Chapter 8
OMA-based Approach for Structural Health Monitoring: the Case of Palazzo Lombardia

F. Lucà, S. Manzoni, S. Pavoni, and M. Vanali

Abstract Palazzo Lombardia in Milan is one of Italy's tallest buildings due to its 161 m height. Since 2015 the building has been equipped with a monitoring system that continuously tracks key parameters such as acceleration and inclination across its structure. In recent years, various Structural Health Monitoring (SHM) techniques have been developed to assess the building's condition throughout its lifespan. One promising approach is Operational Modal Analysis (OMA), which employs variations in modal parameters to monitor structural conditions. By continuously evaluating OMA outcomes, SHM strategies can be refined, enabling more effective tracking of the building's condition over time. This study focuses on an OMA-based strategy for Palazzo Lombardia, using long-term data collected from its monitoring system since 2015. Due to a gap in the monitoring data between 2018 and 2021, the data from before the interruption were used for training, while the data from 2021 onward served for validation. The results from the validation set were compared with those from the training set. Since the building remains in a healthy condition, the analysis of both sets is expected to yield similar results.

Keywords Operational modal analysis · Structural health monitoring · Principal component analysis

Introduction

The ongoing aging of infrastructure has led to a rising need for effective maintenance. This requires not only regular inspections but also a continuous monitoring approach. The field that aims to develop techniques for improving the monitoring systems is known as Structural Health Monitoring (SHM). Among the numerous SHM techniques developed in recent years, those based on vibration measurement are promising. As part of the global approach field, these techniques can determine the general health condition of the structure through measurements performed by transducers that are easy to install, even in already existing structures. The vibration features usually employed in these techniques are the modal parameters outcomes such as natural frequencies, damping ratios, mode shapes and modal curvature. The basic concept of modal-based SHM strategies is that the variation in mass, stiffness or energy dissipation properties of the structure influences its overall vibration response. Therefore, the continuous observation of the modal parameters in long-term monitoring may help to develop effective SHM strategies. In [1] the authors present a non-destruction damage detection technique based on outcomes from an Experimental Modal Analysis (EMA) performed on both reinforced concrete beam and slab. The damage detection is conducted by evaluating the variations in natural frequencies and mode shapes in different conditions of the systems under analysis. However, in operating conditions, the excitation term is often unknown, especially in large structures such as bridges or skyscrapers. In this field, Operational Modal Analysis (OMA) is particularly beneficial. Assuming that environmental excitation can be modeled as a white-noise term, OMA can determine modal parameters by measuring only the system's output. Several SHM techniques have been developed for OMA parameter extraction. In [2] a SHM strategy is proposed by evaluating modal parameters on a long-term monitoring of an offshore wind turbine. In [3] the authors developed an SHM approach using modal parameters collected from an iron arch bridge.

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In this work, an automated OMA is employed to collect modal parameters from the long-term monitoring of Palazzo Lombardia. The outcomes are used to develop an SHM strategy to assess the building's structural conditions. The monitoring system has been installed since 2015, but it was suspended between 2018 and 2021. Therefore, the data collected before the interruption has been used as the training set for the development of a SHM strategy. The data collected after the interruption have been employed as a test set. Since the structure is considered healthy, the modal parameters should not vary significantly between the test and the baseline sets. However, it is known from the state of the art that these parameters are particularly susceptible to environmental variations [4]. Therefore, in this paper, a strategy using the Principal Component Analysis (PCA) is proposed to mitigate the influence of ambient variations as much as possible.

Monitoring System Layout

Thanks to its 161 m height, Palazzo Lombardia is one of Italy's tallest skyscrapers. Since 2015 it has been equipped with a monitoring system that constantly measures useful information related to the structure conditions. Moreover, the state of the building can be assessed in case of exceptional events (e.g., earthquakes, strong gusts of wind). The overall system is briefly summarized below, while its complete details are reported in [5].

The building consists of 45 floors (three underground) and structure features such as accelerations and tilts are constantly measured through appropriate devices (accelerometers and tiltmeters). The sensors have been installed to cover the entire geometry of the skyscraper, comprehending floors -3, 9, 30, 37 and the rooftop. All floors are provided with three accelerometers and two clinometers installed on the concrete core to measure accelerations in the three principal directions and the rotation in the horizontal plane. Moreover, floors 9, 30 and 37 are provided with additional 3 accelerometers placed at a point horizontally farthest in the plane from the principal core.

The sensors adopted in the monitoring system are listed in Table 1. The monitoring system continuously collects data at a sampling frequency of 250 Hz through a DAQ-based device with an antialiasing filter.

The modal parameters extraction is deepened in the following section.

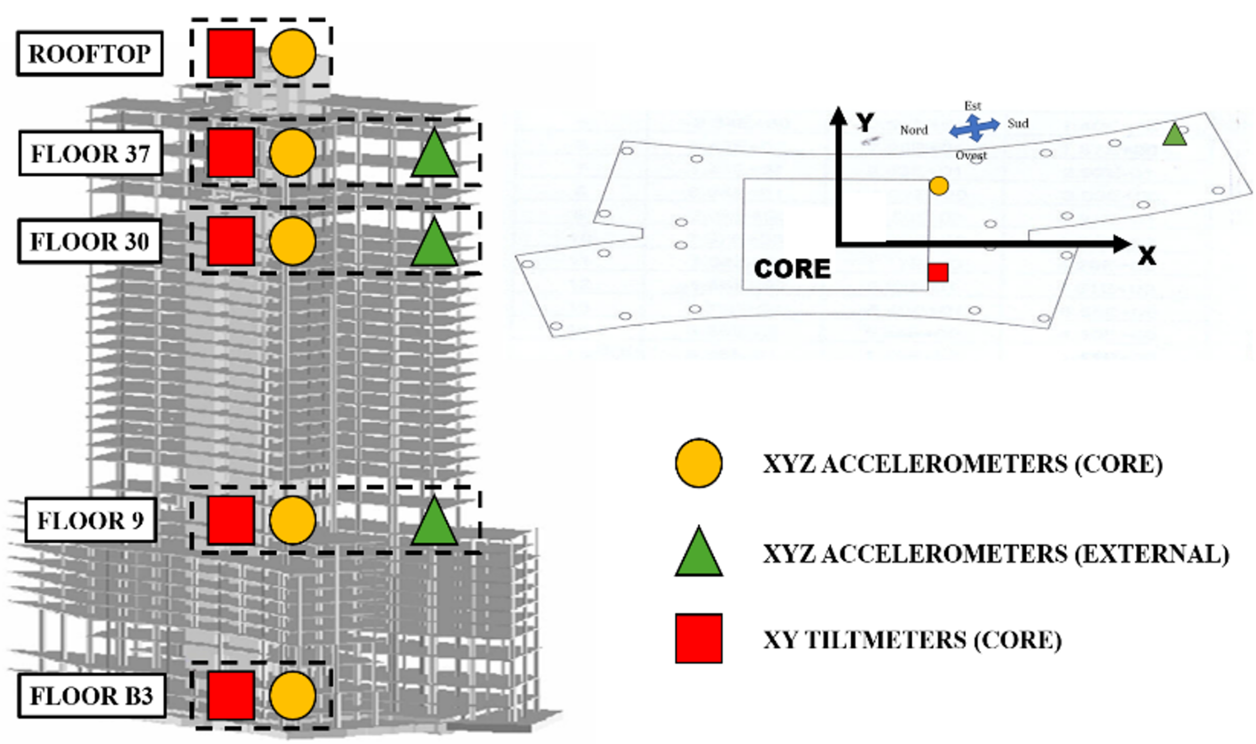

Fig. 1 Layout of the monitoring system and sensor positions

Table 1 List of sensors installed and their characteristics

Sensor	Manufacturer	Model	Full-scale	Bandwidth
Tiltmeter	Singer	Ts	5 [°]	≤ 3 [Hz]
Accelerometer	PCB	393B31	4.9 [m/s^2]	0.1-200 [Hz]

Modal Parameters Extraction

In this work, modal parameter extraction is performed using an automated Frequency Domain Decomposition (FDD) algorithm developed in Matlab. In this technique, assuming the natural excitation represented by a white-noise signal [6], the power spectra of the responses are processed in the frequency domain through the Singular Value Decomposition (SVD) . The whole process can be summarized by the following

$$G_{xx}(\omega) = U(\omega)\, S(\omega) U(\omega)^H \tag{1}$$

where S is a diagonal matrix that contains the scalar singular values and is used to detect the structure modes. Natural frequency and damping are obtained using the Peak Picking (PP) method on $S(\omega)$, while mode shapes are estimated through $U(\omega)$ [7].

The greatest drawback of this method is the frequency resolution due to the cross-spectra processing. Therefore, the peaks in the singular value function have been modelled through a minimization employing the Lorentzian Peak-Shape function [8] by means of the Non-Linear Least-Squares (NLLS) method [9].

Modal parameters extraction for each observation has been performed employing acceleration data covering a period of 2 hours filtered by a Butterworth band-pass filter with a bandwidth of 0.05-3 Hz. Thus, the frequency resolution of the power spectra is $1.38 \cdot 10^{-4}$ Hz. An example of the procedure is shown in Figure 2.

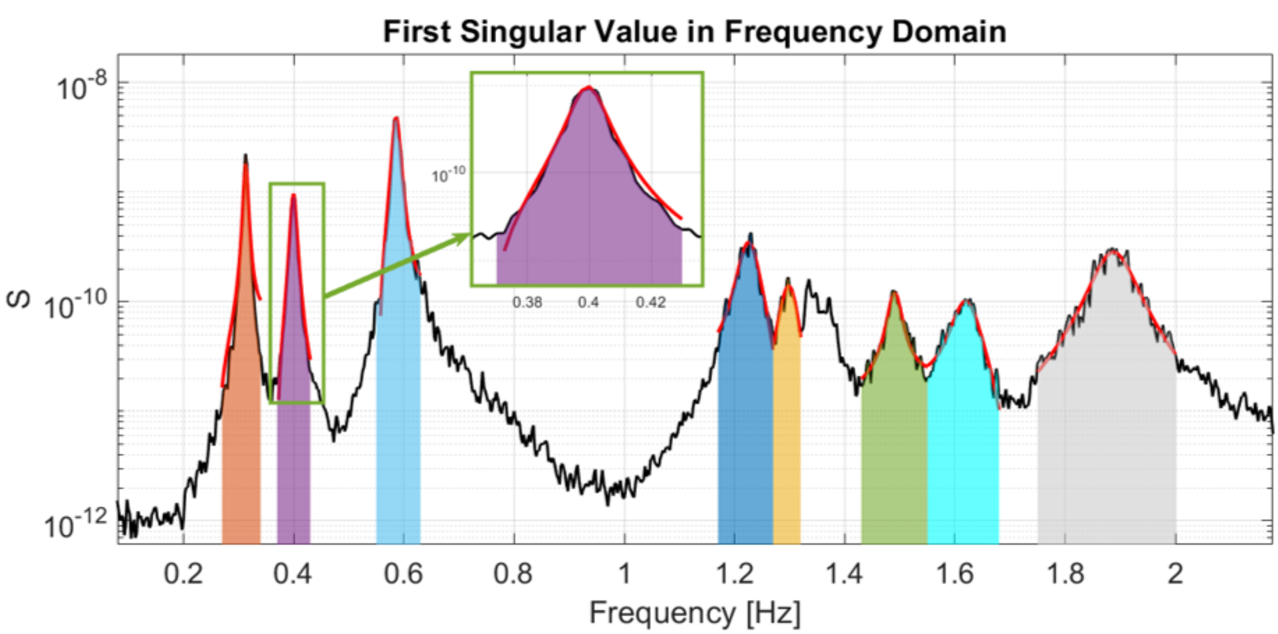

Fig. 2 FDD performed on Palazzo Lombardia data with bands of interest analyzed and reconstruction of the resonance peaks (red)

Since modes at approximately 1.3 and 1.8 Hz did not show consistent reliability during the monitored period, presenting peaks split or attenuation, they have been excluded from the presented analysis. The remaining modes with their characteristics are shown in Table 2.

Results obtained during the monitored period and their processing are presented in the following section.

Table 2 Palazzo Lombardia modes detected

Mode	Type	Natural Frequency [Hz]
1	1st Bending Mode Y-axis	0.31
2	1st Bending Mode X-axis	0.4
3	1st Torsional Mode	0.59
4	2nd Bending Mode Y-axis	1.22
5	2nd Bending Mode X-axis	1.49
6	2nd Torsional Mode	1.62

Modal Analysis Outcomes

Since automated results can be affected by processing or measurement failures, files considered unreliable have been removed using statistical tools applied to raw data. Furthermore, modal parameter outcomes have been filtered with a strategy proposed and deepened in [10]. Natural frequency trends evaluated during the monitored period are shown in Figure 3.

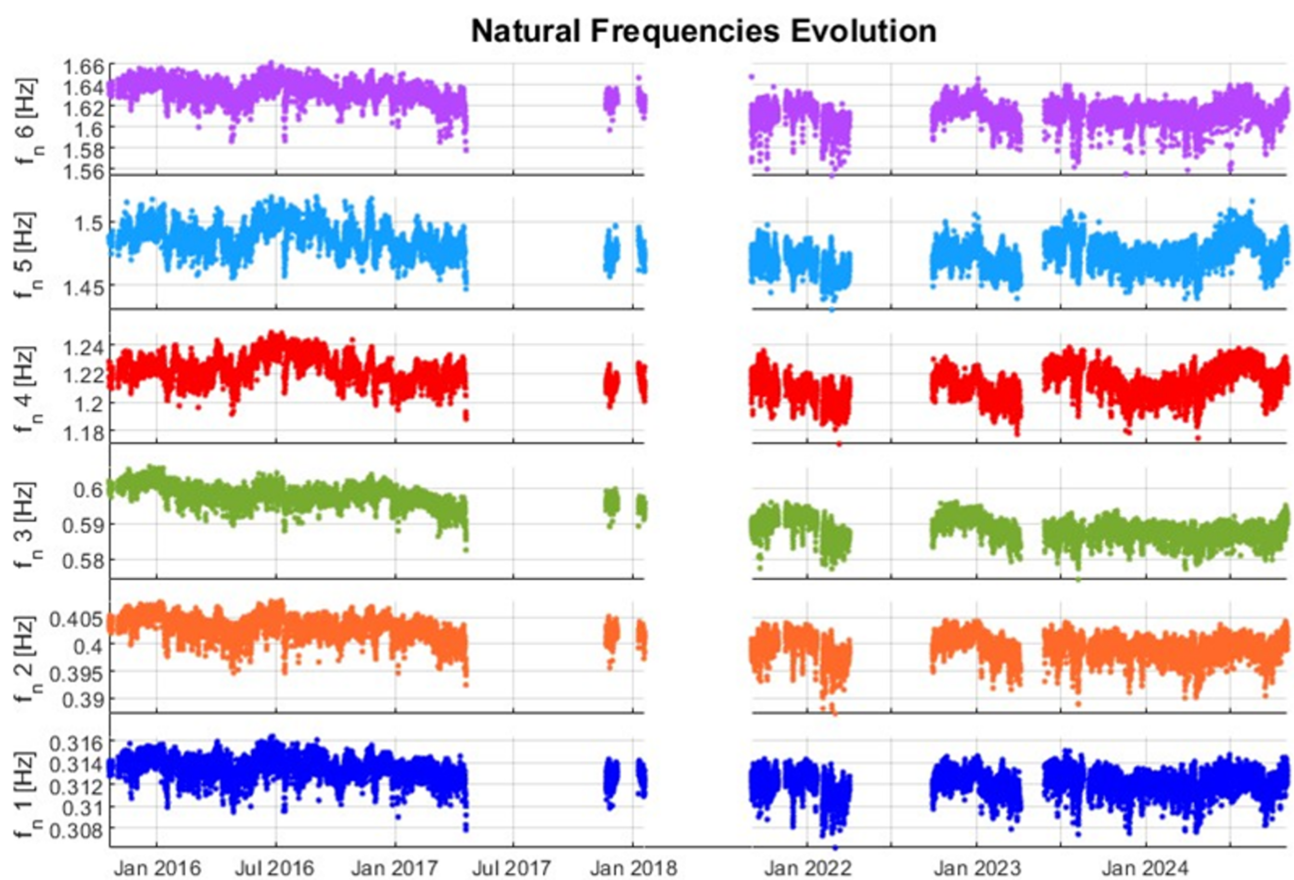

Fig. 3 Palazzo Lombardia natural frequencies evaluated during the monitored period

The natural frequencies obtained through the analysis exhibit a behaviour that is caused by the influence of environmental conditions as shown in [11] for the first three natural frequencies. This hypothesis is extended in this work by comparing the six natural frequencies considered in the baseline set (obtained before the monitoring interruption occurred in January 2018) with environmental measurements.

Principal Component Analysis and Environmental Influence

PCA is a technique derived from multivariate analysis that uses orthogonal projection on a given dataset to reduce its dimensionality. This process maximizes the variance of the projected data onto a lower-dimensional linear space. The new variables, or components, are uncorrelated by definition and are arranged such that the first few components capture most of the variation in the original dataset. The full theory behind PCA is detailed in [12], while the main steps of the calculation are outlined below, based on the natural frequencies set.

Natural frequencies are arranged as columns of the matrix X with dimensions n×m, where n is the number of observations and m is the number of the modes considered. Considering the training set length of 6200 samples, in the proposed analysis, the dimensions of X are 6200×6. After the natural frequencies standardization, the first step of PCA is performed by computing the covariance matrix $\sum$ as follows

$$\sum = \frac{1}{n-1} X^T X \tag{2}$$

and to diagonalize that

$$\sum = A \Lambda A^T \tag{3}$$

In Eq. (3), Λ is a diagonal matrix with eigenvalues arranged in decreasing order along the diagonal, and A is a matrix of eigenvectors (the singular value decomposition is commonly used). The eigenvectors represent the principal axes or principal directions of the data. The projections of the data onto the principal axes are referred to as principal component (PC) scores, which are the columns of the matrix Z, obtained through the following expression

$$Z = XA \tag{4}$$

PC scores from the baseline set are shown in Figure 4.

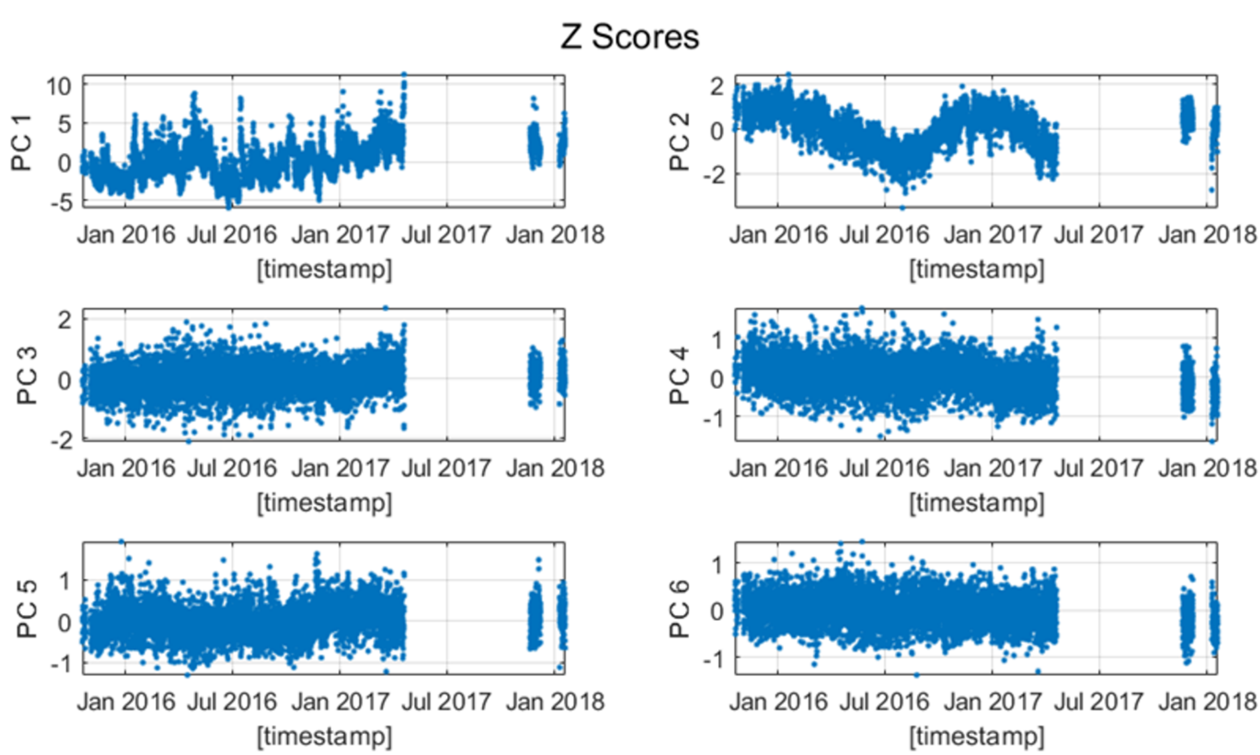

Fig. 4 Z scores evaluated from the baseline set

Observing the PC scores behaviour, the first two PCs seem to present a dependency on external conditions. In order to verify that, environmental data taken from the Linate weather station have been analyzed [13]. Temperature and wind speed measurements are shown in Figure 5.

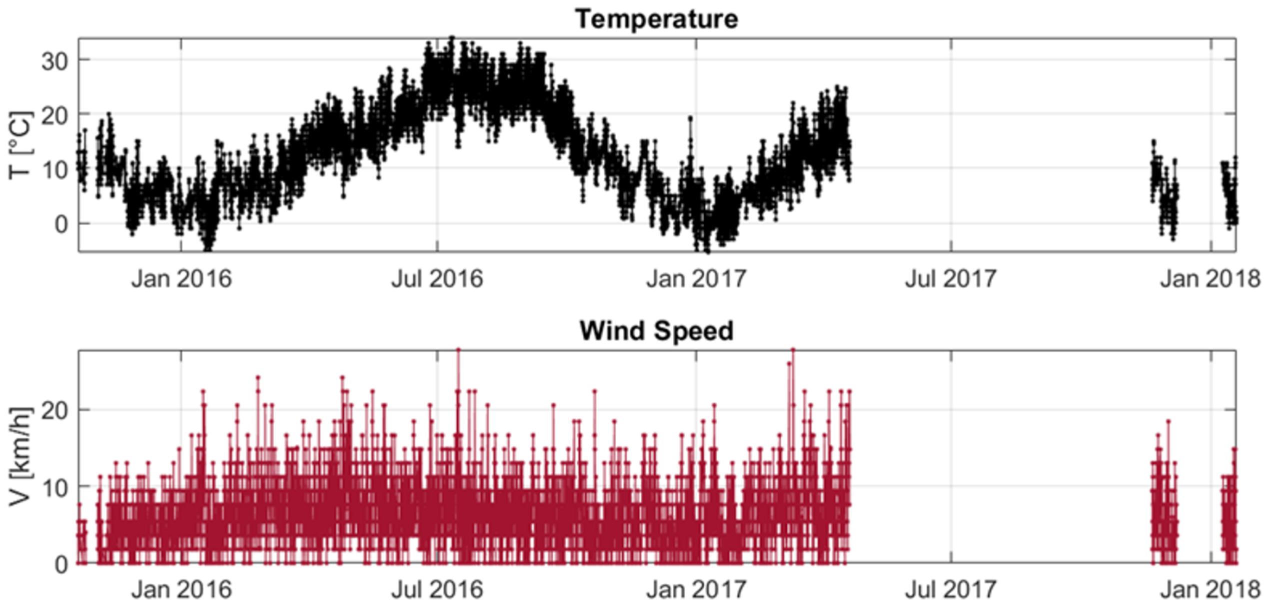

Fig. 5 Environmental data from Linate weather station

The correlation between PC scores and environmental conditions has been investigated through the evaluation of the Pearson's Coefficient, described in the following equation

$$\rho_{xy} = \frac{Cov(x,y)}{\sigma_x \sigma_y} \tag{5}$$

This index demonstrates a high correlation between two variables when its absolute value is greater than 0.7, a good correlation between 0.7 and 0.3, and a weak correlation below 0.3. Concerning the wind speed, only values greater than 7 km/h have been considered. Pearson's coefficient evaluation is reported in Table 3.

Table 3 Pearson's Coefficients evaluated between PC scores and environmental conditions (temperature and wind speed)

	Pearson Coefficient ρ_{xy}	
	Wind Speed	Temperature
PC 1	0.37	-0.19
PC 2	-0.22	-0.78
PC 3	-0.13	0.02
PC 4	0.10	0.01
PC 5	0.05	-0.15
PC 6	0.06	0.05

Results show a good correlation between the first PC and the wind speed, and a strong correlation between the second PC and the temperature. Thus, the first 2 PCs are removed from the structural condition evaluation.

The evaluation of the structure condition is performed by exploiting the Mahalanobis Squared Distance (MSD). MSD is a measure used to quantify the distance between a point and a distribution. It accounts for correlations of the data and normalizes the scale of the features [14]. The synthetic index proposed in this work is evaluated as follows

$$D_i = \left[Z_i^* - \overline{Z_0^*}\right]^T \sum\nolimits^{-1} \left[Z_i^* - \overline{Z_0^*}\right] \tag{6}$$

where Z_i^* is a new observation of natural frequencies standardized with respect to the baseline averages and standard deviations, projected to the baseline PCs and with the first 2 PC scores removed, $\overline{Z_0^*}$ is the baseline average of the PC scores with the first 2 removed and $\sum^{-1}$ is the baseline covariance matrix. The evolution of the index is shown in Figure 6.

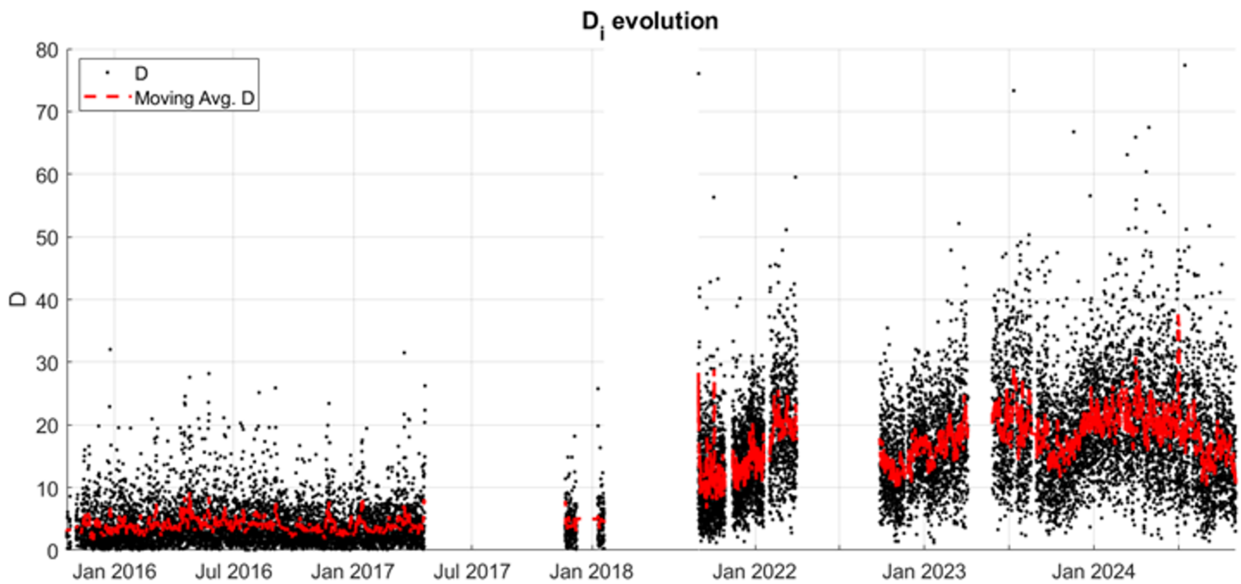

Fig. 6 Synthetic index evolution during the monitored period

The index proposed shows a strong immunity to environmental conditions during the training set since variations due to the wind speed and seasonal temperature seem to be removed. However, a certain discrepancy between the validation and training sets is noticeable. Furthermore, the proposed index in the validation set seems to be influenced by a seasonal variation. The causes behind these discrepancies are still being investigated and are yet to be fully understood.

Conclusions

This article presents a SHM strategy based on OMA outcomes. Acceleration measurements from the monitoring system of Palazzo Lombardia (Milan, Italy) have been employed to develop this technique. Results from OMA demonstrate a consistent variation caused by environmental factors. Therefore, the PCA has been performed to detect and remove the ambient effects. Finally, a synthetic index based on the MSD is evaluated to verify the structure condition without the environmental impact. Results show a strong immunity to ambient variations. However, a certain discrepancy between the validation set and the training set is evident. The deviation of the proposed index is still under further investigation.

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