PAPER • **OPEN ACCESS**

Applying a machine learning method for cumulative fatigue damage estimation of the IEA 15MW wind turbine with monopile support structures

To cite this article: C Ren and Y Xing 2023 *IOP Conf. Ser.: Mater. Sci. Eng.* **1294** 012014

IOP Conf. Series: Materials Science and Engineering 1294 (2023) 012014 doi:10.1088/1757-899X/1294/1/012014

Applying a machine learning method for cumulative fatigue damage estimation of the IEA 15MW wind turbine with monopile support structures

C Ren* and Y Xing

Department of Mechanical and Structural Engineering and Materials Science, University of Stavanger, Norway

E-mail: `chao.ren@uis.no`

Abstract. Offshore support structures are critical for offshore bottom-fixed wind turbines, as they bear nearly all the mass and loading of wind turbine systems. In addition, the support structures are generally subjected to a harsh environment and require a design life of more than 20 years. However, the design validation of the support structure normally needs thousands of simulations, especially considering the fatigue limit state. Each simulation is quite time-consuming. This makes the design optimization of wind turbine support structures lengthy. Therefore, an effective approach for estimating the fatigue damage of wind turbine support structures is essential. This work uses a machine learning method named the AK-DA approach for cumulative fatigue damage of wind turbine support structures. An offshore site in the Atlantic Sea is studied, and the related joint probability distribution of wind-wave occurrences is adopted in this work. The IEA 15MW wind turbine with monopile support structure is investigated, and different wind-wave conditions are considered. The cumulative fatigue damage of the monopile support structure is estimated by the AK-DA approach. The numerical results showed that this machine learning approach can efficiently and accurately estimate the cumulative fatigue damage of the monopile support structure. The efficiency is increased more than 55 times with an error of around 1%. The AK-DA approach can highly enhance the design efficiency of offshore wind support structures.

1. Introduction

In pursuing sustainable energy solutions, wind power has emerged as a prominent source of renewable electricity generation. Many works [1, 2, 3, 4, 5, 6] have been carried out for wind turbine structures. Yang et al.[1] did a reliability-based design of wind turbine sub-structure optimization. Wang and Kolios [3] proposed a framework for system reliability assessment of offshore monopiles considering soil-solid interaction and harsh marine environments. Ren et al. [2, 5] compared different dynamic simulation approaches of wind turbine jacket foundations and carried out structural reliability analysis of jacket structures with machine learning approaches. Yu et al. [6] built a predictive model for the mooring line failure diagnosis and motion control. To increase wind power generation, the new trend is to install wind turbines offshore, as offshore wind has higher and uniform wind speeds. Offshore wind turbines are commonly classified into bottom-fixed and floating wind turbines (FWTs). Compared to the bottom-fixed wind turbines, the technologies of FWTs are not yet mature. Therefore, the installed offshore wind turbines are mostly bottom-fixed. Among the installed bottom-fixed wind turbines, more than 70% offshore

IOP Conf. Series: Materials Science and Engineering 1294 (2023) 012014 doi:10.1088/1757-899X/1294/1/012014

wind turbines are with monopile support structures. Wind turbine support structures like monopiles are critical components that bear the weight of massive turbine components, endure the forces of dynamic wind loads, and ensure the safe and efficient operation of wind turbines throughout their operational lifespan. The design of these support structures is fundamental to the success of wind energy projects. According to the design codes [7] and [8], fatigue limit state and ultimate limit state are the two most essential criteria for offshore wind turbine structure design.

Among these two design criteria, the fatigue limit state is more complex as offshore wind turbine structures experience a large combination of wind and wave conditions during their lifetime. Further, the load responses are highly dynamic, fully coupled, and sensitive to wind and wave combinations. This means one needs to consider all wind-wave combinations individually when estimating fatigue. The fatigue estimation will, therefore, require the computation of a large number of load cases, requiring simulation times of a few thousand hours, for the accurate representation of fatigue damage. To tackle this problem, different solutions [9, 10] have been proposed for the fatigue damage assessment. They can be roughly classified into two types: (1). fatigue damage estimation in the frequency domain [9], and (2). reduced load cases for fatigue damage estimation [10]. In addition, due to the powerful capacity of machine-learning techniques, some researchers used machine-learning approaches for offshore wind turbine reliability assessment [11, 12] and fatigue damage estimation [13, 14]. More recently, Huchet et al. [15] and Ren and Xing [16] proposed efficient active learning approaches for cumulative fatigue damage estimation of offshore wind turbine structures. The proposed active learning approaches have demonstrated high efficiency and accuracy for the fatigue damage assessment of wind turbine towers.

Considering the importance of wind turbine support structures and the efficiency of active learning approaches, we apply an active learning approach named AK-DA proposed by [15] for the cumulative fatigue damage estimation of monopile support structures. The IEA 15MW wind turbine model with monopile support structure [17] is investigated in this work. In addition, the AK-DA approach assumes that the joint probability of wind-wave occurrence is already known. Thus, one offshore site in the Atlantic Sea and its joint probability distribution are considered in this work. The layout of this paper is organized as follows: Section 2 presents the IEA 15MW wind turbine models and monopile support structures. The classical fatigue damage estimation approach is also given in this work. Section 3 overviews the AK-DA approach and the related joint probability of wind-wave occurrences in the Atlantic sea. Section 4 gives the results of cumulative fatigue damage estimation. In the end, the conclusion and discussion are given.

2. Wind turbine model and support structures

2.1. The IEA 15MW wind turbine model with monopile support structures

The IEA 15MW wind turbine with a fixed-bottom monopile support structure [17] is shown in Figure 1. This wind turbine is a Class 1B direct-drive machine with a rotor diameter of 240 meters and a hub height of 150 meters, which is jointly designed by the National Renewable Energy Laboratory (NREL) and the Technical University of Denmark (DTU). The monopile structure is designed as an isotropic steel tube. More detailed information on the wind turbine model can be found in the original report [17]. In this work, the aero-hydro-servo-elastic simulation of the IEA 15MW wind turbine is conducted through OpenFAST codes [18].

2.2. Load-stress in the monopile support structure

For the wind turbine tower and monopile structures, the normal stress typically dominates the fatigue damage. The normal stress at the monopile structures can be calculated as follows:

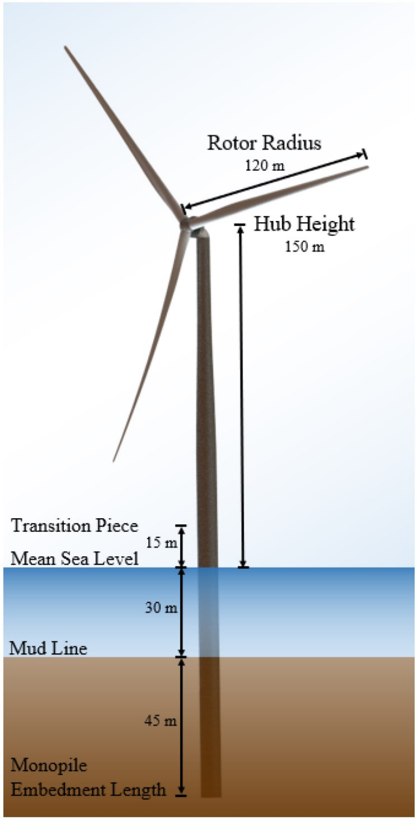


Figure 1. The IEA 15MW wind turbine with monopile support structures [17]

$$\sigma(\alpha) = \frac{F_z}{A} - \frac{M_x}{I_x} R \sin\alpha + \frac{M_y}{I_y} R \cos\alpha \tag{1}$$

Where F_z is axial force; A is nominal cross section area; M_x and M_y are side-to-side bending moment and fore-after bending moment, respectively; I_x and I_y are sectional moments of area; R is the radius of the cross-section; α is the azimuth angle. The force (F_z) and moments (M_x and M_y) can be obtained from the OpenFast simulation. In this study, the fatigue damage caused by the normal stress at the mud line is assessed, and the dimension of the monopile structure at the mud line is given in Table 1.

Table 1. Mudline monopile parameters [17]

Location	Height (m)	Outer diameter (m)	Thickness (mm)
Mudline monpile	-30	10	55.341

2.3. Classicial cumulative fatigue damage estimation approach

The cumulative fatigue damage can be calculated as follows:

$$D = \sum_{i=1}^{n_c} \rho_i d_i \tag{2}$$

Where ρ_i is the probability of occurrence of ith wind-wave case, n_c is the total number of wind-wave cases. and d_i is the fatigue damage value of ith wind-wave case. The fatigue damage d_i value can be calculated based on the time series stress by Rainflow counting technique [19, 20] and the S-N curve of the material property, which gives:

$$d_i = \sum_s \frac{n_s}{N_s} \tag{3}$$

Where s is the stress range in MPa, n_s is the number of cycles obtained using the Rainflow counting method at the stress range s, and N_s is the number of cycles to failure at the stress range s. According to the design code [8], the N_s value can be calculated as follows:

$$\log_{10} N_s = \log_{10} \bar{a} - m \log_{10} \left(s \left(\frac{t}{t_{ref}} \right)^k \right) \tag{4}$$

Where m is the negative slope of the S-N curve and $\log_{10} \bar{a}$ is the intercept of the S-N curve. The parameters t and t_{ref} represent the thickness of the wind turbine structure and the reference thickness, respectively, depending on the connection type of steel structures. In the context of this study, t refers explicitly to the monopile thickness, while t_{ref} is a fixed value of 25mm. For the fatigue analysis of the present study, the S-N curve D in the seawater from the DNV code [8] is employed, with the exponent m set to 3, the logarithm of the reference stress amplitude $\log_{10} \bar{a}$ assigned to 11.764, and the constant k set to 0.20.

3. The AK-DA approach

3.1. The overview of the AK-DA approach

In the AK-DA approach [15], the Kriging model is employed for the prediction of simulated fatigue damage across various wind-wave cases. Subsequently, the expression for the estimated long-term cumulative fatigue damage ($\hat{D}$) is as follows:

$$\hat{D} = \sum_{i=1}^{n_c} \hat{d}_i \rho_i \tag{5}$$

Here, $\hat{d}_i$ represents the predicted damage value by the Kriging model for the ith wind-wave case, and ρ_i is the related probability of occurrences. The variance of the predicted cumulative fatigue damage can be expressed as follows:

$$\sigma^2_{\hat{D}} = \mathbf{VAR}(\sum_{i=1}^{N} p_i \hat{d}_i) = \sum_{i=1}^{N} \sum_{j=1}^{N} p_i p_j \mathbf{COV}(\hat{d}_i, \hat{d}_j) \tag{6}$$

Where $\mathbf{COV}(\hat{d}_i, \hat{d}_j)$ denotes the covariance between $\hat{d}_i$ and $\hat{d}_j$. The coefficient of variation ($\delta_{\hat{D}}$) for the predicted cumulative fatigue damage can be computed as follows:

$$\delta_{\hat{D}} = \frac{\sigma_{\hat{D}}}{\hat{D}} \tag{7}$$

The AK-DA approach aims to reduce the coefficient of variation value ($\delta_{\hat{D}}$) by updating the Kriging model with the enriched samples. The enriched wind-wave cases are selected as follows:

$$i_* = \text{argmax} \quad p_i \sum_{j=1}^{N} p_j \mathbf{COV}(\hat{d}_i, \hat{d}_j) = \text{argmax} \quad C_i \tag{8}$$

Where i_* denotes the enriched wind-wave case number. The active learning process will stop when the convergence criterion ($\delta_{\hat{D}} \leq 0.01$) is satisfied. The general flowchart of the AK-DA approach can be summarized in Figure 2, where n_i is the total number of initial training samples.

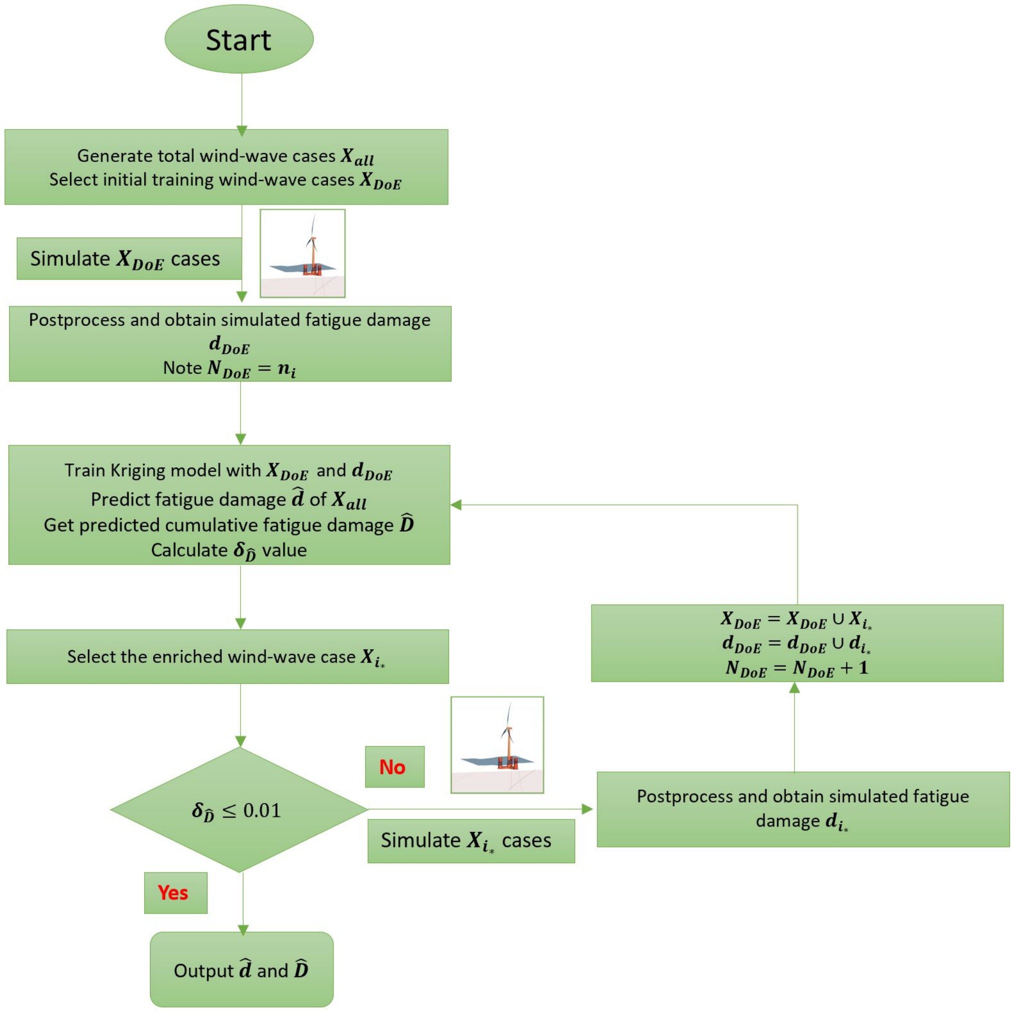


Figure 2. The general flowchart of AK-DA approach

3.2. Wind-wave probability of the occurrences

In the AK-DA approach, it is assumed that the probability of wind-wave occurrences has been pre-established. This paper adopts the joint wind and wave distribution presented in the work of Li et al. [21]. Utilizing the one-hour mean wind speed (U_w), significant wave height (H_s), and wave peak period (T_p), a long-term joint wave and wind distribution are constructed, yielding the following:

$$f_{U_\mathrm{w},H_\mathrm{s},T_\mathrm{p}}(u,h,t) \approx f_{U_\mathrm{w}}(u) \cdot f_{H_\mathrm{s}|U_\mathrm{w}}(h \mid u) \cdot f_{T_\mathrm{p}|H_\mathrm{s}}(t \mid h) \tag{9}$$

$f_{U_\mathrm{w}}()$ represents the marginal distribution of U_w, $f_{H_\mathrm{s}|U_\mathrm{w}}()$ denotes the conditional distribution of H_s given U_w, and $f_{T_\mathrm{p}|H_\mathrm{s}}()$ is the the conditional distribution of T_p given H_s. Li et al. [21] conducted a study on the joint wind-wave distribution of five different sites. In these sites, Site one, Sem Rev, with a water depth of 40 meters, is suitable for the IEA 15MW wind turbine with monopile support structures. Therefore, the simplified joint distribution derived from Site One is utilized in this investigation. Further information regarding the joint distribution can be found in the work by Li et al. [21]. It should be noted that this study assumes alignment between wind and wave direction, and the potential misalignment between wind and wave is not addressed.

IOP Conf. Series: Materials Science and Engineering 1294 (2023) 012014 doi:10.1088/1757-899X/1294/1/012014

4. Cumulative fatigue damage estimation of the monopile support structure

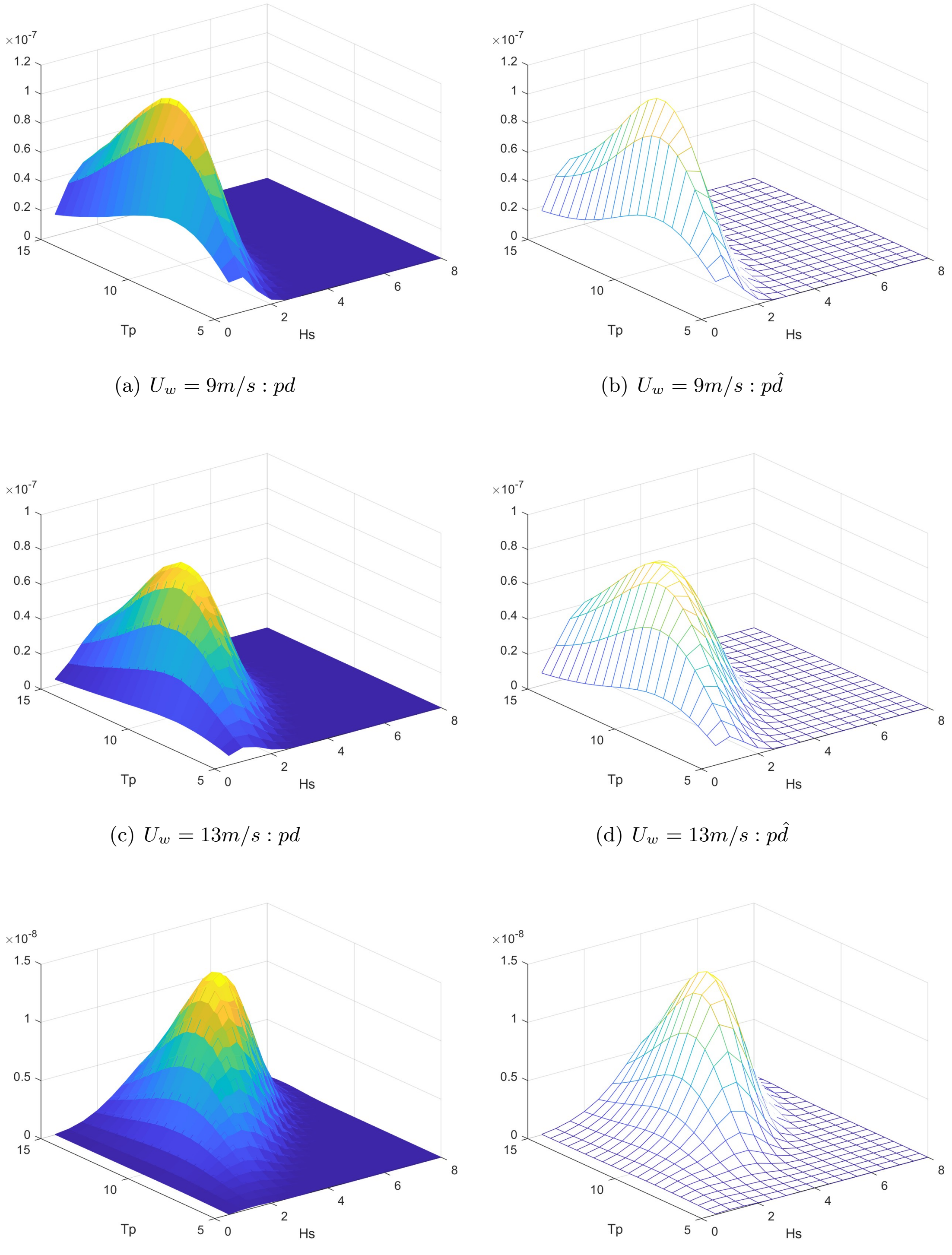
In this section, the cumulative fatigue damage of the mud line monopile support is estimated by the AK-DA approach. Different wind-wave cases are considered and a total of 4032 cases are investigated in this work. As listed in Table 2, the mean wind speed is from the cut-in wind speed (3 m/s) to the cut-out wind speed (25 m/s), with an interval of 2 m/s. The significant wave height is from 0.5m to 8m, with an interval of 0.5m. Also, the peak period time is from 5s to 15s, with an interval of 0.5s. The intervals of U_w, H_s and T_p are following the recommendations from the design code [7]. Also, a 4000-second simulation is conducted for each wind-wave case, but the first 400 seconds are not considered. Furthermore, the initial wind-wave cases for training the Kriging model in the AK-DA approach are also given in Table 2. The initial wind-wave cases can normally be selected by the grid sampling based on each parameter design space. Only 60 wind-wave cases are used to train Kriging model at the beginning of the AK-DA approach.

Table 2. Wind-wave cases considered for the cumulative fatigue estimation

Parameter	Domain of variation	Discretization	Number of cases	Initial grid samples
U_w(m/s)	[3, 25]	2	12	[3, 7, 11, 19, 25]
H_s(m)	[0.5, 8]	0.5	16	[1, 4, 7]
T_p(s)	[5, 15]	0.5	21	[5, 8, 11, 14]
Total cases			$N = 4032$	$n_i = 60$

The global one-hour cumulative fatigue damage at the mud line of monopile support is calculated. The final results of the AK-DA approach and the related simulation results are given in Table 3. In Table 3, the simulation calls mean that a total of simulated wind-wave cases, D^{1H} denotes the global one-hour cumulative fatigue damage, $Diff.$ represents the absolute percentage difference between the simulated and predicted damage values, the increased efficiency is calculated based on the simulation calls between the simulation approach and the AK-DA approach. As shown in Table 3, only 72 wind-wave cases are required for the AK-DA approach to estimate the cumulative fatigue damage. The absolute difference between the simulated reference and the AK-DA approach is just around 1%. The efficiency is increased more than 55 times. The final prediction results of the AK-DA approach at different mean wind velocities are given in Figure 3, compared with the simulated values. As shown in Figure 3, the prediction results of AK-DA approaches are nearly the same compared to the simulated references.

IOP Conf. Series: Materials Science and Engineering 1294 (2023) 012014 doi:10.1088/1757-899X/1294/1/012014



(a) $U_w = 9m/s : pd$

(b) $U_w = 9m/s : p\hat{d}$

(c) $U_w = 13m/s : pd$

(d) $U_w = 13m/s : p\hat{d}$

(e) $U_w = 19m/s : pd$

(f) $U_w = 19m/s : p\hat{d}$

Figure 3. Simulated values pd and Final predicted values $p\hat{d}$ at different mean wind velocities

Table 3. Results of AK-DA approach compared to the simulation reference

Approach	Simulation calls	D^{1H} (10^{-5})	Diff. (%)	Increased efficiency (times)
Simulated reference	4032	2.797	-	-
AK-DA	72	2.826	1.03	56

5. Conclusion

In this work, we apply a machine learning method, the AK-DA approach, to estimate the cumulative fatigue of monopile support structures in the IEA 15MW wind turbine. The joint wind-wave distribution at one offshore site in the Atlantic Sea is used in this paper. The global one-hour cumulative fatigue damage in the mud line of monopile structures is estimated by the AK-DA approach. The predicted results are compared to the simulated references. The results indicate:

The AK-DA approach can efficiently and accurately estimate the cumulative fatigue damage of the monopile support structures. The efficiency can be increased more than 55 times with an error of around 1%. This machine-learning method can significantly reduce the computational effort required for fatigue damage estimation in the design process of wind turbine support structures. The AK-DA approach can be an effective tool for wind turbine support designers, which can greatly reduce the fatigue damage estimation time and accelerate the iterative design process.

Of course, no work is perfect. This work only considers that the wind-wave direction is aligned, and no misalignment between wind-wave directions is considered. Also, only one location at the monopile is considered for fatigue damage estimation. In the future, the wind-wave direction misalignment should be included, and more locations in the monopile support structures will be considered.

References

[1] Yang H, Zhu Y, Lu Q and Zhang J 2015 *Renewable Energy* **78** 16–25
[2] Ren C, Aoues Y, Lemosse D and De Cursi E S 2020 Structural reliability assessment of offshore wind turbine jacket considering corrosion degradation *14th WCCM-ECCOMAS Congress 2020* vol 800
[3] Wang L and Kolios A 2017 A generic framework for reliability assessment of offshore wind turbine monopiles considering soil-solid interaction and harsh marine environments *Proceedings of the 5th International Conference on Marine Structures, MARSTRUCT, Lisbon, Portugal* pp 8–10
[4] Ren C, Aoues Y, Lemosse D and De Cursi E S 2021 Global sensitivity analysis of offshore wind turbine jacket *Proceedings of the 5th International Symposium on Uncertainty Quantification and Stochastic Modelling: Uncertainties 2020* (Springer) pp 35–48
[5] Ren C, Aoues Y, Lemosse D and De Cursi E S 2021 *Engineering Structures* **249** 113308
[6] Yu Y, Cheng S, Cui Y, Zhang X, Zhang P and Yu J 2023 *Ocean Engineering* **280** 114907
[7] IEC I 2009 *International Electrotechnical Commission, Geneva*
[8] DNV D N V *et al.* 2014 *Internet Requests for Comments, DET NORSKE VERITAS AS, OFFSHORE STANDARD DNV-OS-j101*
[9] Kvittem M I and Moan T 2015 *Journal of Offshore Mechanics and Arctic Engineering* **137**
[10] Stieng L E S and Muskulus M 2019 *Wind Energy* **22** 1472–1486
[11] Ren C 2022 *Reliability assessment of an offshore wind turbine jacket with active learning approaches* Ph.D. thesis Normandie Université
[12] Ren C, Aoues Y, Lemosse D and De Cursi E S 2023 *Ocean Engineering* **281** 114657
[13] Wilkie D and Galasso C 2021 *Structural Safety* **88** 102020
[14] Sun K, Xu Z, Li S, Jin J, Wang P, Yue M and Li C 2023 *Renewable Energy* **204** 733–749
[15] Huchet Q, Mattrand C, Beaurepaire P, Relun N and Gayton N 2019 *Wind Energy* **22** 638–652
[16] Ren C and Xing Y 2023 *Renewable Energy* 118977

IOP Conf. Series: Materials Science and Engineering 1294 (2023) 012014 doi:10.1088/1757-899X/1294/1/012014

[17] Gaertner E, Rinker J, Sethuraman L, Zahle F, Anderson B, Barter G, Abbas N, Meng F, Bortolotti P, Skrzypinski W, Scott G, Feil R, Bredmose H, Dykes K, Sheilds M, Allen C and Viselli A 2020 Definition of the IEA 15-megawatt offshore reference wind turbine Tech. rep. International Energy Agency URL `https://www.nrel.gov/docs/fy20osti/75698.pdf`

[18] Jonkman J M and Buhl M L 2005 *National Renewable Energy Laboratory, Golden, Colorado*

[19] Rychlik I 1987 *International journal of fatigue* **9** 119–121

[20] Amzallag C, Gerey J, Robert J L and Bahuaud J 1994 *International journal of fatigue* **16** 287–293

[21] Li L, Gao Z and Moan T 2015 *Journal of Offshore Mechanics and Arctic Engineering* **137**