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Citation for published version:

Qu, K, Garcia Cava, D, Killbourn, S & Logan, A 2023, Operational modal analysis for scour detection in mono-pile offshore wind turbines. in *European Workshop on Structural Health Monitoring : EWSHM 2022 - Volume 2*. vol. 2, Lecture Notes in Civil Engineering , vol. 254, Springer, pp. 668–678, 10th European Workshop on Structural Health Monitoring, Palermo, Italy, 4/07/22. https://doi.org/10.1007/978-3-031-07258-1_67

Digital Object Identifier (DOI):

[10.1007/978-3-031-07258-1_67](https://doi.org/10.1007/978-3-031-07258-1_67)

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Peer reviewed version

Published In:

European Workshop on Structural Health Monitoring

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Operational modal analysis for scour detection in mono-pile offshore wind turbines

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Abstract. Monitoring large structures over their lifetime is becoming increasingly important as robust monitoring will ensure safety and financial benefits. Offshore wind turbines (OWT) are in need of continuous structural health monitoring (SHM) methodologies for scour detection. Reliable detection of scour requires robust selection of structural features to adequately represent the integrity of the OWT. Successful identification of operational modal parameters of OWT is challenging because of the effect of environmental and operational variability (EOV). Therefore, mitigating the effect of EOV is crucial to guarantee that the variability in the extracted features is caused by structural degradation. This work presents a methodology based on stochastic subspace identification enhanced by a clustering technique to identify stable and robust structural modes over time. Gaussian process regression is used to mitigate EOV due to its flexibility and non-parametric nature. Data collected from a control OWT and a scoured OWT in operation over 8-months is used for verification. The results have demonstrated that scour affects OWTs by reducing their natural frequencies. The results also indicate that scour induces OWTs to react differently to EOV. The outcomes of this work provide the basis for real time monitoring of OWTs, thus facilitating a reliable identification of scour.

Keywords: Operational Modal Analysis · Environmental and Operational Variations · Scour · Gaussian Process Regression · Offshore Wind Turbines

1 Introduction

Structural health monitoring (SHM) has been widely used in the engineering community to monitor structures, such as buildings and bridges. The method involves analysis of periodical data continuously, intended to provide real time or near real time information of the structure. This study intends to explore the applications of SHM in wind energy, specifically detecting whether scour has occurred in mono-pile offshore wind turbines during operation and in a continuous manner.

OMA techniques, including Stochastic Subspace Identification (SSI), are now widely applied in wind energy for SHM purposes (see Devriendt et al. [1]). This study approaches SHM using operational modal analysis (OMA) techniques, specifically stochastic subspace identification (SSI). The underlying theory of OMA, and

more specifically SSI, has been broadly outlined in [2], [3] and [4]. [1] developed an automatic OMA algorithm for long-term dynamic monitoring of offshore wind turbines that includes: pre-processing; modal parameter estimation, and clustering (post-processing). Continuous monitoring algorithms similar to automatic OMA utilising SSI have also been applied to large structures such as stadiums [5]. Works by Weitjens et al. [6] have proven that SHM strategies can be developed from OMA techniques to monitor and identify changes in the structure over time. More advanced applications of OMA can be found in [7], where OMA is used in combination with a finite element model to estimate response parameters, such as acceleration, at unmeasured locations of a mono-pile offshore wind turbine.

A major challenge of SSI is that although the technique can identify modal parameters and distinguish between stable and unstable modes, the outputs from each observation are produced individually. This means that the same structural mode may not be consistently identified as the same mode when tracked over a substantial period. Additionally, modal parameters can be affected by Environmental and Operational Variability (EOV), therefore changes in modal parameters may not always reflect change in structural behaviour. Previous work has demonstrated that utilising machine learning techniques is a powerful approach to mitigating EOV, whether information regarding the EOV is available [8] or not [9]. This paper proposes using clustering techniques to aid SSI so that outputs from new observations can be grouped according to previous observations without human interference and, therefore, selecting reliable features while also applying Gaussian Process Regression (GPR) to mitigate EOV. Thus, clear and reliable data is produced enabling precise detection of scour and also forming a basis for further developments leading to automatic identification of scour. An example of previous applications of GPR in SHM can be found in [10]. The methodology is illustrated in this paper using data collected from an in-operation healthy (control) turbine and a scoured turbine over an 8-month period.

2 Methodology

The analysis in this study is two-fold. Firstly, robust damage sensitive features (DSFs) are identified by applying SSI-COV in combination with a clustering technique, so that structural features of interest can be consistently identified as DSFs. Secondly, GPR is applied to the identified DSFs to mitigate EOV and provide more reliable identification of scour.

2.1 Clustering Technique for Robust Feature Extraction

Continuous acceleration measurements $a(t), t \in \mathbb{R}$ can be obtained from the m sensors mounted on the structure of interest due to operational loading. The measurements are distributed in time segment vectors $\mathbf{y} \in \mathbb{R}^N$. All \mathbf{y} vectors from the m sensors are processed using SSI-COV to identify the operational vibration modes of the structure.

To ensure consistent identification of structural modes, the first step is to remove any noise modes that have been identified as unstable by the SSI-COV algorithm. A model order shall be selected by the user based on the stabilization diagrams. More about stabilization diagrams can be found in Section 5 of [11]. It is generally beneficial to over-specify the model order to ensure that the structural modes can be correctly identified for multiple model orders. In this method, only modes that are consistently stable over multiple model orders are kept while unstable modes are disregarded. The average value of each stable mode across all model orders are adopted as the value of that mode for the observation.

For each j observation, $j = 1 \dots J$, where J is the total number of observations considered, a set of P stable modes can be identified as such $\mathbf{F} = \{f_p : p = 1 \dots P\}$. The initial conditions are set to $j = 1$ where for each f_p a cluster is constructed, the reference value for each cluster is therefore $f_p^r, p = 1 \dots P$. For all consequent j , each newly identified operational mode, $f_p^j, p = 1 \dots P_j$, where P_j is the number of modes identified at this observation, is individually compared with each of f_1^r to f_P^r to obtain:

$$\varepsilon_p^j = \frac{|f_p^r - f_p^j|}{f_p^r} \quad (1)$$

The value of ε_p^j dictates the clustering of f_p^j by the following criteria:

$$C_1 : \varepsilon_p^j \leq \varepsilon \quad (2)$$

$$C_2 : \varepsilon_p^j > \varepsilon \quad (3)$$

In case of C_1 , f_p^j belongs to cluster p . In case of C_2 , f_p^j does not belong to cluster p . ε is a user defined value that can be adjusted according to the desired sensitivity.

If C_2 is met by f_p^j for all P clusters, it is then placed in cluster P^* , where $P^* = P + 1$, P^* indicates a temporary variable that is updated at each observation, $f_{P^*}^r = f_p^j$, and values of $f_{P^*}^1$ to $f_{P^*}^{j-1}$ are set as null. If C_2 is met by cluster p for all f_p^j , then the j^{th} value of cluster p is set as null.

After all P_j modes at observation j have been clustered according to the method described above, P is updated to $P := P^*$ before the next observation is processed. For each new observation, new reference values are computed for each cluster:

$$f_p^r = \frac{\sum_{j=1}^J f_p^j}{J} \quad (4)$$

The method is then repeated until all identified modes from each of the J observations have been clustered accordingly.

Using the clusters generated, noise modes can be easily identified as they do not consistently appear in every observation, while although structural modes may be missing in certain observations, they appear in most of the observations. Since null values are used when no modes belong to the cluster at any observation, after generating clusters, the user can easily identify structural modes of interest by defining a threshold and disregarding any modes with a number of values below this threshold.

2.2 Gaussian Process Regression for Mitigating EOV

Modelling To construct a GPR model for a number of observations, $n = 1, \dots, N$, a number of training points, $N_{tr} < N$, must be defined. The zero-mean training DSF vector and EOV matrix are therefore defined as $\mathbf{f}_{tr} = [f_1, \dots, f_n, \dots, f_{N_{tr}}]$ and $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_n, \dots, \mathbf{x}_{N_{tr}}]$ respectively, where \mathbf{x} is the column vector of length i , containing all the EOVs at each observation, $\mathbf{x}_n = [x_{1,n}, \dots, x_{i,n}]'$. \mathbf{f}_{tr} can be multivariate when there is more than one DSF of interest, however, the one-dimensional form is presented here.

Using similar notation as shown in [12], considering the noise present and assuming that the DSF vector used for training is a function of the EOV, \mathbf{f}_{tr} can be expressed in the form:

$$\mathbf{f}_{tr} = g(\mathbf{X}) + \epsilon \quad (5)$$

Where $g(\mathbf{X})$ denotes the underlying functions of the Gaussian process, and ϵ is a zero mean Gaussian noise, with variance σ_n^2

A model can then be constructed by defining the mean function, $m(\mathbf{x})$, and covariance function, $k(\mathbf{x}, \mathbf{x}')$:

$$m(\mathbf{x}) = \mathbb{E}[g(\mathbf{x})] \quad (6)$$

$$k(\mathbf{x}, \mathbf{x}') = \mathbb{E}[(g(\mathbf{x}) - m(\mathbf{x}))(g(\mathbf{x}') - m(\mathbf{x}'))] \quad (7)$$

Where $\mathbb{E}[g(\mathbf{x})]$ denotes the expected value of $g(\mathbf{x})$.

The covariance function $k(\mathbf{x}, \mathbf{x}')$ serves to define a covariance matrix \mathbf{K} , where its elements are covariances measured at the points \mathbf{x} and \mathbf{x}' . There are a number of different covariance functions that can be selected or combined depending on the nature of the problem. Some examples of covariance functions include squared exponential, Matérn, γ -exponential, rational quadratic and piecewise polynomial [13]. The covariance function used in this study is the squared exponential covariance function:

$$k_{SE}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{1}{2l^2}|\mathbf{x} - \mathbf{x}'|^2\right) \quad (8)$$

Where σ_f^2 is a hyperparameter controlling the overall variance of the signal and l is a hyperparameter controlling the length-scale, which determines how smooth the function is.

Assuming zero-mean the joint Gaussian distribution between the training DSFs \mathbf{f}_{tr} with EOV \mathbf{X} and the unknown/predicted DSFs $\hat{\mathbf{f}}$ with EOV $\hat{\mathbf{X}}$ can be written as:

$$\begin{bmatrix} \mathbf{f}_{tr} \\ \hat{\mathbf{f}} \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} \mathbf{K}(\mathbf{X}, \mathbf{X} + \sigma_n^2 \mathbf{I}) & \mathbf{K}(\mathbf{X}, \hat{\mathbf{X}}) \\ \mathbf{K}(\hat{\mathbf{X}}, \mathbf{X}) & \mathbf{K}(\hat{\mathbf{X}}, \hat{\mathbf{X}}) \end{bmatrix}\right) \quad (9)$$

The model can then be constructed by establishing the hyperparameters which is achieved by minimising the negative log marginal likelihood using the training data. The negative log marginal likelihood is expressed in the form:

$$\log p(\mathbf{f}_{tr}|\mathbf{X}) = -\frac{1}{2}\mathbf{f}_{tr}^T \mathbf{K}_\theta^{-1} \mathbf{f}_{tr} - \frac{1}{2} \log |\mathbf{K}_\theta| - \frac{N_{tr}}{2} \log(2\pi) \quad (10)$$

Where \mathbf{K}_θ is the covariance matrix $\mathbf{K}(\mathbf{X}, \mathbf{X} + \sigma_n^2 \mathbf{I})$ of the training covariance matrix with noise included.

Details on Gaussian process regression and the computation involved can be found in Chapter two of [13].

Mitigation Using the model constructed, predicted DSFs, $\hat{\mathbf{f}} = [\hat{f}_1, \dots, \hat{f}_n, \dots, \hat{f}_N]$, can be obtained for all observations, $n = 1, \dots, N$, by referring to the EOV matrix, $\hat{\mathbf{X}} = [\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_n, \dots, \hat{\mathbf{x}}_N]$, with \mathbf{X} being a subset of $\hat{\mathbf{X}}$. Assuming zero-mean, the effect of EOVs can be removed by generating a compensated DSF vector, $\tilde{\mathbf{f}}$, which can be computed by subtracting $\hat{\mathbf{f}}$ from the original measured values \mathbf{f} :

$$\tilde{\mathbf{f}} = \mathbf{f} - \hat{\mathbf{f}} \quad (11)$$

The procedure in equation 11 is capable of removing any variations in \mathbf{f} that are caused by the EOVs present in the training EOV matrix \mathbf{X} .

2.3 Data Collection

The data used in this paper were collected from two offshore wind turbines positioned closely together in the North Sea. The structures were monitored from 21 March to 30 November 2019, with two sensors installed in each wind turbine structure. Data collection had been interrupted on 8 occasions throughout the measurement campaign for maintenance purposes. For each structure, the lower sensor was installed 31m above the mudline, while the upper sensor was installed 99m above the mudline. Figure 1a provides a scheme of how the sensors were installed. Each sensor package recorded structural motion responses from six degrees of freedom, providing acceleration readings and angular rate readings each in three directions. Both sensor packages are aligned in the same orientation, shown in Figure 1b. Only the X-direction first natural frequency has been used for verification in this study. Of the two turbines measured, one was a healthy structure and served as the control (labeled F04), while the other one was noted to be scoured during commissioning (labeled E03). The healthy structure remained operational throughout most of the measurement campaign, while the scoured structure was not operational at all. The sampling frequency was 10Hz and the measurements have been divided into 1-hour observations in the analysis.

3 Results and Discussion

3.1 Verification of clustering technique

First the performance of proposed clustering methodology is demonstrated by using observations between 4 May, 2019 to 16 May, 2019. A model order of 20 and a $\varepsilon = 0.1$ are used in this study. Only modes that have consistently appeared for more than 80% of the observations have been identified as stable structural modes. Such practice is adopted in this study as all the data throughout the measurement campaign is available.

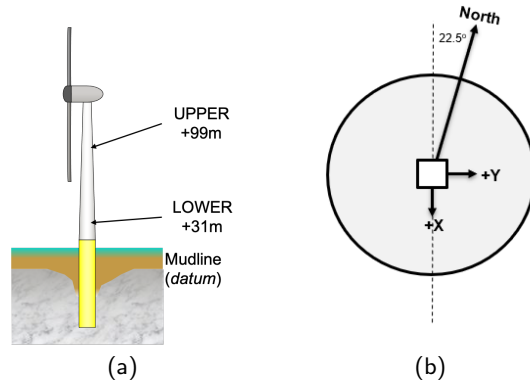


Fig. 1. Wind turbine instrumentation set up. a) Sensor location and b) sensor orientation

Figure 2(a) shows the direct output of the SSI-COV algorithm, selecting the eighth model order of the 20 model orders. Model order 8 was selected as using higher model orders will include higher frequency modes beyond the second natural frequency, which are not desired, while using lower model orders will neglect the second natural frequency. Figure 2(b) presents the results of using the average value of stable modes without applying the clustering algorithm, while Figure 2(c) presents the results of applying all steps of the methodology presented above.

The results presented indicate that the direct output from SSI-COV provides little to no useful information, as it includes all modes identified, whether stable or not, which generates distraction when attempting to identify a trend in the data. When comparing Figure 2(a) with Figures 2(b) and 2(c), it can also be seen that using a single model order could result in failure to identify the structural modes of interest for certain observations when there is enhanced distraction from the noise modes identified. At the same time, the time varying nature of the structure may not allow for the same model order to always be present.

From Figure 2(b) it is clear that using only the stable modes avoids most of the noise modes and allows for the two structural modes to be clearly identified. However, there are still limitations present as there is still some noise present, while at the same time there is no grouping of the modes, since what is actually the first and second structural mode may be identified as different modes. This means that tracking any one of the five modes in Figure 2(b) would not fully provide the information needed and may even, to an extent, induce distraction.

Figure 2(c) demonstrates that utilising the clustering technique presented in this study solves the previously mentioned problems, and two clear structural modes without any confusion are identified. This indicates that the proposed technique is capable of extracting the structural modes from the noise modes by exploiting the characteristic that structural modes can be consistently identified for most, if not all, observations, while noise modes often appear spontaneously and do not usually demonstrate similar values over time. Since all new values that do not belong in any

of the previous groups are identified as new groups, there will be a large amount of null data points in the noise mode groups, making structural modes easily identifiable by extracting groups with consistent data points. A significant drawback of this method is that consistent modes, such as the rotor frequency, may also be identified as stable modes along with the structural modes and can only be identified using prior knowledge of the system. On the other hand, this should not be any problem as this information is generally known.

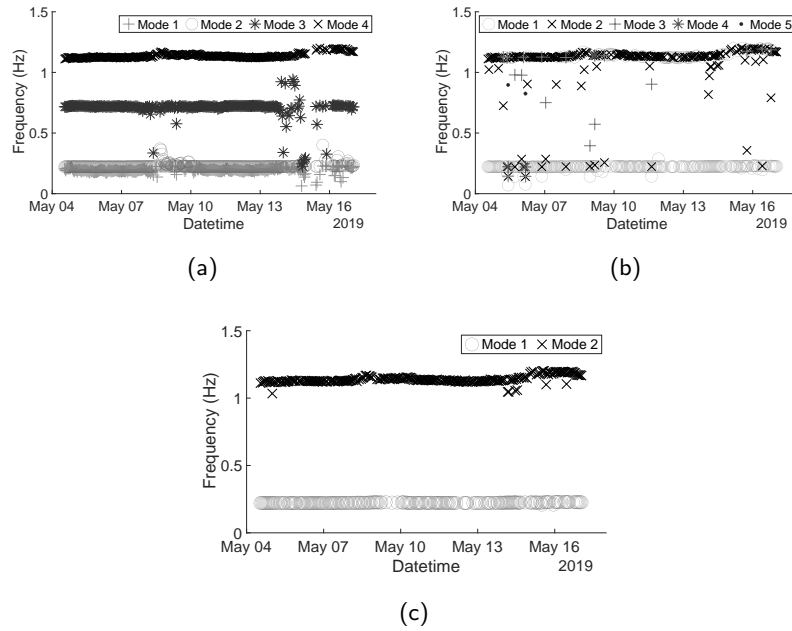


Fig. 2. Operational mode identification with a) direct results from SSI-COV, using a total of 20 model orders and selecting model order 8, b) using the average value of sufficiently frequent stable modes without clustering, and c) using the average value of sufficiently frequent stable modes with clustering and only selecting modes with number of values above threshold.

3.2 Verification of Removing EOV

The specific environmental and operational parameter (EOP) being mitigated in this study are the displacement measurements obtained by computing the double time integrals of the acceleration measured at the lower and upper sensors as shown in Figure 1(a). These measurements serve as a proxy of the wave height, since the structure's motion and therefore amplitude of displacement would be correlated to the wave height at the location of the structure. Data between 21 March and 24 May 2019 have been used as the training set for the GP model.

The results presented in Figure 3 demonstrate that the effectiveness of mitigating the EOVS using GPR varies between the control and scoured case. The healthy case presented in Figure 3(a) shows that there are little to no differences between the measured values and the compensated values, while the scoured case presented in Figure 3(b) shows distinct differences. This is most likely due to the fact that the measured values in the control case do not have an identifiable correlation with the displacement measurements, while the measured values in the scoured case demonstrate a clear negative correlation. This phenomenon indicates that the scoured structure is more sensitive to EOVS, specifically wave height, which would be reasonable speculation as structures damaged by scour tend to have weaker foundations and lower overall stiffness. However, in the case of the scoured structure where a clear correlation is present, it is clear that the method employed is capable of mitigating the negative correlation and that the corrected values do not demonstrate an identifiable correlation with the EOP analysed.

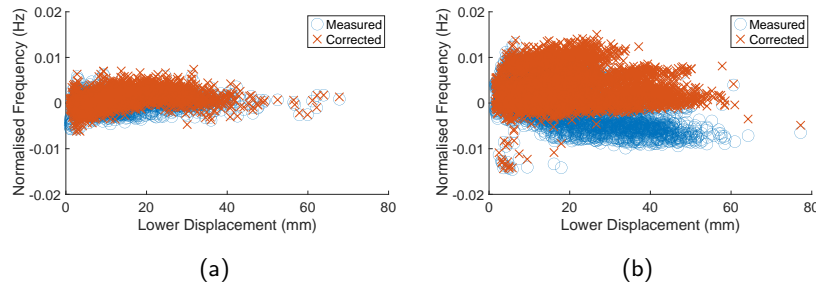


Fig. 3. Comparison of DSF of interest, first natural frequency, plotted against the EOP modelled before and after mitigation of EOVS: a) Control turbine (F04) and b) Scoured turbine (E03). Only the lower displacement EOP is shown here as similar trends had been obtained from the comparison with the upper displacement.

3.3 Tracking of Scour Repairation via Reliable Structural Operational Modes

The proposed methodology have been applied to the full 8-month time scale of the collected data, for both the scoured and the control turbine. The variation of the first structural mode of both turbines have been presented in Figure 4, note that major gaps in the data are due to the planned pauses in data collection, as mentioned earlier. The structural modes are well identified with little noise present, while at the same time the identifiable periodic variations present in figure 4(a) have been successfully mitigated by GPR, as shown in figure 4(b).

The tracking of the structural modes within the period of monitoring can be deemed successful for both structures. The scoured turbine demonstrates a lower value than that of the control turbine for most of the monitoring period. Additionally, the tracking methodology has been able to identify that the scoured turbine had,

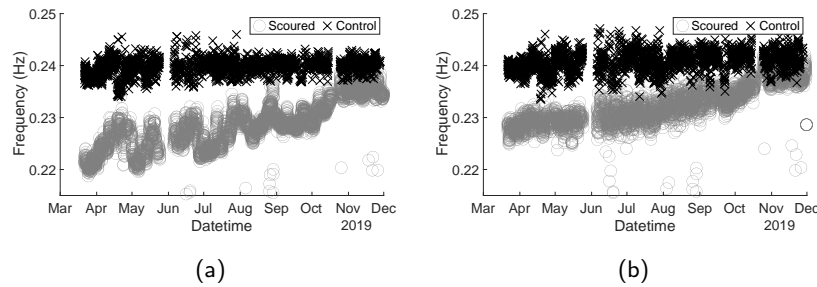


Fig. 4. Comparison between scoured and control turbine monitored a) before mitigation of EOVS and b) after mitigation. The clustering technique has been applied in both cases.

to an extent, been repaired towards the end of the measurement campaign. This can be seen through the fact that for the structural mode monitored, the value of the scoured turbine appears to approach or even overlap that of the healthy turbine after November, 2019.

4 Conclusion

This study presents a clustering methodology that provides reliable operational modal identification for continuous structural health monitoring. The proposed methodology utilizes a clustering technique that evaluates each continuous observation against all previously identified modes, while combining it with a technique to mitigate EOVS based on GPR.

The performance of the clustering methodology has been compared to more traditional/simple procedures of OMA, and respective limitations and advantages have been evaluated. The effectiveness of the mitigation methodology has been established by identifying that it is capable of removing correlations between the DSF of interest and the analysed EOP. The main advantage of the proposed methodology is that reliable structural modes can be correctly identified and used for continuous monitoring under operational conditions.

The methodology has also been implemented on a long-term monitoring scheme of two offshore wind turbines, tracking the repair of a scoured turbine and comparing it to a healthy(control) turbine that has been taken as reference in the repairing process. The results from applying the methodology to the long-term monitoring scheme has demonstrated that the tracking of operational modes is robust enough to describe the current state of the wind turbine, indicating whether scour has developed.

The methodology proposed in this study provides rudimentary levels of automation in using OMA to monitor the scour status of offshore wind turbines continuously, as it allows for tracking of operational modes over time. Simple adjustments may be sufficient for developing real-time continuous monitoring techniques, which could form the basis of developing further techniques that could lead to higher levels of

automation, thus significantly reducing the maintenance costs and risks currently associated with offshore wind turbines.

Acknowledgements

The authors would like to thank EPSRC Institutional Sponsorship through International Partnerships grant for supporting this work.

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