PAPER • OPEN ACCESS

Predictive Maintenance of Floating Offshore Wind Turbine Mooring Lines using Deep Neural Networks

To cite this article: N Gorostidi *et al* 2022 *J. Phys.: Conf. Ser.* **2257** 012008

Predictive Maintenance of Floating Offshore Wind Turbine Mooring Lines using Deep Neural Networks

N Gorostidi[1,2], V Nava[1,3], A Aristondo[3] and D Pardo[2,1,4]

[1] Basque Center for Applied Mathematics, Alameda Mazarredo 14, 48009 Bilbao, Spain
[2] University of the Basque Country (UPV/EHU), Barrio Sarriena S/N, 48940 Leioa, Spain
[3] TECNALIA, Basque Research and Technology Alliance (BRTA), Astondo Bidea, Edificio 700, Derio, 48160, Spain
[4] Ikerbasque (Basque Foundation for Sciences), Bilbao, Spain

E-mail: ngorostidi@bcamath.org

Abstract. The recent massive deployment of onshore wind farms has caused controversy to arise mainly around the issues of land occupation, noise and visual pollution and impact on wildlife. Fixed offshore turbines, albeit beneficial in those aspects, become economically unfeasible when installed far away from coastlines. The possibility of installing floating offshore wind turbines is currently hindered by their excessive operation and maintenance costs. We have developed a comprehensive model to help companies plan their operations in advance by detecting failure in mooring lines in almost real time using supervised deep learning techniques. Given the lack of real data, we have coupled numerical methods and OpenFAST simulations to build a dataset containing the displacements and rotations of a turbine's floating platform across all directions. These time series and their corresponding frequency spectra are used to obtain a set of key statistical parameters, including means and standard deviations, peak frequencies, and several relevant momenta. We have designed and trained a Deep Neural Network to understand and distinguish amongst a series of common failure modes for mooring lines considering a range of metocean and structural conditions. We have obtained promising results when monitoring severe changes in the line's mass and damping using short time spans, achieving a 95.7% validation accuracy when detecting severe biofouling failure.

1. Introduction

The rapid development of cost-effective, green forms of energy is one of humanity's main assets in the fight for environmental conservation. In particular, wind power systems play a huge role in the current scenario. Controversy, however, has recently arisen following the worldwide massive installation of onshore wind turbines, mainly around issues such as land occupation, impact on wildlife and noise and visual pollution. That is one of the many reasons for which research has turned its focus towards offshore wind rather than onshore wind. Fixed offshore turbines are already being deployed all around the world but, despite their environmental benefits, their installation costs increase exponentially when moving further away into the seas, as seabed depth escalates. Floating Offshore Wind Turbines (FOWT), albeit more affordable in deeper waters than their fixed counterparts, are still economically unfeasible due to their excessive Operation and Maintenance (O&M) costs. In fact, Figure 1 suggests O&M accounts for approximately a third of the total costs associated to a floating wind project [1].

 doi:10.1088/1742-6596/2257/1/012008

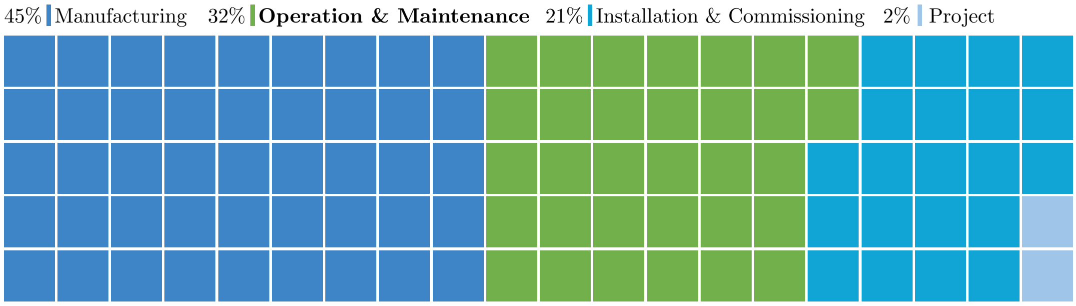


Figure 1. Simplified cost breakdown of a floating offshore wind project [1].

Cost optimisation is one of the main reasons for which Structural Health Monitoring (SHM) techniques are used in industry. This paper applies the notion of spectral analysis, whose first implementation for SHM purposes dates back to the 1960s, when Lifshitz and Rotem [2] observed dynamic modulus variations under vibrating loads to detect damage in composite materials. This technique has ever since then been implemented for an extensive range of engineering disciplines, including amongst others the aerospace and civil industries [3]. This condition-based monitoring approach has been widely applied to floating oil platforms [4]. In fact, Prislin and Maroju [5] implemented a machine learning model to evaluate the integrity of mooring systems for oil platforms. Over the past few years, researchers have focused on the concept of Failure Modes and Effects Analysis (FMEA) to establish strategic criteria for maintenance operations by relating the frequency of different forms of damage with their corresponding economic impact [6, 7].

The world is currently turning its eyes towards big data and artificial intelligence, and wind power research is no exception. As the ever-increasing computational resources allow for previously inconceivable calculations, researchers are nowadays implementing deep learning algorithms to detect damages in different components for wind systems [8]. Coupling deep neural networks and vibration-based fundamentals for the structural health monitoring of floating wind turbine mooring lines nonetheless constitutes a complete innovation in the field. Our research applies some of the concepts introduced by Li et al. [9], who presented a model to recreate the response of a floating platform under different mooring configurations; and Jaiswal and Ruskin [10], who implemented computer vision techniques to detect floating vessel mooring failure. Martinez-Luengo et al. [11] and Joshuva et al. [12] have extensively reviewed other methods applied for O&M cost minimisation purposes, including for instance thermal imaging and acoustic emission monitoring.

This research aims at extending the work presented by Gorostidi and Nava [13] by developing an AI-based algorithm to predict failure in FOWT mooring lines. From the displacements and rotations of the turbine's platform, a series of key modal parameters is identified and fed into a deep learning structure [14], which is ultimately able to discern whether a mooring line is failing or not, and what kind of damage is affecting its performance. This approach is intended to help companies plan their operations in advance, and could potentially reduce their total costs substantially by keeping unnecessary commissions and sensorization costs to a minimum.

The main limitations of the method we use arise from the fact that floating offshore wind turbines are still not mass-produced as of today, and thus real data is very limited. Instead, we carry out numerical simulations to recreate the external and structural characteristics affecting a turbine's behaviour as truthfully as possible, but the model's performance under real conditions still remains a challenge. Furthermore, we have built a neural network using a classification approach. As with any supervised learning technique, this method relies on establishing labels for the potential forms and severities of damage. The main advantage of these models with respect to unsupervised algorithms is the fact that we are able to determine what kind of damage is affecting a turbine's performance rather than just detecting anomalies. However, classifying failure implies imposing a binary choice of whether a mooring system is damaged or not. This poses the challenge of setting a discrete threshold for the minimum damage severity at which repairs should be performed. A set of intermediate labels should therefore be simulated and coupled with a compatible reliability model so as to estimate at what point in time a given mooring system will transition from an intermediate state to a severely damaged one.

2. Methodology

We divide the method's workflow into two phases: simulation and training. The former includes all preprocessing, simulation and data postprocessing operations that end once the training and validation datasets are generated. This step is necessary given the current scarcity of real data. In the training phase we design and train a Deep Neural Network using said datasets to build an effective algorithm for the prediction of mooring line damage. A short overview of the initial stages of the project is given to introduce the studied scenario and some of the model's key variables.

2.1. Preliminary approach

The introductory work published in [13] presented a simple 1-DOF differential equation, which we used to recreate the dynamics of a generic FOWT platform.

$$M \cdot \ddot{x} + C \cdot \dot{x} + K_3 \cdot x^3 + K_1 \cdot x + K_0 = F_{wave}\left(H_S, T_P, t\right) + F_{drift}\left(H_S^2\right) + F_{wind}\left(V\right). \qquad (1)$$

In this instance we only studied the platform's surge. A set of ranging metocean parameters, including wind velocity and the waves' significant height and peak period, was defined to create an extensive set of training data. This contained a collection of synthetic statistics extracted from the platform's response in both time and frequency domains. A series of alterations to the system's original structural characteristics was defined to simulate a range of failing configurations. These included biofouling damage to the mooring lines, resulting in increased mass and damping coefficients, which eventually yielded longer periods and hence lower peak frequencies; pitting wear, and anchoring point displacements, which caused different effects on the line's non-linear stiffness coefficients.

2.2. Simulation and dataset generation

Our research currently extends this idea by considering not only the longitudinal displacements of the floating platform, but a fully comprehensive 6-DOF system in which all transverse effects and rotations are included. We therefore consider six time series, from which we calculate and extract statistics such as means and standard deviations, peak frequencies and some relevant momenta. These parameters are ultimately the inputs to the implemented deep learning algorithm, which then infers whether the mooring lines are damaged or not, and if so, what causes might be affecting their performance. Figure 2 presents a simplified diagram of the method's workflow.

We have generated the training and validation datasets by using NREL's open-source wind turbine simulation tool OpenFAST [15] to perform simulations on the semisubmersible floating system depicted in Figure 3(a), developed within the DeepCwind project [16]. Considering a simple catenary mooring system, we computed a series of scenarios combining both metocean and structural parameters by rewriting the modules shown in Figure 3(b). In particular, *InflowWind* was modified to adjust the horizontal, steady wind velocity. *HydroDyn* was used to generate the

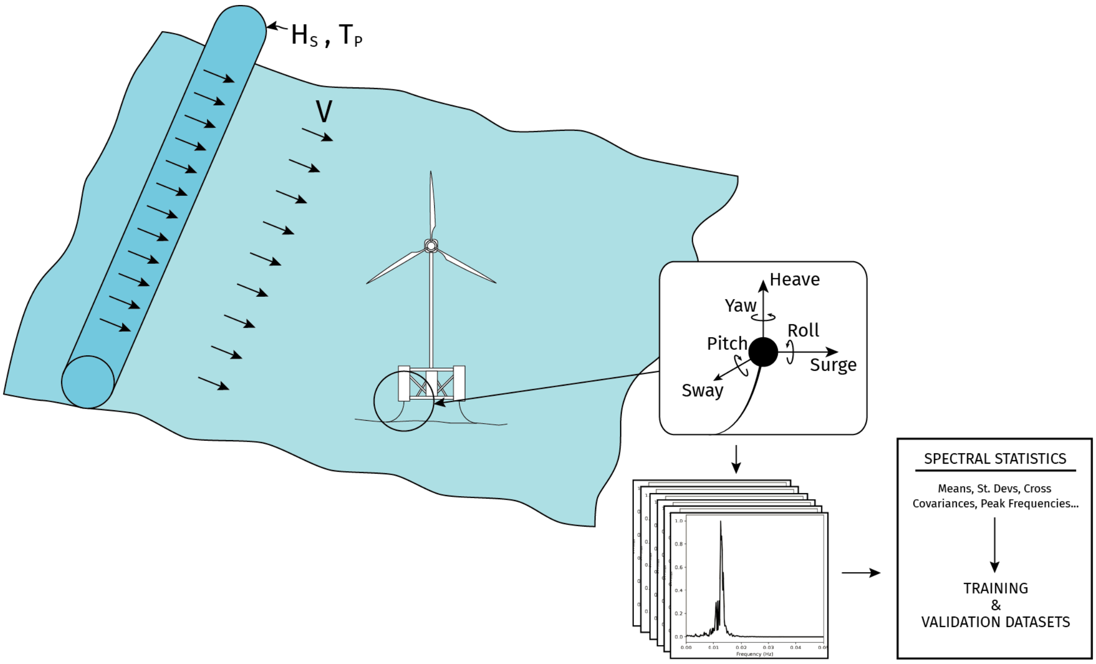


Figure 2. Schematic representation of the method's workflow, including simulation and data extraction and visualisation processes.

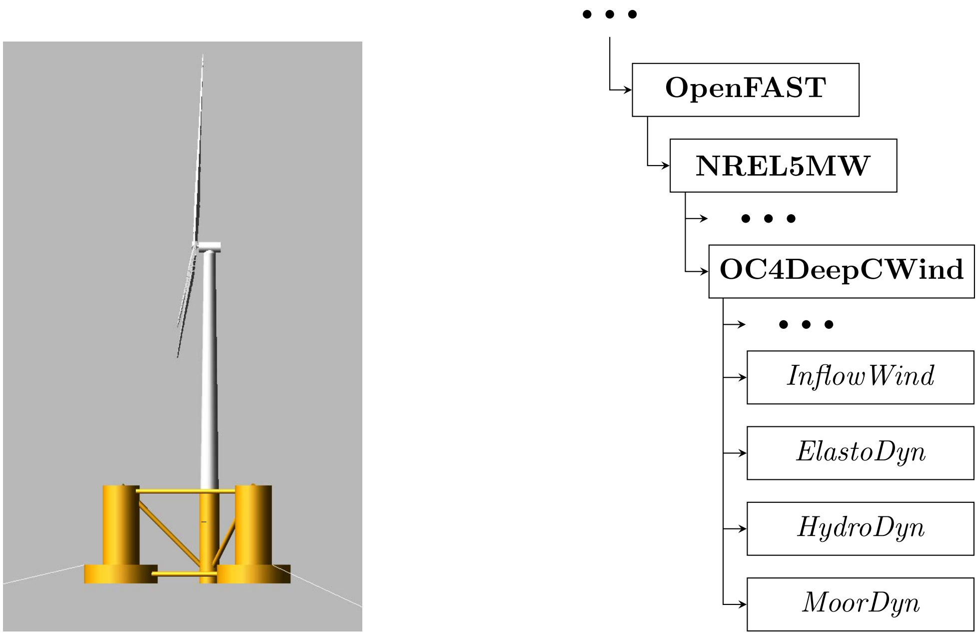
time domain hydrodynamics behaviour of the platform in different sea states, characterised by the significant wave height, H_S, and peak period, T_P. The structural properties of the mooring lines, e.g. mass, damping and stiffness, were modified using *MoorDyn*.

Thanks to the *ElastoDyn* module, we simulated the time evolution of the platform's displacements across all six degrees of freedom. Their respective frequency spectra were calculated using a postprocessing script. From these, the desired datasets were built, containing the statistics shown in Table 1. The implemented network is designed to be agnostic to external factors. This means that wind and wave characteristics are dropped out of the dataset before training, and are only included at first for data analysis purposes, e.g. filtering and visualisation. The result of this is an algorithm capable of predicting FOWT mooring failure without needing any sensors to describe wind and wave conditions, thus saving even more on measuring costs. The model is therefore trained using mean, standard deviation, peak frequency and zero-order momentum of the response for each of the 6 DOFs, hence resulting in 24 total dataset features.

In the end, the aim is for the DNN to identify discrepancies in these modal parameters for different mooring line health states. To give an oversimplistic example, an unexpectedly heavy line might cause inertial effects to increase, thus causing the platform to move more slowly than predicted. This movement is then characterised by longer periods, and hence smaller frequencies. Once trained, the implemented network should therefore understand and associate lower peak frequencies to this kind of damage, which could possibly arise from biofouling issues.

2.3. Network design and training

We use supervised deep learning techniques to model this problem by imposing a series of changes to the mooring line's structural properties. More specifically, we employ a simple feed-forward, fully-connected deep neural network following the topology shown in Figure 4. As stated before, its inputs, denoted by i_m, are the modal statistics obtained from the floating



(a) (b)

Figure 3. Simulation setup in OpenFAST (a) Sketch of the DeepCwind semisubmersible floating platform (b) OpenFAST's default folder structure.

platform's displacements. The outputs, indicated as p_k, are the supplementary probabilities of the given line being assigned to any of the k labels or, in this case, health status scenarios. The idea, once the network has been trained, is for one of these probabilities to be as close as possible to one, with the rest being approximately equal to zero.

The algorithm designed in [13] contained all the damaged configurations shown in Table 2. The implemented 6-DOF model considers fully-functioning mooring lines, as well as those affected by biofouling issues, that is, with increased mass due to the undesired attachment of

Table 1. Parameters stored in the training and validation datasets. Significant wave height ranged from 4 to 10 m. Peak wave period, from 5 to 15 s. Wind speed varied from 2 to 15 m/s.

Symbol	Parameter
$\bar{x}_r$	Response mean
σ_r	Response standard deviation
f_P	Peak frequency
m_0	Zero-order momentum
H_S	Significant wave height
T_P	Peak period
V	Wind speed
Label	Health status label

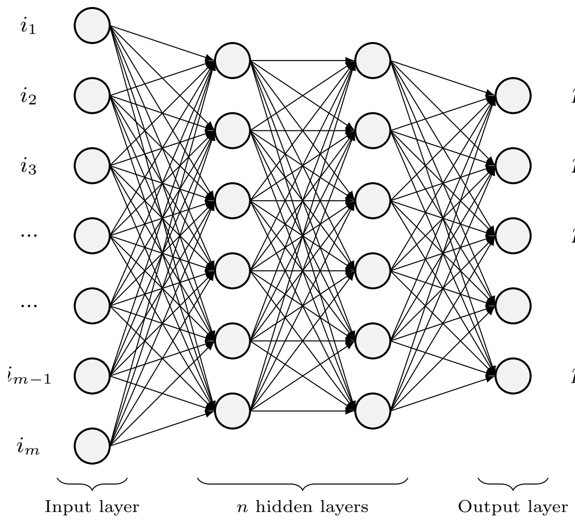


Figure 4. Generic topology of a four-layer, feed-forward deep neural network.

marine life. This condition is recreated in OpenFAST by specifying an increment in mass per unit length in *MoorDyn*, whose default value is 113.35 kg/m. In this instance, we have considered a 10% mass increase to constitute severe biofouling failure. The damaged lines therefore have a mass per unit length of 124.69 kg/m, with all the consequences this causes in the dynamics of the mooring system.

A total of 3,140 cases were computed from OpenFAST simulations combining different wave and wind conditions for both undamaged and damaged lines. The obtained signals have a duration of three hours to mitigate any transient and/or unsteady effects, following the conclusions obtained in [13]. A dataset containing 2,355 samples, that is, 75% of the total computed cases, was built to train the network, while the remaining 785 samples were used to simultaneously validate the model. These validation cases do not affect neither the algorithm's training process nor its coefficients, and are only employed to estimate the performance of the model with respect to unseen data. The implemented neural network was tuned using the hyperparameter values shown in Table 3, all of which are standard for classification tasks with only two classes.

Table 2. Simulated damage configurations for the health status of mooring systems for both the initial and current models.

Condition	Definition	1-DOF	6-DOF
Anchoring	Displaced mooring line anchor	✓	
Biofouling	Attached mussels, algae and other marine organisms	✓	✓
Fatigue	Damaged links in a mooring line due to wear or fatigue	✓	
Undamaged	Default mooring line properties	✓	✓

Table 3. Hyperameters used in the training stage of the project.

Parameter	Definition
Neurons per layer	24, 16, 12, 2
Activation functions	ReLU, Softmax
Layer connection	Fully-connected layers
Optimiser and learning rate	Adam, 0.0001
Cost function	Binary cross-entropy
Early-stop criterion and patience	Validation loss, 500 epochs
Training epochs	10,000

3. Analysis of Results

We have carried out a series of OpenFAST simulations combining both external conditions and structural characteristics of a FOWT's mooring system. The displacements and rotations of the floating platform have been computed for each case, yielding a set of six time series such as the one plotted in Figure 5. The unsteady appearance of the signals is caused by the irregular nature of the waves, which have been computed using a Pierson-Moskowitz spectrum with second-order mean-drift forces. A predominantly sinusoidal behaviour can be observed for each individual degree of freedom, thus justifying the use of peak frequencies as a key statistic to include in the training process. Moreover, it is a positive sign that the patterns presented in all directions and rotations are consistent with other studies [17].

Looking at the specific values for the displacements of the floating platform, and given the one-dimensional constraint imposed for both waves and wind, it bodes well that the surge, shown in Figure 5(a), presents much higher mean and amplitude in comparison to the transverse movements, sway and heave, displayed in Figure 5(b) and Figure 5(c), respectively.

The previously implemented 1-DOF model was trained obtaining a promising 96% validation accuracy when severe biofouling and anchor displacement issues were considered [13]. Separate analyses were carried out on each failure mode individually to estimate the network's sensitivity to increasingly severe damage. The most relevant outcome from these studies is the fact that an approximately 92% accuracy was obtained after a binary classification test between default mooring lines and 10% heavier ones.

The current status of our research already considers the displacements and rotations of the turbine's floating platform across all directions, thus producing much more realistic results. The evolution of the algorithm's training and validation processes is shown in Figure 6(a) and Figure 6(b) for loss and accuracy, respectively. A plateau is reached after training the network for more than 6,000 epochs, yielding a validation accuracy of 95.7%. This is already a significant improvement from the previously computed results in [13], and is promising considering the increasing complexity of the data. These outcomes are numerically displayed on Table 4, which presents a series of standard metrics for classification problems. Precision is a way to measure the quality of the implemented model by computing the proportion of all the instances identified as *positive*, that is, damaged, that are appropriately defined. Recall measures the quantity of *positive* cases that the model is able to properly identify. F-Score is a weighted average of precision and recall, with F1-Score in particular being equal to their harmonic mean. A comprehensive analysis of the performance of any classification model discusses all of these metrics, bringing increased attention to either one depending on the nature of the problem. Recall is more sensitive with respect to false negatives, that is, failing mooring lines being wrongly identified as undamaged. That is the reason for which we should maximise this over

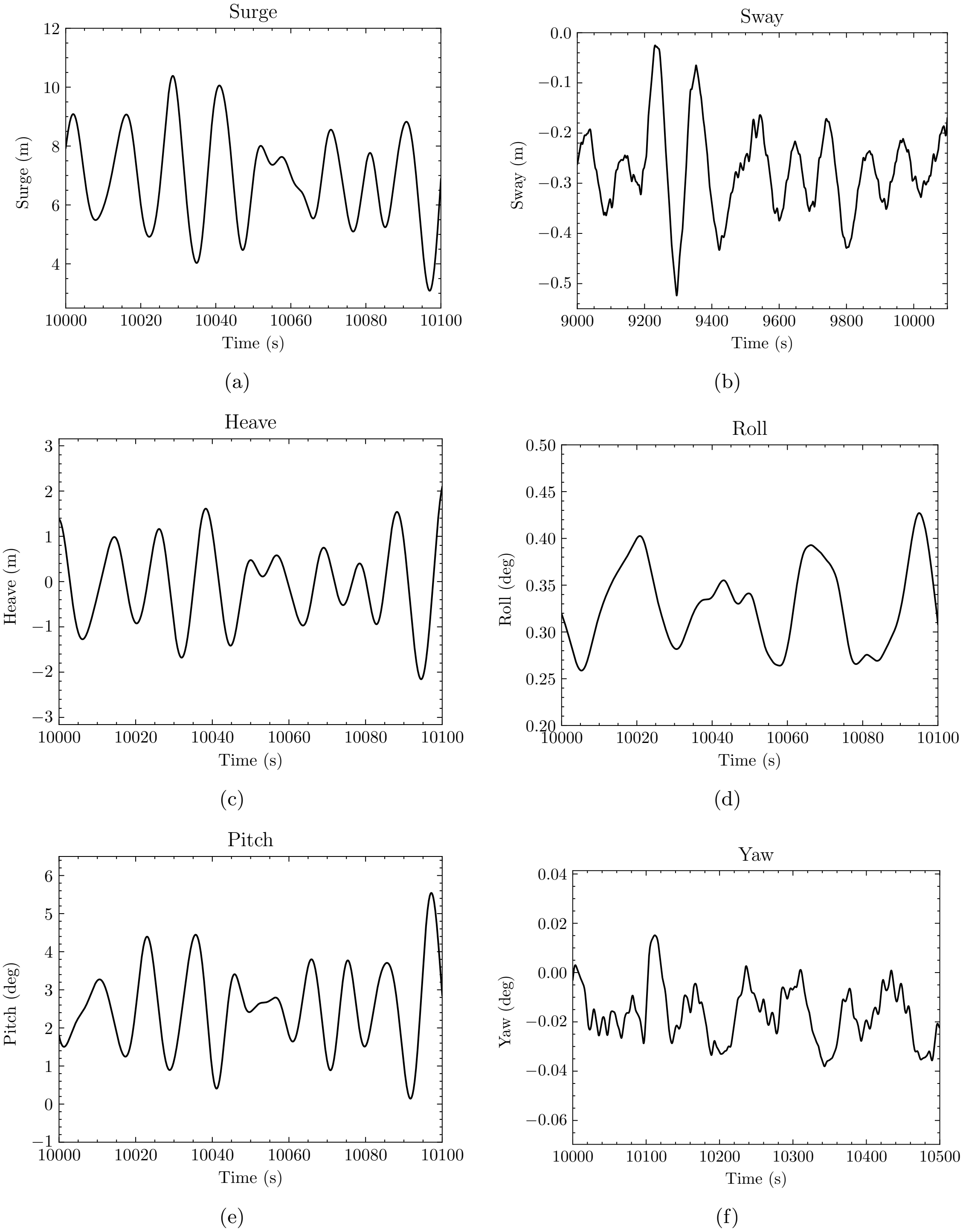


Figure 5. Observed displacements and rotations of a floating platform with undamaged mooring lines under $H_S = 10$ m, $T_P = 13$ s and $V = 8$ m/s: (a) surge, (b) sway, (c) heave, (d) roll, (e) pitch and (f) yaw. Sway and yaw have been plotted using a broader window for clarity.

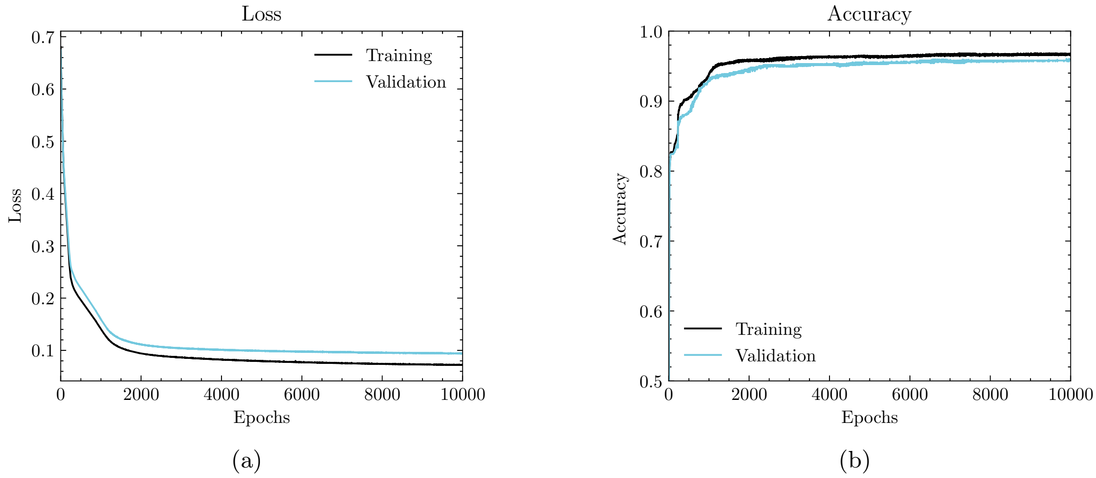


Figure 6. Evolution of training and validation (a) loss and (b) accuracy as training progresses.

any other metric in our scenario, as low recall would imply underestimating mooring line damage, thus hindering the model's potential benefits. The fact that the obtained 97.5% biofouling recall is the maximum out of all the metrics presented in Table 4 is very positive.

Another common way to illustrate the behaviour of a machine learning model is through the use of confusion matrices, such as the one shown on Table 5, which presents the algorithm's performance in a more intuitive manner. It shows that out of 400 damaged mooring systems provided by the validation dataset, only 10 have been classified as undamaged. The idea is for the model to eventually discern among a larger array of labels, thus being able to identify more kinds of damages.

Table 4. Model performance metrics for the validation set after 10,000 training epochs.

	Precision	Recall	F1-Score
Undamaged	0.973	0.938	0.955
Biofouling	0.942	0.975	0.958
Accuracy	0.957	0.957	0.957

Table 5. Confusion matrix for the validation set after 10,000 training epochs.

	Undamaged	Biofouling
Undamaged	361	24
Biofouling	10	390

4. Conclusions

We have developed a deep learning algorithm to predict failure in FOWT mooring lines using simple measurements. A series of numerical methods and OpenFAST simulations have been used to generate a database containing modal statistics from short-term displacements and rotations of a floating turbine's platform. We have defined a range of external conditions and structural characteristics to simulate different damaged mooring line configurations. We have designed and trained a deep neural network to so far detect biofouling failure in almost real time. The computed displacements show consistency and match those obtained in similar studies. The implemented network reaches over 95% accuracy when predicting moderate-to-high biofouling damage to a turbine's mooring lines. This spectral analysis could reduce O&M costs massively, thus increasing overall profitability, as only a few key sensors would be needed to remotely estimate the future of a mooring system's health status. The implemented method could potentially be extended to other subsystems of a floating offshore wind turbine, such as its blades, gearbox or tower.

Acknowledgments

N Gorostidi has received funding from the Spanish Ministry of Science and Innovation project DEEPINVERSE, with reference PID2019-108111RB-I00 (FEDER/AEI). V Nava has received funding from the project IA4TES - *Inteligencia Artificial para la Transición Energética Sostenible* funded by Ministry of Economic Affairs and Digital Transformation (MIA.2021.M04.0008); the "BCAM Severo Ochoa" accreditation of excellence (SEV-2017-0718); and the Basque Government through the BERC 2022-2025 program, the Elkartek project EXPERTIA (KK-2021/00048).

References

[1] Nava V, Ruiz-Minguela P, Perez-Moran G, Rodriguez Arias R, Lopez Mendia J and Villate-Martinez J L 2019 *Installation, operation and maintenance of offshore renewables* (Institution of Engineering and Technology) pp 397–424
[2] Lifshitz J and Rotem A 1969 *Journal of Composite Materials* **3** 412–423
[3] Doebling S, Farrar C and Prime M 1998 *The Shock and Vibration Digest* **30** 91–105
[4] Chang P, Flatau A and Liu S 2003 *Structural Health Monitoring - an International Journal* **2** 257–267
[5] Prislin I and Maroju S 2017 *OTC Offshore Technology Conference* **3** 1–12
[6] Carroll J, McDonald A and McMillan D 2016 *Wind Energy* **19** 1107–1119
[7] Arabian-Hoseynabadi H, Oraee H and Tavner P J 2016 *International journal of electrical power and energy systems* **32** 817–824
[8] Rafiee J, Arvani F, Harifi A and Sadeghi M 2007 *Mechanical Systems and Signal Processing* **21** 1746–1754
[9] Li Y, Le C, Ding H, Zhang P and Zhang J 2019 *Journal of Marine Science and Engineering* **7** 115
[10] Jaiswal V and Ruskin A 2019 *OTC Offshore Technology Conference* **1** 1–7
[11] Martinez-Luengo M, Kolios A and Wang L 2016 *Renewable & Sustainable Energy Reviews* **64** 91–105
[12] Joshuva A D, Aslesh A and Sugumaran V 2019 *International Journal of Mechanical Sciences* **9** 95–112
[13] Gorostidi N and Nava V 2021 *Book of Proceedings of the 17th EAWE PhD Seminar* **1** 149–156
[14] Antoniadou I, Manson G, Staszewski W, Barszcz T and Worden K 2015 *Mechanical Systems and Signal Processing* **64-65** 188–216
[15] Laboratory N R E 2021 Openfast documentation [Online; accessed 10-February-2022] URL `https://openfast.readthedocs.io/en/main/`
[16] Robertson A, Jonkman J, Masciola M and Song H 2014 Definition of the semisubmersible floating system for Phase II of OC4 Tech. Rep. 1 National Renewable Energy Laboratory (NREL) Denver, CO
[17] Lee S, Churchfield M, Driscoll F, Sirnivas S, Jonkman J, Moriarty P, Skaare B, Nielsen F G and Byklum E 2018 *Energies* **11**