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Structural health monitoring of mooring systems for floating wind turbines.

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Abstract. Over the years, a remarkable growth in the installation of offshore wind turbines (OWTs) has been noticed since OWTs are great clean and green energy sources. Moreover, floating offshore wind turbines (FOWTs) have been deployed in deep ocean beds to exploit large ocean areas to extract vast, steady wind resources. Spar type FOWTs are highly complex structures consisting of different mechanical, electrical components which affects their overall dynamics under different environmental and operational conditions. But these slender, taller structures when installed in deep ocean beds are subjected to constant wind-wave-current loading, which poses fatigue and can cause unexpected failure of FOWTs in extreme ocean environments. Hence, structural health monitoring (SHM) of FOWTs can significantly contribute to maintaining their structural integrity. SHM of FOWTs has been an active research area among the scholars to identify the highly challenging damages. It is also crucial as damage in mooring cables significantly alters the dynamics of FOWTs. Therefore, this study investigates the effects of environmental and operational conditions on SHM of a spar type FOWT. The damage scenarios corresponding to marine growth and corrosion on mooring of a 5MW NREL OC3-hywind spar FOWT, are considered. Numerical simulations are carried out in OpenFAST, considering the severe environmental and operational conditions (EOC) from a site located in the northern coast of Scotland. The acceleration responses at several points along the tower of the healthy and damaged turbines are accumulated and a data driven technique is adopted for damage identification.

Keywords: floating wind, biofouling, corrosion, time series methods.

1. Introduction

The installation of offshore wind has significantly increased over the years to meet the energy demand. Up to 80% of offshore wind resources are located in water depths greater than 60 m [1]. With advances in offshore wind, floating offshore wind turbines

(FOWTs) are being designed to be larger than their onshore counterparts enabling them to harness clean energy effectively by exploiting the large ocean area available. Typically, floating wind turbines are considered to be economical and feasible for deep water ($>50\text{m}$). To maintain the station keeping the anchor and mooring systems are employed to secure the floating platform. But the traditional mooring systems may be uneconomical, as the FOWTs are more vulnerable to wind, wave and current load, resulting continuous platform motions. Moreover, excessive costs associated with mooring systems still keeps the floating wind farms unprofitable. In addition, maintenance of these structure within serviceability limit is expensive and has been a great concern.

Hence, structural health monitoring of these FOWTs for damage detection is crucial for lengthening their operational period. Deep learning techniques have been widely used by the scholars for solving forecasting and monitoring problems [2], [3], [4], [5], [6]. These techniques have been employed for the damage detection in the mooring cables for semi-submersible platform, tension leg platform [7], [8], [9], [10]. Moreover, effectiveness of deep neural network (DNN) has been explored for health monitoring of other modules of the FOWTs such as blades and towers [10], [11], [12], [13].

Other researchers [14], [15], [16] performed Frequency domain decomposition (FDD) for structural health monitoring of offshore wind turbines. But it is essential to understand different damage scenarios that impact the overall dynamics of the floating offshore wind turbines. It is worth notify that limited investigation has been carried out for structural health monitoring of spar type floating offshore wind turbine mooring cables. Hence, this has been undertaken in this study via adopting NREL's OpenFAST simulation package. The simulations are carried out for both healthy and damaged conditions, considering the FOWT at its operating conditions. Two separate KNN model has been modeled for the assessment. The results indicated that, platform surge displacement response is more sensitive to the damage and the developed model shows 70% accuracy in identification of damage scenario.

2. Floating offshore wind and damage scenarios

2.1 A 5MW OC3 Hy-wind spar

The nonlinear model of 5 MW NREL spar-supported FOWT is developed in OpenFAST in this investigation. A multibody dynamic model of spar FOWT is developed using Kane's method. The equation of motion derived by Kane's method is more readily solvable. Moreover, the wind turbine simulation tool OpenFAST employs Kane's method, which offers significant advantages over the Euler-Lagrangian formulation. It is necessary that each component must be defined in its local coordinate for accurate modeling of multibody systems. The blades have more than one coordinate system assigned to them. For a detailed modelling of the blades, they are referred to their coned coordination system followed by the pitched coordinate system. Similarly, the platform and tower rotations occur simultaneously about more than one axis.

NREL 5MW offshore wind turbine has 22 degrees of freedom in OpenFAST [16] and the properties are listed in Table (1). The software includes four important modules

such as Aerodyn, ServoDyn, HydroDyn and ElastoDyn to provide a fully coupled model.

Table (1) The gross properties of the NREL 5MW offshore wind turbine

Descriptions	Values
Rated power	5 MW
Rotor diameter	126 m
Hub diameter	3 m
Hub height	90 m
Cut-In, Rated, Cut-out wind speed	3m/s, 11.4m/s, 25m/s
Rotor Mass	110,000 kg
Nacelle Mass	240,000 kg
Tower Mass	249,718 kg
Tower structural damping ratio	1%
Cut in, Rated rotor speed	6.9 rpm, 12.1 rpm

2.2. Load Cases

The three-dimensional wind fields are generated using TurbSim package provided by National Renewable Energy Laboratory (NREL), USA. The aerodynamic load on the wind turbine are estimated using steady state blade element momentum (BEM) theory. The TurbSim package enable producing the turbulent wind filed while varying the turbulence intensity levels and characteristics wind speeds. The steady BEM theory interpolates the wind speed at the blade nodes from the TurbSim generated three dimensional wind field to estimate aerodynamic loads based on the quasi-static aerodynamic properties.

In this study, the vibration response of the FOWTs are obtained under varying environmental conditions. Details of the wind, wave and current parameters are listed in Table (2). However, the wind-wave misalignment remains out of scope for this study.

Table (2) Environmental loading conditions

Load Case	Wind speed (m/s)	Wave height (m)	Wave time pe- riod (T)	Current speed (m/s)
Lc1	11.4	2.16	5.405	0.22
Lc2	18	2.95	7.14	0.22

2.3. Damage Scenario

In this work, two types of dominant mooring damages are identified, such as pitting corrosion and biofouling. In particular the biofouling in the mooring cables are represented by attachment of algae, mussels, bacteria and another marine organism. To recreate these, modifications are introduced in OpenFAST, to perform the numerical simulations. Furthermore, inadequate adjustments to replicate the various degree of

degradation in mooring lines may shift the FOWT towards new equilibrium and may mislead the results. In this context the severity of the damages for each case varies from 5%- 30%. and provide the sufficient accuracy. By incorporating these degradation, the numerical simulations are carried for 1000 s, with sampling frequency of 80 Hz.

3. Methodology

The proposed approach for health monitoring of mooring cables consists of four steps, which is shown in Fig (3).

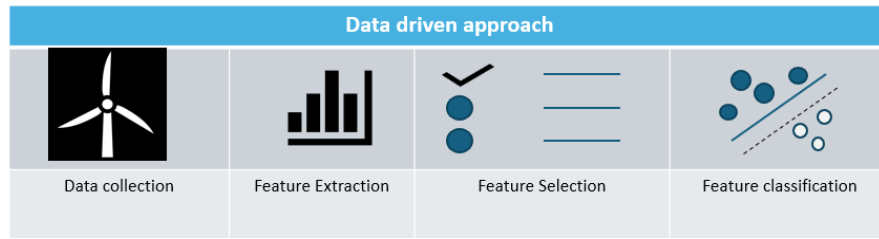


Figure (3) Proposed framework for monitoring of FOWTs

In the first step the platform surge displacement and acceleration response of the spar floating offshore wind turbine is recorded under the selected load case scenarios. Secondly, the time domain features are extracted using the diagnostic feature explorer toolbox in MATLAB, 2023R2. These features are computed in time domain and provide summary of statistical features from acceleration and displacement in 1000 point windows. The feature vectors are listed in Table (3). Subsequently, the best feature subset is selected by the ANOVA analysis of FS algorithm [17]. In the final step, the selected features are trained using the kNN algorithm.

Table (3) Time domain features

Feature	Functions	Feature	Function
Root mean square	$rms = \sqrt{\frac{\sum_{n=1}^N (x(n))^2}{N}}$	Shape factor	$sf = \frac{rms}{\frac{1}{N} \sum_{n=1}^N x(n) }$
Variance	$var = \sigma^2 = \frac{\sum_{n=1}^N (x(n) - mean(x))^2}{(N - 1)}$	Impulse factor	$\frac{max x(n) }{\left(\frac{1}{N} \sum_{n=1}^N \sqrt{ x(n) }\right)^2}$
Skewness	$\frac{\sum_{n=1}^N (x(n) - mean(x))^3}{(N - 1)\sigma^3}$	Crest factor	$\frac{max x(n) }{rms}$
Kurtosis	$\frac{\sum_{n=1}^N (x(n) - mean(x))^4}{(N - 1)\sigma^4}$	Signal to noise and Distortion ratio	Ratio of total signal power to total noise plus distortion power

Total harmonic distortion (THD)	Ratio of total harmonic component power to fundamental power	(SINAD) Signal to Noise Ratio (SNR)	Ratio of signal power to noise power
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4. Results

In this study, the platform surge displacement and acceleration responses are recorded under two different load cases with varying degree of damage in the mooring cables. A total of 25 number of simulations are carried out for damage detection. The sensitivity assessment is conducted for both platform displacement and acceleration response.

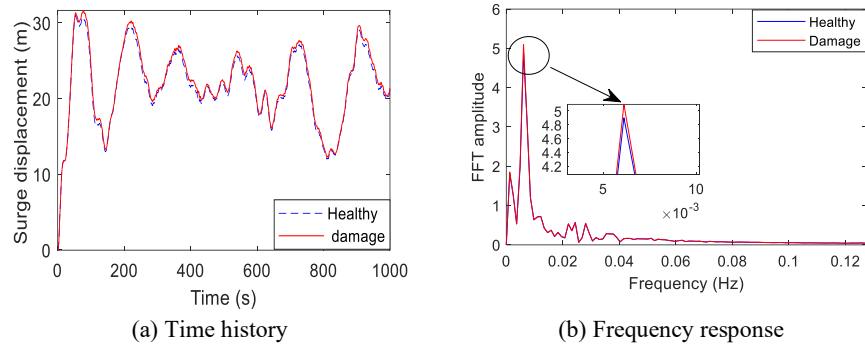


Figure (4). Comparison of healthy and damaged response of platform surge displacement under LC1.

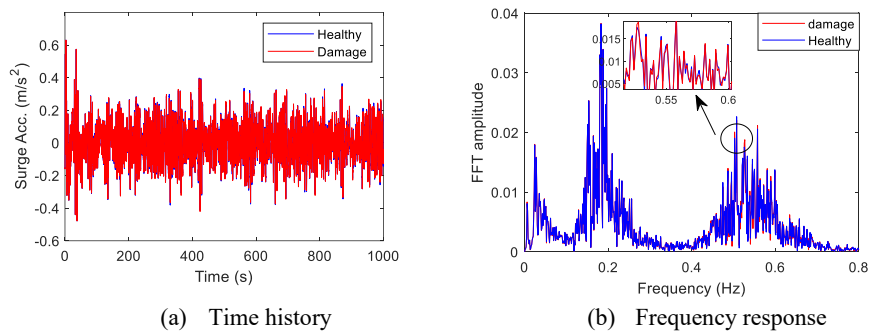


Figure (5) Comparison between healthy and damaged response of platform surge acceleration under LC1.

The platform surge displacement between the healthy and corroded mooring (15% severity) systems are compared and shown in Fig. 4 and 5. The time history of platform surge displacement and accelerations are shown in Fig. 4(a) and 5(a) respectively. The frequency response of the displacement and acceleration is plotted and shown in Fig. 4 (b) and 5(b). Similarly, the displacement response for the healthy and damaged due to biofouling (10% severity) mooring system is shown in Fig. (6). It is clearly evident that the precise identification of the damage with frequency domain decomposition from the surge acceleration response is critical, due to the fact that, the varying environmental conditions

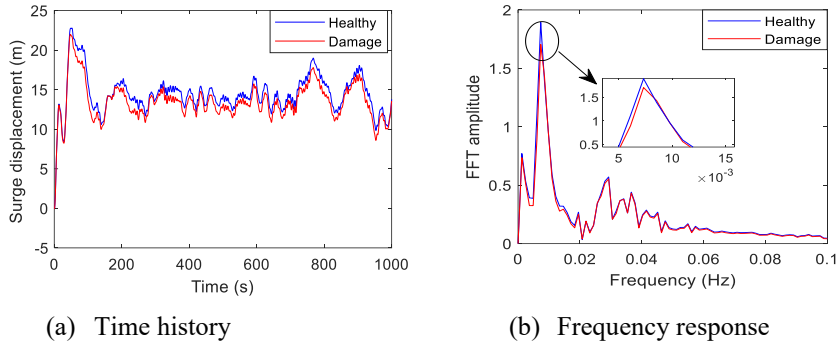


Figure (6). Comparison between healthy and damaged response of platform surge displacement under LC2.

As mentioned in Section 3, 13 features are extracted from each sensor direction. In this study, this resulted in a total of 26 features per data window. The extracted feature set is then ranked based on its ability to distinguish between different data classes (three classes: healthy data, biofouling data, and corrosion data) using the Analysis of Variance (ANOVA) algorithm. This algorithm selects features based on the distance between their mean values across different classes. High-ranking features are those where the data distribution in each class is more separable compared to the others.

Based on the ANOVA results, the five highest-ranked features are selected as inputs for the classification model. The box plot of the top feature, peak displacement value, is shown in Fig. 7, illustrating the differences in mean values across classes. Furthermore, the results indicate that all selected features belong to the displacement sensor, highlighting its greater sensitivity to damage compared to the accelerometer. The results of the binary classification model, based on the K-Nearest Neighbors (KNN) algorithm, are shown in Fig. 8. The accuracy was calculated using the k-fold cross-validation method with $k=5$, resulting in an average accuracy of 70% for detecting biofouling. It is worth noting that two different binary models were used in this study: one for detecting biofouling and another for detecting corrosion. The accuracy of the second model dropped to 60%, suggesting that detecting corrosion using this feature set and sensor type is less reliable.

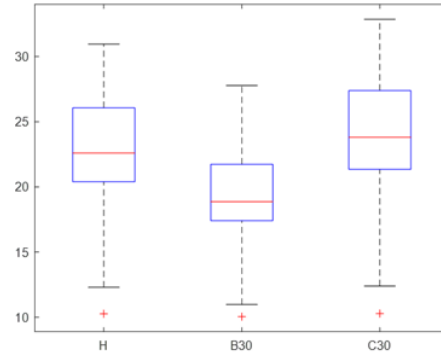


Figure (7). Box plot

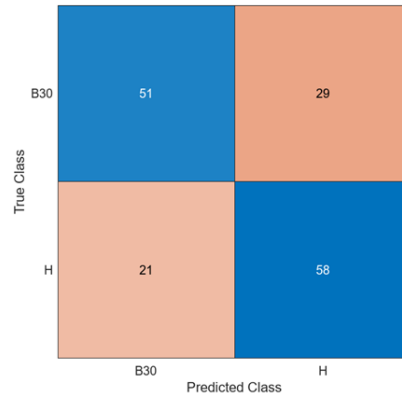


Figure (8). Confusion matrix

5. Conclusion

The damage detection problem in mooring systems for FOWTs has been investigated. The examined structure is a 5MW NREL benchmark offshore wind turbines, which is connected with 3 mooring cables. The platform surge displacement and acceleration response are recorded for the analysis. Two different damages are modelled in OpenFAST software, where the severity of the damage is kept between 5%-30% which has practical applications in real practice. In summary, the proposed framework demonstrates its capability in detecting damage in FOWTs. As future work, the usability of additional feature types and an increased number of sensors will be explored. Additionally, further studies are needed to determine the optimal placement of sensors.

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