Chapter 20
Vibration-Based Damage Detection of a Monopile Specimen Using Output-Only Environmental Models

Emmanouil Lydakis, Sandro D. R. Amador, Holger Koss, and Rune Brincker

Abstract The field of vibration-based Structural Health Monitoring (SHM) relies on the evolution of the dynamic characteristics to identify the current health state of a monitored structure. In reality, these parameters are influenced either by a potential degradation of the structural integrity or by the varying environmental conditions. Therefore, a robust SHM scheme must clearly distinguish the different sources of changes in the monitored modal parameters. Along these lines, this study aims to identify structural changes in a monitored structure subjected to ambient vibrations and varying environmental conditions. The investigated structure consists of a wooden mast with a steel frame topside and is clamped to a concrete block at the bottom. During the monitoring campaign, the vibration response is acquired by a measurement system with four 3D sensors placed at strategic locations on the topside.

Keywords SHM · OMA · Modal identification · Environmental influence · Damage detection

20.1 Introduction

One of the main challenges in vibration-based SHM lies in the fact that the modal parameters of civil structures are heavily influenced by the varying environmental and operational conditions (e.g., temperature, humidity, wind speed). In fact, even though changes in the modal parameters can reflect a potential structural degradation, they can also be caused by the aforementioned environmental variability [1–8]. As a result, to ensure reliable damage detection of structures exposed to different environmental conditions, it is of significant importance to identify and separate the different environmental and operational effects from the modal parameters. To accomplish that, numerous statistical methods have been proposed in literature over the years, such as but not limited to principal component analysis (PCA), multivariate linear regression (MLR), and autoregressive (AR) models [1–3]. Especially when it comes to environmental variability, it is common to consider that a full year of monitoring is essential to develop a robust environmental model, suitable to describe the changing environmental factors as well as the seasonal variability. Nevertheless, there are various cases that a faster evaluation of the structural integrity is required; thus, the monitored modal parameters need to be obtained much sooner [2, 3]. In recent studies, for instance [1, 2], an environmental model was developed based on a monitoring campaign of only few months (3 and 1 months, respectively), leading to remarkable results in terms of damage detection of a wooden mast specimen. Consequently, an efficient environmental model is a solid basis where the corrected modal parameters can be assessed in the context of a vibration-based damage detection technique, to investigate whether structural changes are present in the monitored structures.

Based on the above, this study aims to eliminate the varying environmental effects from the modal parameters of a medium-sized monopile structure. This is achieved by an output-only environmental model utilizing the PCA approach. Moreover, the performance of a damage detection scheme based on statistical tools, namely control charts, is evaluated. Last but not least, it is worth noting that this investigation is carried out based on experimental data obtained during a previous monitoring campaign of the same specimen, conducted by [1].

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20.2 Methodology

In this section, the fundamental theoretical background utilized in this study is briefly discussed. First, the main principles of the PCA approach are presented, while a short description of control charts for damage detection follows. Principal component analysis is an output-only statistical approach to estimate a lower-dimensional representation of a data set, while retaining most of its variance [1, 4–6]. The application of PCA is based on the initial data matrix Y containing N observations of n observed features. A singular value decomposition (SVD) of the covariance matrix $Y^{\mathrm{T}}Y$ is performed as

$$Y^{\mathrm{T}}Y = US^2U^{\mathrm{T}} \tag{20.1}$$

where U is an $n \times n$ matrix containing the singular vectors and S is a diagonal matrix including the n singular values. The diagonal terms of S are organized in ascending order and are associated with the so-called principal components, which represent the directions of the data that explain the maximum amount of variance. Therefore, the first principal components are associated with the physical information, while the last ones include residual contributions related to noise effects. Along these lines, a robust PCA model lies in the optimal selection of $m(<n)$ singular values that represent sufficient amount of the data's variance. Once this condition is fulfilled, the loading matrix T is formed by taking into account only the first m number of features (i.e., columns) from U. Based on that, an estimate of the observed features is expressed as

$$Y = YTT^{\mathrm{T}} \tag{20.2}$$

The loss of information between the initial data matrix Y and the estimate $\hat{Y}$ obtained from PCA is estimated in terms of the residual error matrix $\hat{E}$ as [1].

$$\hat{E} = Y - \hat{Y} \tag{20.3}$$

The performance and efficiency of PCA in modeling environmental effects can be assessed, for instance, by means of control charts, which are tools of statistical quality control to detect whether a process is out of control. When an unexpected event occurs, the variability of this event in terms of an outlier index exceeds the range of predefined control limits. In this study, the Shewhart or T^2-chart is utilized, where structural changes are detected by means of the novelty index T^2-statistic, given by the expression

$$T^2 = \frac{N_k}{N_{k+1}} \left(x - \bar{\bar{x}}\right) R^{-1} \left(x - \bar{\bar{x}}\right)^{\mathrm{T}} \tag{20.4}$$

where N_k is the number of observations when the process is in control, meaning in this case the reference period where the investigated structure is in its undamaged condition. Moreover, x denotes the observations over the monitoring period, while $\bar{\bar{x}}$ and R designate the subgroup average and the covariance matrix of the observations during the reference period, respectively. To control the deviation of T^2-statistic, an upper and a lower control limit are estimated. The lower control limit (LCL) coincides with the x-axis, while the upper control limit (UCL) is given by

$$\mathrm{UCL} = \frac{(N_k - 1)\, n}{N_k - n} F_{n,n-m}\,(\alpha) \tag{20.5}$$

where $F_{n,\,n-m}$ denotes the α percentage point of the F distribution with n and $n - m$ degrees of freedom [4, 5].

20.3 Experimental Study

The theoretical framework described above is implemented to assess induced damage cases in a medium-sized monopile structure, exposed to ambient vibrations and varying environmental conditions. In a previous study by [1], a 3-month monitoring campaign has been carried out in the same structure to apply a vibration-based SHM scheme. Based on the same collected data, this work aims to further assess the efficiency of the PCA-based model created to remove the varying environmental conditions from the observed (i.e., estimated) natural frequencies and apply a damage detection scheme.

Fig. 20.1 Left: Medium-sized monopile specimen. Top middle: Two sensors clamped on the upper plate of the topside. Bottom middle: Steel topside with the four sensors clamped on different corners. Right: Cuts on the wooden mast [1]

The experimental model consists of a 3.6-m wooden mast with a square cross section of 0.1×0.1 m. A steel topside is placed at the top of the mast, while its bottom part is founded on a concrete block. The vibration responses are collected by four 3D geophone nodes, vibration sensors that are selected due to their high sensitivity and low noise floor. The monitoring campaign initiated on November 30, 2021, and lasted until March 4, 2022. Several damage cases are introduced to the experimental model over a 10-day time span, starting from February 15, 2022. The induced damages are practically 11 cuts on the wooden mast, as illustrated in the right pane of Fig. 20.1. In the X direction, the depth of each cut is initiated at 2 mm and is gradually increasing by 2 mm, until it reaches the maximum depth of 10 mm. On the contrary, the Y direction of the mast is only damaged once by inflicting a cut of 10 mm.

The measured vibration responses are utilized to apply OMA and more specifically, the Eigensystem Realization Algorithm (ERA) is used to estimate the modal parameters [9]. In this study, a shorter time window of 1 month is investigated, to assess whether that period is sufficient to develop a robust environmental model and identify the structural changes. The evolution of the natural frequencies over the 1-month monitoring period for the first two modes is presented in Fig. 20.2, where the different damage scenarios are indicated with vertical lines.

20.4 Environmental Model

As previously discussed, a PCA model is developed to describe the varying environmental conditions over the monitoring period. This model is built using two principal components (PCs), as they are capable of explaining the 99.99% of the data's variance. The monitoring period is split into training, validation, and prediction periods, where the PCA model is trained and subsequently validated through the reference (i.e., undamaged) period. Based on this training, the model is extrapolated and provides an estimate for the remaining period, where the state of the structure is considered unknown. The training, validation, and prediction periods of the PCA model are presented in Fig. 20.3, where a comparison is made with the actual natural frequency observations.

According to this figure, it is concluded that even though the PCA model provides an efficient estimate for the reference period, it can no longer represent the actual evolution of the natural frequencies over the damage period, especially for the first mode. Obviously, this is the case as the model is trained over the reference state where no structural changes are apparent; thus, it cannot predict the damage cases that followed. In fact, the environmental model seems to work as a damage indicator itself, since the actual frequency decrease compared to the PCA estimate reflects a potential structural degradation.

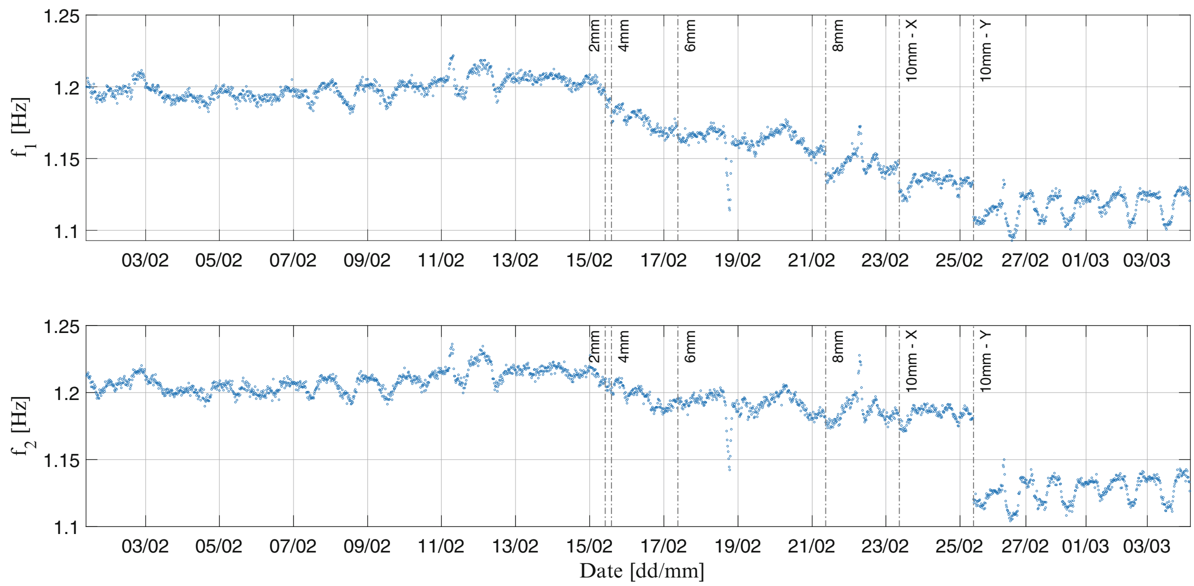

Fig. 20.2 Natural frequency evolution over the monitoring campaign for the first two modes. The induced damage cases are indicated with vertical lines [1]

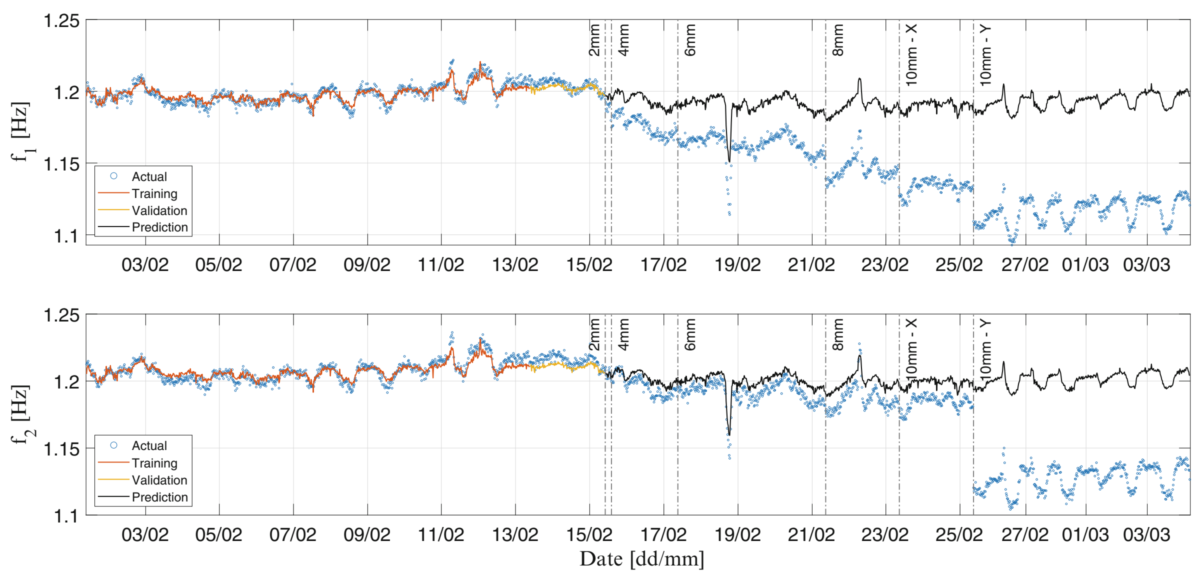

Fig. 20.3 Comparison between the PCA estimate with the actual natural frequencies. The PCA estimate is split into training (orange), validation (yellow), and prediction (black) periods

Furthermore, the corrected values of the natural frequencies are estimated based on the residual error, defined in Eq. (20.3). The PCA estimate including the environmental effects is subtracted from the observed values; thus, it provides a clearer picture of the structural degradation. In this way, the fluctuation due to the varying environmental conditions is eliminated, leading to a steadier evolution of the frequencies over time. On top of that, the damage presence becomes even more apparent, as the different damage cases are identified as sharper discontinuities in the evolution of the corrected natural frequencies. Specifically, in Fig. 20.4, six discontinuities are observed in the natural frequencies of the first mode, while only one significant offset is observed in the second mode.

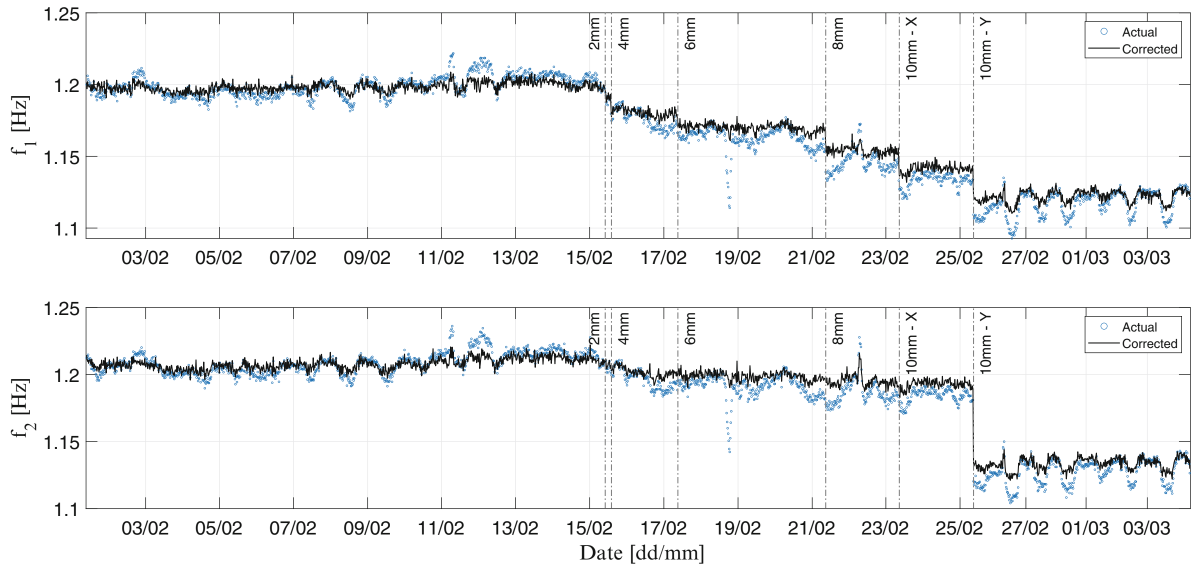

Fig. 20.4 Actual and corrected (from the PCA model) values of the natural frequencies for the first two modes. After removing the environmental effects, the corrected values show smaller variability and sharper discontinuities

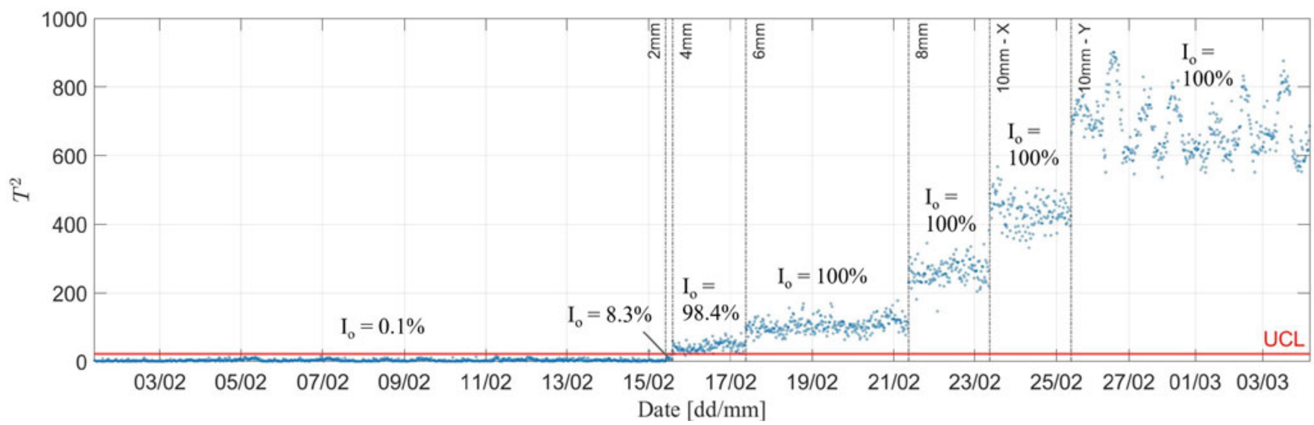

Fig. 20.5 T^2-chart and outlier index I_o over the monitoring period. The gradual increase in damage depth causes a remarkable increase of the T^2-statistic values, far above UCL

20.5 Damage Detection Based on Control Charts

Despite that the structural degradation is already apparent based on the environmental model described above, this section presents the performance of the T^2-chart for damage detection. The T^2-chart identifies the structural changes by means of the novelty index T^2-statistic, illustrated in Fig. 20.5 over the monitoring period. To control the deviation of this index, the UCL is estimated by considering an F distribution with $m = 2$, $n - m = 3$ degrees of freedom and a confidence interval of 95%. According to Fig. 20.5, it is clearly observed that the T^2-index follows the same increasing trend as the damage depth increases, leading it to far exceed the UCL. This can also be verified by the outlier rate I_o, estimated for the different periods of the monitoring campaign. In Fig. 20.5, it is observed that even a 2 mm cut on the wooden mast is enough to raise I_o from 0.1% to 8.3%. Moreover, it becomes obvious that the more the cut depth increases, the more T^2-statistic values exceed the UCL, leading to an outlier rate of 100% after the cut of 6 mm and above.

20.6 Conclusions

To sum up, this study focused on the damage detection of a medium-sized monopile specimen, exposed to ambient vibrations and varying environmental conditions. More specifically, the output-only PCA approach was used to eliminate the environmental effects from the observed natural frequencies, while the T^2 control chart was utilized as the main damage detection technique. Overall, this investigation showed the following:

- The induced damage scenarios on the experimental model caused a reduction of the natural frequencies of the first two vibration modes.
- The gradually increased damage depth in the X direction of the mast resulted in a gradual frequency decrease in the first mode, while the cut in the Y direction is mainly associated with the sharp reduction of the corresponding frequencies in the second mode.
- After eliminating the environmental variability, the structural degradation became significantly more apparent, as the different damage cases were identified as sharper discontinuities in the time evolution of the natural frequencies.
- The T^2-chart proved to be a robust damage detection scheme, as the T^2 index clearly indicated the induced damage cases as outlier observations that exceeded the control limit UCL.

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