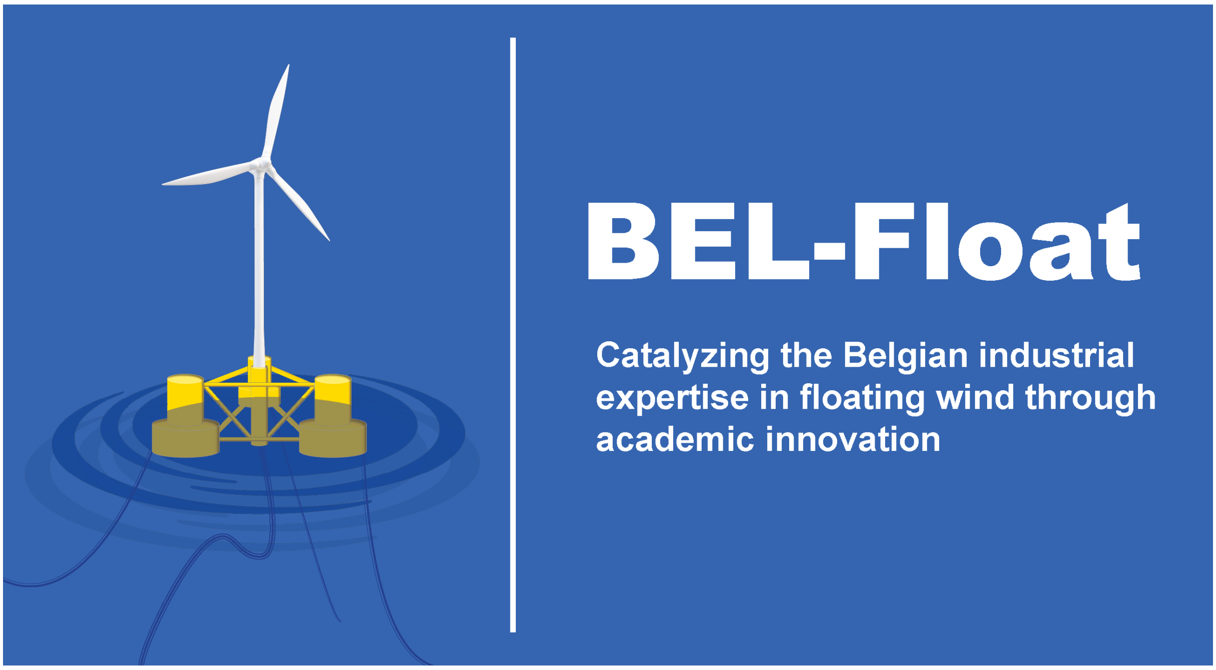

BEL-Float

Topic 3 - Low frequency dynamics of a floating platform

Deliverable 1 - Guidance notes and demonstrator report on the use of operational modal analysis for the determination of the dynamics of a FOWT

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Contents

1 BEL-Float Context

The BEL-Float project aims to position Belgium at the forefront of the floating offshore wind (FOW) sector by bridging the gap between industrial needs and academic innovation. Although FOW farms will not be installed in Belgian waters, the initiative recognizes the vast potential for Belgian industry to transition its expertise from bottom-fixed to floating wind structures.

This deliverable is part of BEL-Float project (research topic 3: low frequency dynamics of a floating platform) among 6 other research topics tackling challenges within the floating industry. Understanding and monitoring the platform's low-frequency behavior is essential for safe and efficient floating wind operations. The development of advanced sensor configurations and operational modal analysis (OMA) techniques contributes to BEL-Float's goal of building foundational knowledge and innovative methodologies that will unlock the industry's evolution toward floating technologies.

1.1 Overview

Operational modal analysis (OMA) is a powerful technique used in the field of structural health monitoring (SHM) to determine the dynamic properties of structures in their operating conditions. Unlike traditional experimental modal analysis (EMA), which requires controlled excitation (such as impact or shaker tests), OMA extracts modal parameters solely from ambient vibrations or operational loads acting on the structure. This makes it particularly valuable for structures that cannot be easily or safely excited artificially, such as bridges, skyscrapers, wind turbines, and other large civil engineering structures.

1.2 Scope of Work

OMA works by placing a sensor (e.g., accelerometer) on the desired location of interest or even multiple points. These sensors record the response of the structures in time-series signals (e.g., acceleration). By using OMA algorithms, the recorded time-series signal by the sensors is processed and the dynamic properties of structures (e.g., Floating Offshore Wind Turbines, FOWT) are estimated. This process is referred to as Modal Parameter Estimation (MPE), where the natural frequencies, damping ratios, and mode shapes are obtained. The purpose of this deliverable is to investigate the reliability of applying operational modal analysis to detect these low-frequency modes of floating wind turbines.

2 Methodology and Results

The methodology and results of this deliverable are presented in a conference paper submitted to Journal of Physics: Conference Series (EERA DeepWind Conference 2025). The confernce paper is hereby attached in the appendix and serves as the deliverable of this document. The work is still evolving and an extended publication on this topic is planned for 2025.

Appendices

Appendix A: Journal of Physics Conference Paper

Abstract

The dynamic interaction between mooring systems, floating platforms, and wind turbines is complex, leading to greater uncertainties in design and higher operational and maintenance costs (OPEX). A potential solution to mitigate these uncertainties and reduce OPEX is the application of remote Structural Health Monitoring (SHM) systems. Among SHM techniques, Operational Modal Analysis (OMA) is particularly valuable for assessing the dynamic properties of structures under actual operating conditions. This research explores the reliability of detecting low-frequency modes of Floating Offshore Wind Turbines (FOWTs) using OMA. The analysis employs the Least Squares Complex Frequency (LSCF) algorithm and numerical sensor data. The NREL 5MW reference wind turbine mounted on the OC4 semi-submersible platform was used as the reference FOWT. Acceleration time-series signals were generated using the time-domain software OpenFAST at various points on the FOWT, simulating accelerometer placements. The pre-processed signals were then analyzed using the LSCF algorithm to estimate the natural frequencies and damping ratios of the low-frequency modes, including the first tower mode, via stabilization diagrams. Additionally, a sensitivity study was conducted on the initial LSCF settings for modal parameter estimation, focusing on signal window length and optimal sensor placement on the FOWT.

Introduction

By using Floating Offshore Wind Turbines (FOWTs), a huge potential in harvesting wind energy will be unlocked for sites with deeper water depth (more than 50m) [1]. Despite the various advantages of FOWTs, their commercialization has been slow. Currently, only few FOWTs are installed in real-world settings, mostly for testing purposes [2]. One significant drawback of FOWTs is the high Operation and Maintenance costs (OPEX). For example, predicting the dynamics of mooring systems, floating platform and wind turbine is more complex than for fixed systems, leading to greater uncertainties and higher costs [3]. A potential solution to reduce these uncertainties and OPEX is the implementation of remote Structural Health Monitoring (SHM) system.

Operational Modal Analysis (OMA) is a powerful technique used in the field of SHM to determine the dynamic properties of structures in their operational conditions. Unlike traditional Experimental Modal Analysis (EMA), which requires controlled excitation (such as impact or shaker tests), OMA extracts modal parameters solely from the ambient vibrations or operational loads acting on the structure [4, 5]. This makes it particularly valuable for structures that cannot be easily or safely excited artificially, like bridges, skyscrapers, wind turbines, and other large civil engineering structures.

The application of OMA for system identification of bottom-fixed offshore wind turbines has been extensively studied and has reached a good level of maturity [4, 6]. However, its application in identifying the dynamic characteristics of FOWTs—such as natural frequencies, damping ratios, and mode shapes—is still not fully explored. Additionally, there is a lack of experimental data from commercial FOWT units for system identification using OMA [7]. This limitation can, however, be addressed by utilizing numerical data obtained from time-domain simulations.

In their study [2], OMA Frequency Domain Decomposition (FDD) method was applied to numerical signals from fully-coupled time-domain simulations to extract modal properties of the tower and blades. The estimated natural frequencies of the blades and tower were compared with a Finite Element Model (FEM), showing good agreement. Using two FOWT concepts (semi-submersible and spar) simulated in ANSYS AQWA, the Covariance-driven Stochastic Subspace Identification (SSI-COV) algorithm was applied to obtain their dynamic properties. The study showed the feasibility of using SSI-COV under various load cases under hydrodynamic loading to estimate the modal properties of the two FOWT concepts [8]. The FDD method was used in [9] to identify the dynamic properties of a spar floating platform under hydrodynamic loading using ANSYS AQWA, with the rotor in a fully parked state and the rotor-nacelle assembly represented as a lumped mass. However, the FDD method requires the resonance frequencies to be sufficiently far from those of the excitation loads with a long measurement window for accurate identification. Using real-life data of full-scale FOWT in parked and operational cases, SSI-COV method was used to identify the tower modes and confirmed the relation between the platform motions and tower with an analytical model [7]. For the identification of the FOWT low-frequency modes, SSI-COV was applied to experimental data of full scale FOWT [10]. The raw time series signal was pre-processed to properly detect the low-frequency modes and provide clearer stabilization diagrams.

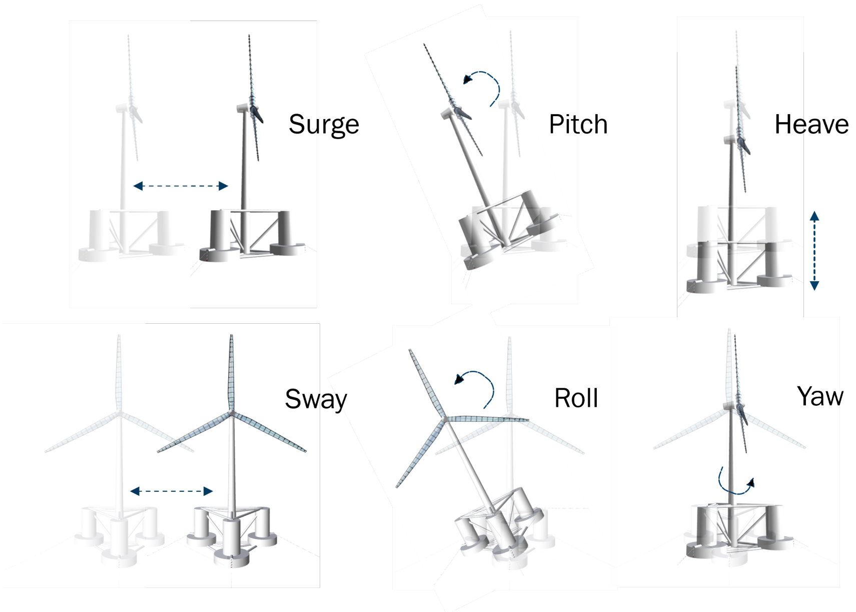


Figure 1: Low-frequency rigid body modes of a FOWT platform.

This paper aims to present a methodology for reliably detecting low-frequency platform modes, including the first tower mode, using the Least Squares Complex Frequency (LSCF) method applied to numerical signals under operational conditions. The low-frequency platform motions of a FOWT are shown in Figure 1, consisting of three translational (Surge, Sway, and Heave) and three rotational (Roll, Pitch, and Yaw) degrees of freedom [11]. Although previous studies have applied different OMA algorithms to numerical data from time-domain simulations to identify platform low-frequency modes, most have focused solely on hydrodynamic excitation, simplifying or neglecting the effects of wind. Moreover, the applicability of the LSCF method in identifying FOWT low-frequency modes remains unexplored.

Methodology

Time-Domain Simulation

The National Renewable Energy Laboratory (NREL) 5MW reference wind turbine, mounted on the OC4-DeepCwind semi-submersible platform [12], is used as the reference FOWT for this analysis. Figure 2 shows the geometric details and model properties defined in [12] which was used in an OpenFAST model. The Offshore Code Comparison Collaboration Continuation (OC4) FOWT is anchored to the seabed using three mooring lines (ML1, ML2, and ML3) connected to the platform's fairleads. The OpenFAST output signals are based on a reference coordinate system (xt, yt, and zt) at the tower base. It is fixed to the support platform, moving and rotating along with it when platform accelerations are considered. In contrast, tower accelerations are expressed in a local coordinate system that aligns with the standard tower system but orient themselves with the deflected tower [13].

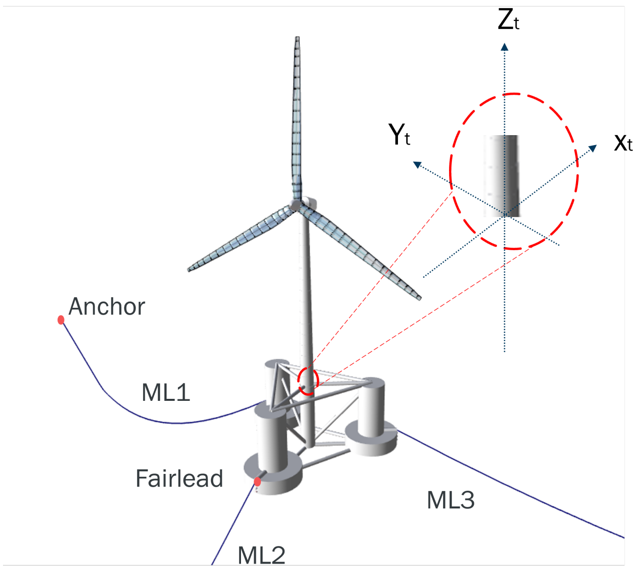


Figure 2: Detailed description of OC4-DeepCwind FOWT.

Table 1 shows the natural frequencies design values of the OC4 FOWT as reported in [14]. FA and SS refer to Fore-Aft and Side-Side vibrations of the tower, respectively. Time-domain software called OpenFAST is used to generate the time-series signals at different desired points on the FOWT resembling the placement of accelerometer sensors.

A load case is simulated in OpenFAST using a turbulent wind field generated by TurbSim [15]. The simulation considers a reference wind speed of 13 m/s with a wind heading of 0° which is aligned to the xt direction. JONSWAP spectrum is used to generate the irregular wave with significant wave height H_s of 1.5 m and wave peak period T_p of 8 seconds with 0° wave heading (aligned with xt axis). The simulation dataset was provided by Topic 1 of the BEL-Float project and is publicly available [16]. The response of the OC4

Table 1: Natural frequencies design values of OC4 FOWT [14]

DOF	Frequency (Hz)	Period (s)
Surge/Sway	0.0093	107
Yaw	0.0131	76.28
Roll/Pitch	0.039	25.64
Heave	0.058	17.30
Tower 1st SS	0.418	2.39
Tower 1st FA	0.426	2.35

FOWT is recorded (e.g., accelerations, displacement) on the tower and platform. Figure 3 shows the selected points for measurements resembling the placement of accelerometers in real-life settings. The sensors on the tower are tri-axial, measuring acceleration in the fore-aft (FA), side-to-side (SS), and vertical (ZZ) directions. The platform acceleration sensors include three translational and three rotational sensors at the platform-tower joint, corresponding to the six Degrees of Freedom (6DOF) of the FOWT.

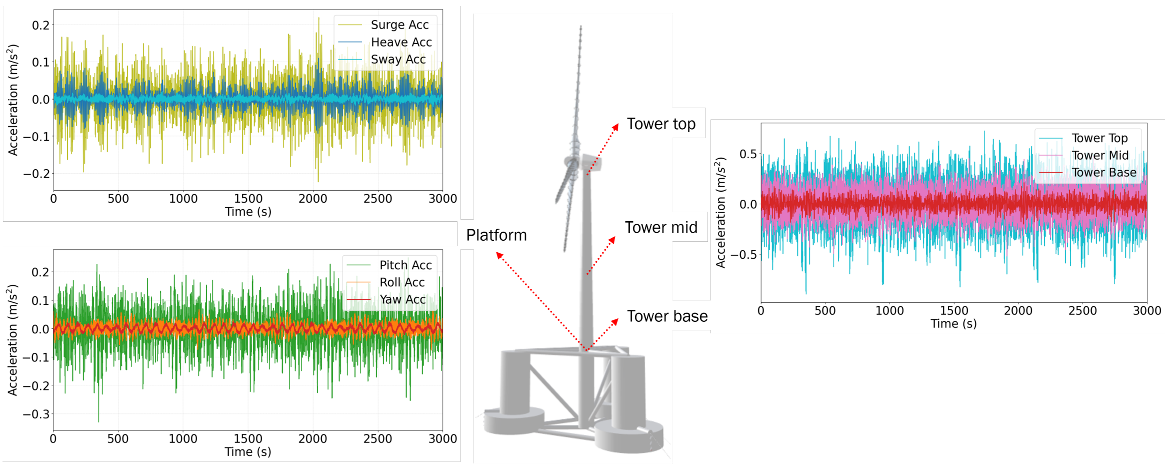
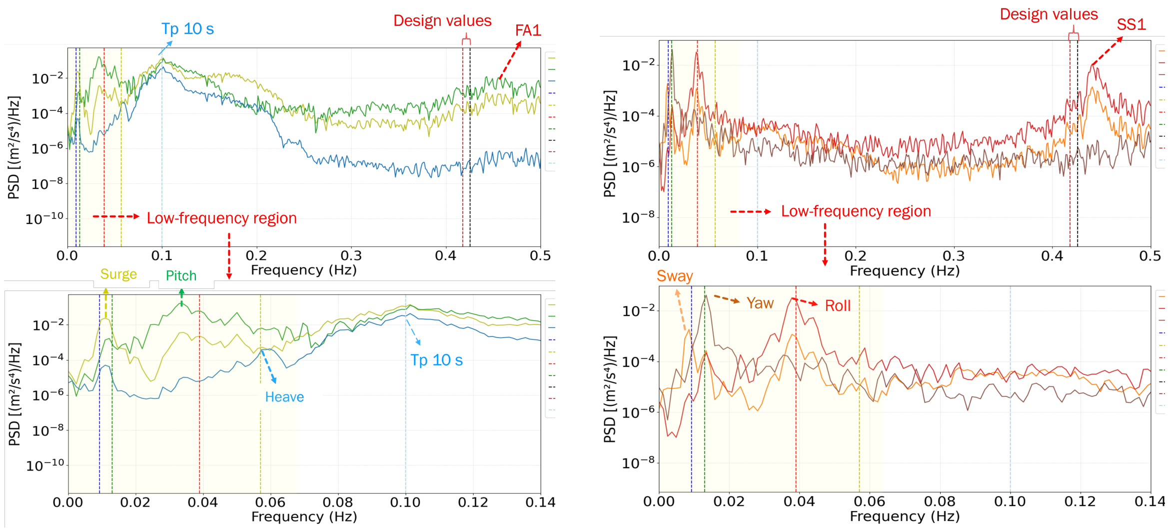


Figure 3: Location of time-series signals recorded by the acceleration sensors in OpenFAST.

The 6-DOF acceleration signals of the platform are used to examine the dynamic behavior of OC4 FOWT under normal operational condition. Figure 4a shows the power Spectral Density (PSD) of surge, pitch and heave acceleration signals. The PSD results indicate that the first FA tower mode is slightly shifted compared to the design value reported in Table 1. The highest energy is observed in the pitch and surge signals, whereas the heave signal exhibits lower energy with respect to FA1. All three signals exhibit high energy around the wave peak frequency (0.1 Hz).

Examining the low-frequency region in Figure 4a, the heave sensor exhibits a peak near its natural frequency, which closely matches the design value in Table 1 (yellow vertical dashed line). For pitch, the peak appears lower than the design value (red vertical dashed line). This same peak is also captured by the surge sensor, indicating dynamic coupling between the two motions. The surge sensor exhibits a prominent peak near its natural frequency, slightly higher than the design value (blue vertical dashed line). In addition, all sensors showed a peak around surge natural frequency where coupling effect exist.

The PSD of sway, roll and yaw acceleration signals is shown in Figure 4b. The first SS tower mode also appears higher than those reported in Table 1 with high energy in the roll



(a) surge, pitch, and heave **(b)** sway, roll, and yaw.

Figure 4: PSD of the platform acceleration signals. Vertical dashed lines represent the natural frequencies design values in Table 1.

and sway signals. Here, the wave peak frequency do not appear as sensors axes are not aligned with the wave heading. For the low-frequency region, roll mode appears in both roll and sway sensors which implies coupling of these two modes. The value of roll mode is relatively close to the design value (vertical red dashed line). All sensors exhibited a peak around yaw natural frequency that matched the design value (green vertical dashed line). Sway sensor shows a peak around its natural frequency, a bit lower than the design value (blue vertical dashed line)

Least Squares Complex Function

When using OMA, the first step after measuring structural vibrations under normal operating conditions is to compute the auto- and cross-correlation functions [17]. By applying the Fast Fourier Transform (FFT) to the positive lags of these correlation functions, the auto- and cross-power spectra are obtained, which then serve as inputs for frequency-domain OMA methods [17, 18]. The Least Squares Complex Frequency (LSCF) method is a frequency-domain technique and it works by minimizing the least squares error between the measured response and the response predicted by a mathematical model of the system. Through this process, poles are identified at different model orders, corresponding to the physical modes of the structure. These poles are then visualized in a stabilization diagram, where physical modes can be distinguished from mathematical ones [17]. A more detailed explanation of the LSCF method can be found in [19].

Figure 5 shows the LSCF methodology applied to a recorded numerical signal (e.g., surge displacement) of a FOWT under normal operation. When applying LSCF for estimating FOWT low-frequency modes, several settings can be adjusted for accurate detection. These initial settings of LSCF including the window length and the exponential window (β) applied to the auto-cross correlation of the measured signal and the frequency band of the auto-cross power spectra as shown in Figure 5. The exponential window places more emphasis on early lags with physical modal information and it works by introducing

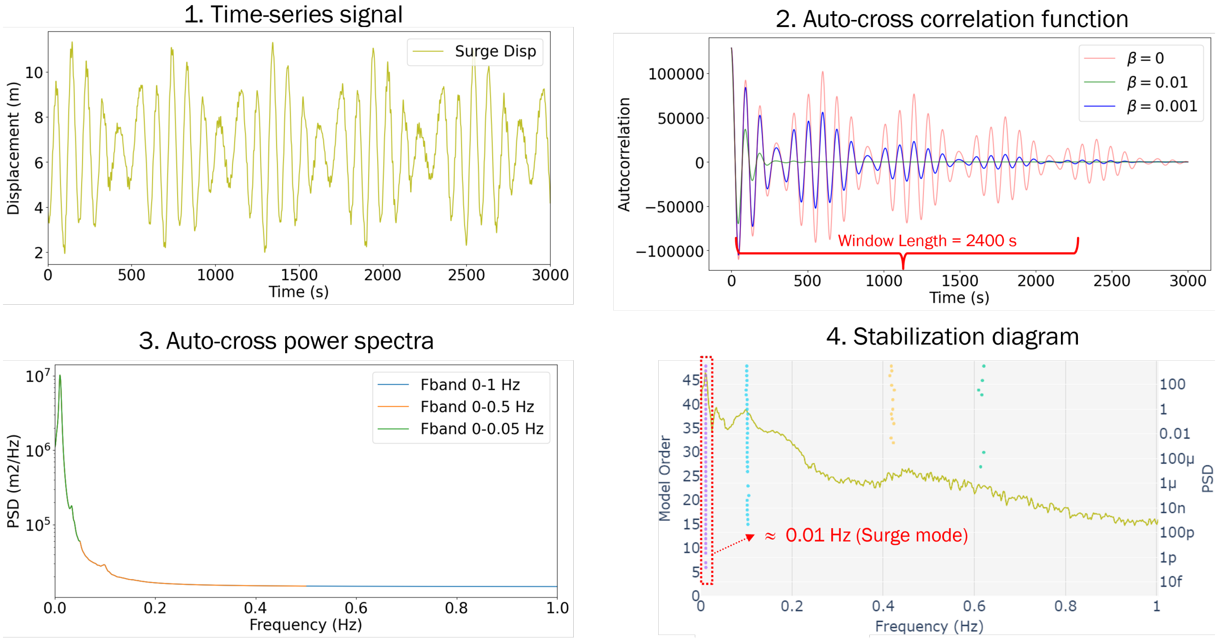


Figure 5: LSCF methodology applied to a numerical signal.

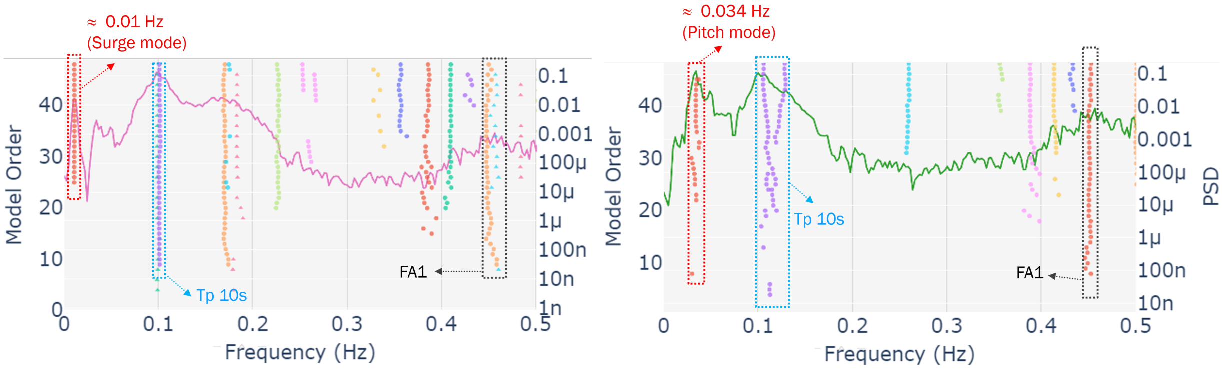
additional damping to the signal (β) to minimize leakage. This is particularly important when computing the FFT of signals. A window length is a critical parameter in defining the frequency resolution. Since the low-frequency components of the signal is the focus of this work, longer window length is needed. In addition, the frequency band of the auto-cross spectra can be varied to target the FOWT low-frequency modes. A clustering algorithm is used for the automatic selection of physical poles representing the modes of interest. The cluster size indicates how many poles are in one cluster. Each cluster can contain only a limited number of poles, determined by the maximum selected model order minus the excluded orders [17].

Results

Modal Parameter Estimation

In this section, the platform's time-series acceleration signals, shown in Figure 3, are used as inputs to the LSCF algorithm following the methodology illustrated in Figure 5. The estimated modal properties are then presented in stabilization diagrams. Figure 6 shows the stabilization diagrams for the pitch and surge acceleration sensors. Both sensors exhibit pole stabilization around the wave peak frequency 0.1 Hz, with the surge sensor showing more consistent stabilization, as it aligns with the wave heading. In Figure 6a, the poles stabilize around the surge natural frequency and the first tower fore-aft mode (FA1). In Figure 6b, the poles near the pitch natural frequency (0.034 Hz) attempt to stabilize; however, they appear more consistent in the FA1 mode.

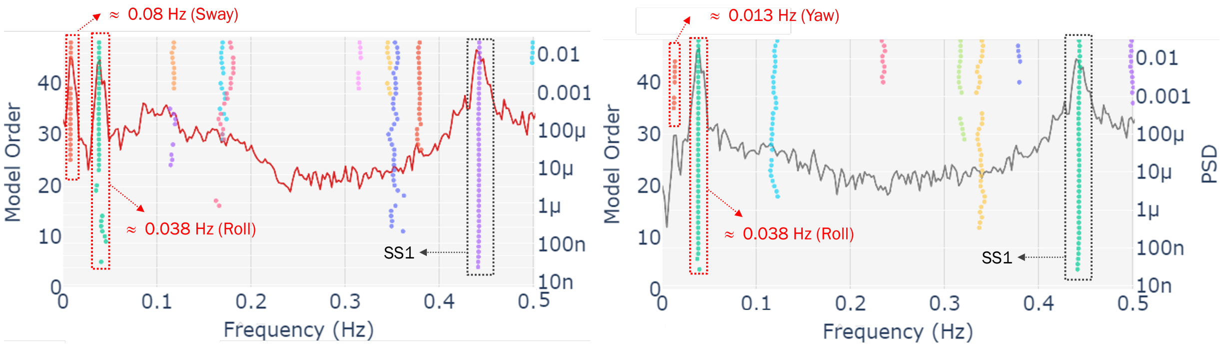
Stabilization diagrams for the side-to-side (SS) direction are shown in Figure 7. Both the sway and roll acceleration sensors exhibit stabilized poles around the SS1 tower mode. In Figure 7a, poles are observed at the sway natural frequency (0.08 Hz) as well as at the roll mode (0.038 Hz), indicating that the sway sensor detects coupling between these two



(a) surge acceleration sensor. **(b)** pitch acceleration sensor.

Figure 6: Stabilization diagrams for X_t axis (FA direction).

modes.



(a) sway acceleration sensor. **(b)** roll acceleration sensor.

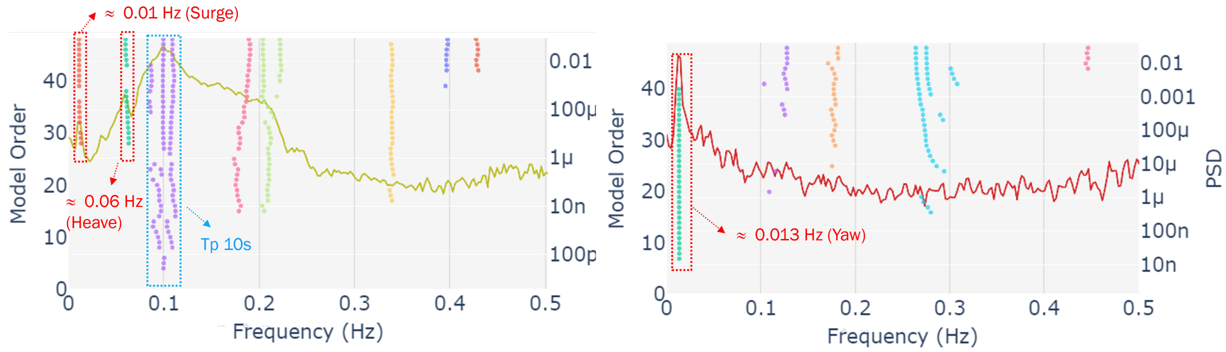
Figure 7: Stabilization diagrams for Y_t axis (SS direction).

The roll sensor, as shown in Figure 7b, consistently estimates the roll mode around 0.038 Hz and also detects the yaw mode at 0.013 Hz, suggesting a coupling effect between these two modes.

For the vertical (Z) direction, the stabilization diagrams of the heave and yaw acceleration sensors are shown in Figure 8. In Figure 8a, the heave sensor's poles attempt to stabilize around the wave frequency. Additionally, the heave (0.06 Hz) and surge (0.01 Hz) natural frequencies are identified, indicating a coupling effect detectable by this sensor. The yaw sensor, shown in Figure 8b, successfully estimates the yaw natural frequency, with poles appearing more consistently. However, no coupling with other modes is observed.

Window Length

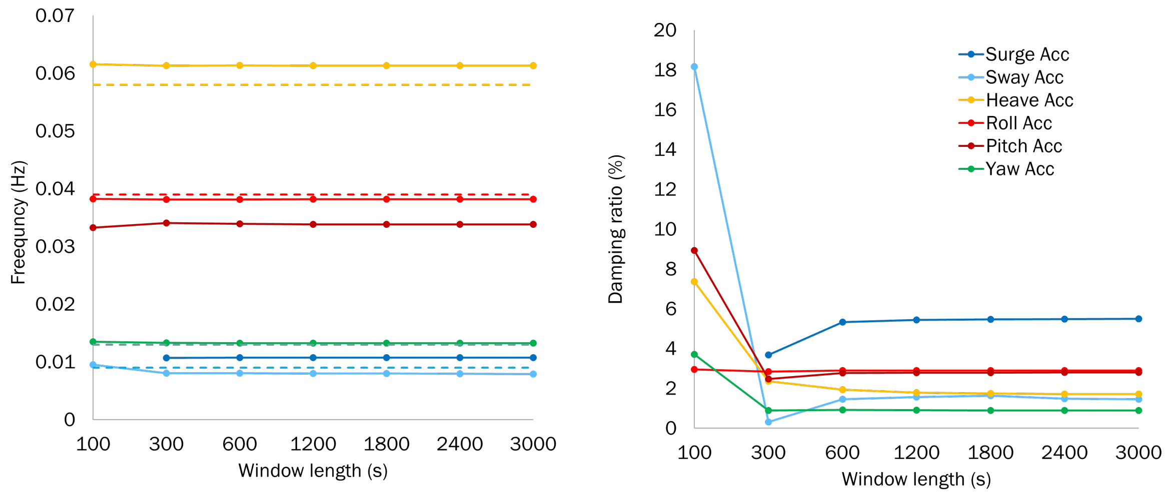
The window length is a crucial parameter in defining the frequency resolution of a signal. Shorter windows help maintain the time-invariant assumption of OMA, whereas longer windows increase the risk of system changes within the selected time window. A 10-minute time segment is assumed to be sufficient for maintaining relatively constant ambient conditions, such as wind speeds, which is essential for the time-invariant assumption in OMA. This duration is also commonly used for SCADA and Meteo data, offering



(a) heave acceleration sensor. **(b)** yaw acceleration sensor.

Figure 8: Stabilization diagrams for Z_t axis (ZZ direction).

the advantage of facilitating future data analyses [17]. This section analyzes the window length required to detect the low-frequency modes of the FOWT by varying it within the LSCF algorithm.



(a) Frequency sensitivity. **(b)** Damping sensitivity.

Figure 9: Sensitivity of modal parameter estimation of the low-frequncy modes to different window length.

Figure 9 illustrates the sensitivity of modal parameter estimation to different window lengths for estimating the low-frequency modes of the OC4 FOWT platform. In Figure 9a, the estimated resonance frequencies remain consistent across different window lengths, except for surge and sway. When using a short window (e.g., 100s), surge natural frequency was not detected because its natural period exceed 100s. Despite this limitation, the resonance frequencies are correctly identified at sufficient window lengths. However, damping estimation is more sensitive to window length selection. As shown in Figure 9b, using a window length shorter than 600s results in variation of the damping estimates. This highlights the importance of selecting an appropriate window length to ensure reliable modal parameter estimation for the FOWT low-frequncy modes.

Sensors Location

The sensitivity of sensor placement for optimal modal parameter estimation was analyzed for four locations on the FOWT: the tower top, mid-tower, tower base, and the platform-tower intersection. A window length of 1200s is used for the LSCF method. The accelerations at these points were recorded from the time-domain simulation, as shown in Figure 3. As mentioned, The sensors on the tower are tri-axial, measuring acceleration in the fore-aft (FA), side-to-side (SS), and vertical (ZZ) directions. The platform acceleration sensors include three translational and three rotational sensors, corresponding to the 6DOF of the FOWT.

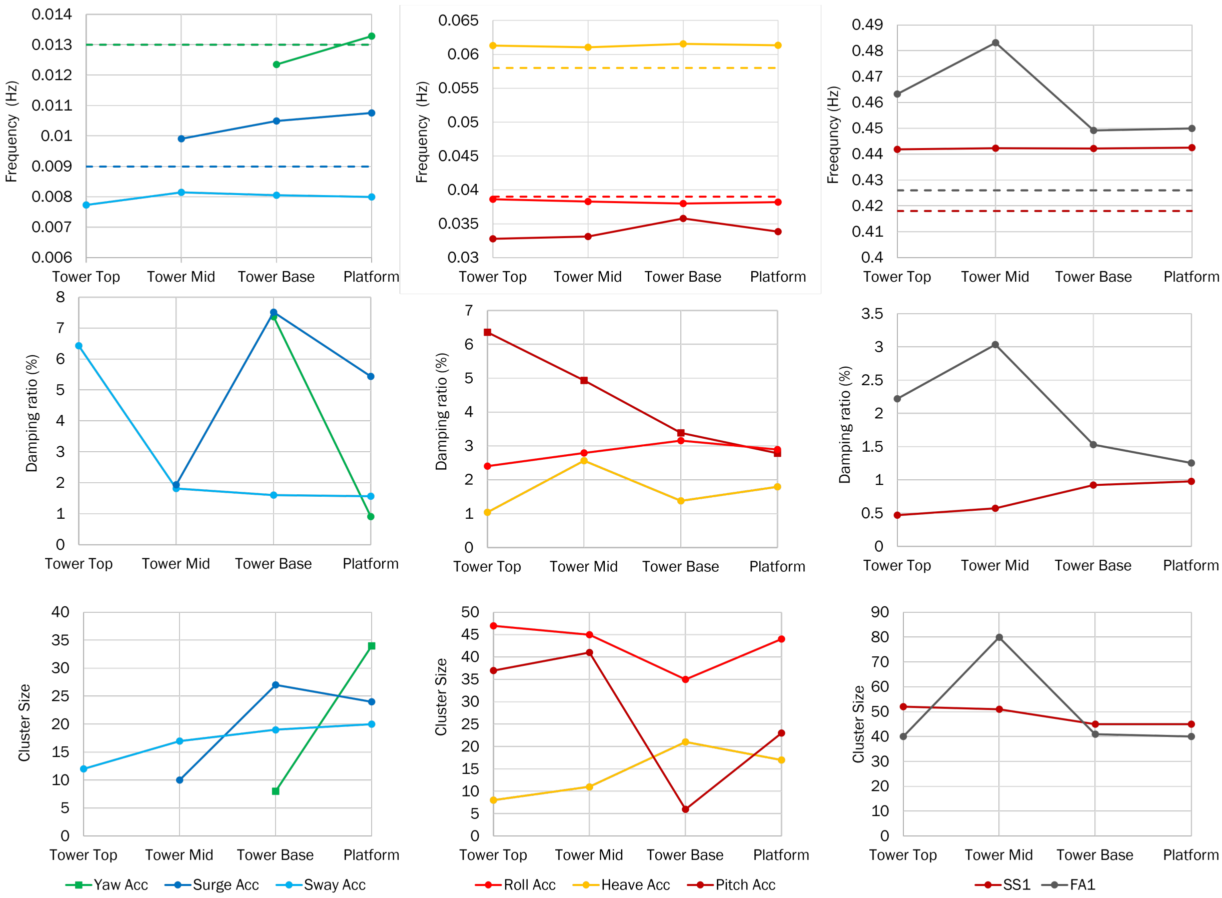


Figure 10: Sensitivity of modal parameter estimation to sensors location.

Figure 10 illustrates the effect of sensor location on modal parameter estimation in terms of natural frequencies, damping ratios, and cluster size. For very low-frequency modes (surge, sway, and yaw), resonance frequency estimation was more accurate when sensors were placed close to the platform, particularly for yaw. This is evident from the cluster size, where more poles clustered when sensors were positioned near the platform. While damping ratios varied, sway damping appeared more consistent when sensors were placed near the platform.

For roll and heave, resonance frequency estimation was consistent across all sensor locations, unlike pitch, which showed some discrepancies. This difference is reflected in the estimated damping ratios, where pitch exhibited the highest variation. In terms of cluster size, the heave mode was more pronounced when the sensor was near the platform.

However, this was not the case for pitch and roll, where more poles were estimated when sensors were placed at the tower top, especially for pitch.

The estimated first tower bending modes (FA1 and SS1) were higher than the design values reported in Table 1. SS1 showed more consistency across all sensor locations than FA1. This trend is also observed in the damping values, where FA1 exhibited greater variation. Furthermore, both SS1 and FA1 had a high cluster size across all sensor locations, except for FA1 at the mid-tower, where more poles were estimated.

Conclusion and Future Work

This paper demonstrated the application of Operational Modal Analysis (OMA) in determining the dynamics of Floating Offshore Wind Turbines (FOWTs) through a numerical case study on the OC4 NREL 5MW FOWT. The methodology involved using OpenFAST to generate time-series signals, simulating the placement of accelerometers in real-life conditions. The Least Squares Complex Frequency (LSCF) algorithm was then applied to estimate the modal parameters of the FOWT under operational conditions.

Before applying LSCF to the acceleration time-series data, key settings were defined, including window length, frequency band, and sensor location. The results showed that the LSCF algorithm successfully detected all low-frequency modes of the FOWT, up to the first tower bending mode. The study on window length sensitivity indicated that a window length above 600s is required for consistent modal parameter estimation. Additionally, the analysis of sensor placement revealed that placing translational and rotational accelerometers close to the platform has good estimates for the platform low-frequency motions, particularly yaw.

For future work, further investigation is needed into the sensitivity of the LSCF algorithm to different load cases (LCs) in detecting low-frequency modes up to the tower bending mode. The goal is to understand the influence of environmental conditions on modal parameter estimation. Additionally, the proposed LSCF methodology will be tested under damage scenarios, such as mooring line failure, to assess whether the algorithm can detect changes in the dynamic properties of the FOWT when structural damage occurs.

Acknowledgments

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