.43 \times 10^{-2}$	$7.61 \times 10^{-2}$	2.47
4	8	1.74	6.68	17.21	$1.08 \times 10^{-1}$	$1.10 \times 10^{-1}$	2.27
5	10	1.95	7.20	10.89	$1.51 \times 10^{-1}$	$1.53 \times 10^{-1}$	1.40
6	12	2.20	7.79	7.92	$9.52 \times 10^{-1}$	$9.54 \times 10^{-1}$	0.27
7	14	2.42	8.25	6.60	$2.38 \times 10^{-2}$	$2.43 \times 10^{-2}$	1.79
8	16	2.68	8.76	4.45	$1.54 \times 10^{-2}$	$1.55 \times 10^{-2}$	0.94
9	18	3.23	9.63	3.04	$1.76 \times 10^{-2}$	$1.78 \times 10^{-2}$	0.98
10	20	3.66	10.16	1.64	$1.06 \times 10^{-2}$	$1.05 \times 10^{-2}$	1.26
11	22	4.25	10.63	1.01	$8.35 \times 10^{-3}$	$7.95 \times 10^{-3}$	4.93
12	24	4.70	10.80	0.58	$6.77 \times 10^{-3}$	$6.32 \times 10^{-3}$	6.84
13	26	4.98	10.83	0.17	$8.87 \times 10^{-4}$	$6.66 \times 10^{-4}$	28.46
				98.87%	1.39	1.40	-

**Table 1.** Lumped dataset based on FINO1 measurements, and corresponding simulated yearly damage fractions, and percentage difference (%diff.) between implementation of fully non-linear (FNL) and linear (L) wave kinematics.

The results presented in Table 1 reveal the accumulated damage over the example year  $D_{j,year}$  to be 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 reveals differences of up to 7 %, with the exception of case 13, which reveals linear waves result in lower damage by ~28 % which is likely attributed to the largest wave height, especially in combination with parked wind turbines as wind speed is above the cut-out speed in agreement with the results in §3.1. This example is dominated by the damage produced near the rated wind speed (12 ms<sup>-1</sup>) where the negligible difference in damage due to wave kinematic type is recorded at moderate wave heights, thus negligible difference in accumulated damage value.

It was previously shown that that the inclusion of FNL wave kinematics is most critical at larger significant wave heights, yet the lumped load cases do not include significant wave heights over 5 m. Furthermore, over 70% of yearly data falls within loading cases 3 to 10, which only express a differences of up to 2.5%. This loading case simplification provides reasoning for the similar damage values regardless of wave kinematics. Given the conditions associated with higher magnitude damage are not discretely included in lumping methods, it is posed this will result in an underestimation of accumulated damage. These findings motivate the use of fully non-linear waves in the application of the previously introduced CNN meta-model and the use of hourly data to provide more accurate temporal damage estimations.

#### 3.3 Meta-model development and evaluation

The simulated damage fraction for each environmental-operational scenario using fully non-linear waves was used to train a deep learning meta-model based on Convolutional Neural Networks (CNN) using the Python libary Keras. The deep learning model is 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 is applied on our max pooling layer (0.2) and the first dense layer (0.1). The model is 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%. Inverse scaling was applied to output real values of  $D_{j,hr}$  during model application. Figure 3a presents the model's prediction accuracy when evaluated against the reserved test data by plotting normalised predicted values over normalised simulated models (black dots) while the one-to-one fit is marked with a red dashed line. The two clusters of values corresponding to the main loading and the higher loading at rated wind speed are present, just as previously in Figure 2a. This model fit results in a coefficient of determination  $(r^2)$  of 0.982. Figure 3b presents the model learning mean-squared-error for the training (black line) and validation (red line), illustrating a converged application of a suitable training duration and achieved accuracy.



**Fig. 3.** (a) Model accuracy - normalised predicted  $D_{j,year}$  values over normalised simulated  $D_{j,year}$  values, with red dashed line denoting 1:1 fit. (b) model loss over simulated time for both training (black) and validation (red).

#### 3.4 Meta-model application

The machine learning based meta-model is demonstrated through application of the same 1-year duration measured hourly metocean data from research platform FINO1

as described in §3.2. This data was inputted into the CNN meta-model, resulting in hourly predictions of damage fraction based on the metocean data. Figure 4 presents the cumulative damage over this period, which can be continually updated on an hourly basis throughout the wind turbine lifespan.

The cumulative damage throughout the example year determined by the metamodel is 1.41, demonstrating good agreement with the data lumping approach of 1.39 (Table 1). 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.



Fig. 4. Cumulative damage determined based on machine learning and measured hourly metocean data.

Although substantial computational time is required to conduct initial simulations for a specific turbine across all environmental conditions for training of the machine learnt meta-model, the requirement is negligible in respect to the wind-farm lifetime. No further modeling would be required through time, and it would be possible to obtain damage estimates using hourly measured environmental data. Here the concept of implementing machine learning in monopile fatigue prediction is presented. Future work will evaluate multiple years of historic data, to provide a broader understanding of temporal variation in damage throughout an annual year, as well as incorporate non-operating (hence more prone to wave nonlinearities) wind turbine configurations at a wider variety of sea states due to downtime or faults. Application of this approach to a real-world case would require cross-validation against direct measurements to validate the accuracy of output damage values. Moreover, there is a further need to explore model variability and use of alternative neural networks and the possibility of improving training efficiency.

# 4 Concluding Remarks

This paper presents the development of a meta-model for offshore wind turbine monopile fatigue, its comparison to damage assessed with lumped sea state method, and an investigation into the importance of nonlinearities in wave kinematics. The implementation of numerical simulations and deep learning has supported assessment of monopile damage, and the influence of including fully non-linear waves.

It is shown that the inclusion of fully non-linear waves results in larger magnitude damage fraction values than linear waves, although the difference is most substantial during waves with largest wave heights. When the turbine is operational, the effects of wind speed amplify the differences around the rated wind speed. While the differences associated with the inclusion of fully non-linear waves distinct during assessment of short-term damage, the effects are not minimal when evaluating accumulated damage measurements. This is due to the dominance of conditions with limited difference in damage fraction value due to use of higher order wave kinematics.

Advances in fatigue calculations are implemented through the benefits of deep learning, notably by presenting an approach to rapidly assess fatigue at any given point in the monopile structure lifespan. This is of particular value to operational and maintenance decisions, along with evaluation of the remaining useful lifetime. Furthermore, the high temporal capacity of the presented model will support future assessment on the effect of sequential cyclic loading and non-linear damage accumulation. The presented methods and model may now be adapted and implemented to evaluate the actual fatigue of an existing real-world turbine to provide a comparison between the predicted fatigue versus accumulated during development, and an updated assessment of fatigue based on measured conditions. While the meta-model presented can reproduce the damage based on the numerically simulations, real-world application requires cross-validation against direct measurements (i.e. strain gauge data) to assess accuracy of real damage values. Future work is also required to implement turbine downtime within the lifetime, along with assessment of potential of meta-model variability.

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