Applications and Open Issues in the Structural Health Monitoring of Historic Buildings

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Abstract This chapter describes the main features and components of the Structural Health Monitoring of historic buildings, including experimental campaigns (in which dynamic and environmental data are recorded), data processing, anomaly detection and finite element nonlinear simulations. The results of the dynamic monitoring campaigns conducted on three masonry towers in the historic centre of Lucca from 2015 to 2022 are then presented. The vibrations of the San Frediano bell tower, the Clock Tower and the Guinigi Tower were continuously monitored: high–sensitivity seismic stations were installed on the structures to record their response to the dynamic actions of the surrounding environment. The effects of natural and anthropic vibration sources on the dynamic behaviour of the towers were also investigated to detect novelties and anomalies that occurred during the monitoring period.

1 Introduction

The environmental excitations of natural and anthropic origin (earthquakes, wind, traffic, machinery, moving crowds) are a source of information for monitoring and assessing the structural behaviour of buildings. Using ambient vibrations to characterize the dynamic properties of constructions dates back to the 1970s [31] and has spread out in the last decades, thanks to the availability of high–sensitivity in-

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struments that measure very low vibration levels. Monitoring ambient vibrations is not invasive and allows measurements to be made without artificial forces and interruptions of the use of the structures involved. These characteristics make the ambient vibration measurement particularly suitable for heritage buildings.

Data recorded by the sensors installed on the building in operating conditions are processed using suitable numerical procedures to determine its dynamic properties, such as frequencies, damping ratios and mode shapes. This approach is called Operational Modal Analysis (OMA) [8]. Tracking the variation of frequencies over time, assessing environmental effects and analyzing changes and anomalies in the dynamic behaviour of a building are essential ingredients of Structural Health Monitoring (SHM). Applying this technology to a building can provide helpful information on the vibration sources, the variation of dynamic properties and the building's structural "safety" state. Moreover, SHM makes damage detection possible: in fact, changes in the dynamic properties over time can represent structural damage indicators [17], [28], [32].

This chapter describes the results of the dynamic monitoring campaigns conducted by the authors on three historic towers in Lucca from 2015 to 2022.

The main features of SHM are introduced in Section 2, where the path from experimental campaigns, in which dynamic and environmental data are recorded and processed, to finite element (FE) numerical simulation is briefly described. The experiments carried out on three masonry towers in the historic centre of Lucca are presented in Sections 3, 4 and 5. The vibrations of the San Frediano bell tower [1], the Clock Tower [2], and the Guinigi Tower [3] were continuously monitored: high–sensitivity seismic stations were installed on the structures to record their response to the dynamic actions of the surrounding environment. The effects of natural and anthropic vibration sources on the dynamic behaviour of the towers are also investigated to detect novelties and anomalies that occurred during the monitoring period. Some open issues about damage detection are also addressed, and the digital twin paradigm is introduced in Section 6.

2 Structural Health Monitoring

SHM is based on long–term continuous dynamic monitoring of structures. It is a non–destructive investigation technique in which sensors are installed on the structure to measure the vibrations induced by the environmental excitations of natural and anthropic origin (earthquakes, wind, traffic, machinery, moving crowds). This procedure makes it possible to measure the vibration level of the structure and identify the different vibration sources.

Monitoring campaigns usually use piezoelectric [15] and MEMS [6] accelerometers. In the last decade, the employment of velocimeters, traditionally adopted to record ground motions, such as those caused by earthquakes, volcanic eruptions, and explosions, has increased, mainly because of their high sensitivity [4, 1, 16].

Data recorded by the velocimeters and accelerometers installed on the building in operating conditions are the inputs of OMA [8], whose outcomes are the building's dynamic properties (frequencies, mode shapes, damping ratios). Tracking the frequencies over time provides information on the variation of dynamic properties, the influence of the environmental parameters (temperature, humidity, wind) on the dynamic properties, the building's structural "safety" state and makes damage detection possible, as changes in the dynamic properties over time can represent structural damage indicators.

The large amount of data recorded by the sensors installed on a structure during the experimental campaigns can be processed and used for three main activities: dynamic identification, anomaly detection and FE model updating.

Dynamic identification. In OMA, velocities or acceleration time series are processed to determine the dynamic properties of the structure (natural frequencies, mode shapes, damping ratios) in operational conditions. The structure, subjected to unknown input, is modelled in the time domain as a discrete linear time–invariant system whose dynamic behaviour is governed by the following stochastic state–space model (of order r):

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{w}_k, \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k + \mathbf{v}_k, \end{aligned} \tag{1}$$

where $\mathbf{A}$ is the $r \times r$ state matrix, $\mathbf{C}$ the $s \times r$ influence matrix ($r, s \in \mathbb{N}$), $\mathbf{x}_k \in \mathbb{R}^r$ the state vector at the kth time, $\mathbf{y}_k \in \mathbb{R}^s$ the vector of observations. Moreover, $\mathbf{w}_k \in \mathbb{R}^r$ is the processes noise due to disturbance/modelling inaccuracies and $\mathbf{v}_k \in \mathbb{R}^s$ is the measurement noise caused by sensor inaccuracy; $\mathbf{w}_k$ and $\mathbf{v}_k$ are unmeasurable and modelled as zero mean, stationary, white noise random processes.

The state matrix $\mathbf{A}$ describes the dynamics of the system, whose modal properties are characterized by the eigenvalues of $\mathbf{A}$ [26]. The most popular algorithms in OMA are the stochastic subspace identification methods [26] in the time domain. In particular, velocities recorded on the case studies presented in this paper were processed via the Covariance–driven Stochastic Subspace Identification method (SSI/Cov) implemented in the MACEC code [29] to calculate the modal properties.

Anomaly detection. Modal tracking consists of calculating the dynamic properties over time and following their evolution during the monitoring period [13]. Modal tracking makes it possible to determine normal dynamic behaviour and detect anomalies due to structural damage; thus, anomaly detection plays a crucial role in SHM.

Numerical techniques commonly employed to recognise deviations from normality are AutoRegressive eXogenous (ARX) models [23], Principal Component Analysis (PCA) [14] and Deep Learning (DL) [25].

Algorithms for anomaly detection are trained on the existing experimental data [15], [32], [1], [10]. The goal is to understand the normality patterns in the structure's response to the actions coming from the environment. Thus, the algorithms can predict the normal dynamics of the structure under observation. The more significant deviations (in the new experimental data) from the learned normality patterns are considered anomalies. Monitoring campaigns have shown that changes in the natural frequencies over time can represent effective structural damage indicators [15].

The PCA approach is widely used in SHM [14] and can detect novelty in the experimental frequencies by comparing them with the values predicted by a model calibrated on suitable training data. It is an output–only model: only the structure's natural frequencies are required, without any explicit information on the environmental conditions. An alternative novelty detection method is the Temporal Fusion Transformer (TFT) introduced in [22]. TFT has been experimented on electricity, traffic, retail and volatility problems, but its applications to SHM are still scarce [10], [11]. TFT is an attention–based deep neural network architecture for multi–horizon time series forecasting.

The TFT network is trained on datasets, collecting data from the high–sensitivity sensors directly installed on the building, enriched with other environmental parameters recorded by nearby sites and data coming from elaborations, like the hourly main frequencies of vibrations. The transformer is then used to predict the vibrational features of the building (main frequencies of vibrations) and detect possible anomalies or unexpected events by inspecting how much the actual frequencies deviate from the predicted ones.

Input data are split into observed inputs $\mathbf{z}_t$, measured at each $t \in [0, T]$ by the sensors and inputs $\mathbf{x}_t$ that are known without measurements (known inputs, such as the date at a prescribed time t). Input data and past targets are used to train the TFT model, which is then employed to predict the scalar targets $y_{i,t}$ (e.g. the ith natural frequency) from t on. TFT can simultaneously predict various percentiles (e.g. the 1st, 50-th and 99th) of the targets at each future time step of interest (hence the name multi–horizon forecasting). Each quantile forecast can be written as

$$\hat{y}_i(q, t, \tau) = f_q(\tau, y_{i,t-k:t}, \mathbf{z}_{t-k:t}, \mathbf{x}_{t-k:t+\tau}; \omega). \tag{2}$$

In equation (2) $\hat{y}_i(q, t, \tau)$ is the predicted qth quantile (e.g. 0.01, 0.5, 0.99) of the ith target referred to the τ–step ahead the starting time t, $f_q(\cdot\,; \omega)$ is the model induced by the TFT architecture depending on the parameters ω, $y_{i,t-k:t}$ and $\mathbf{z}_{t-k:t}$ represent the past target values and the observed input from the starting time t up to k time steps before, $\mathbf{x}_{t-k:t+\tau}$ are known inputs across the entire range. The parameters vector ω is calculated by the TFT network solving a minimisation problem on the domain of the input training data: such a minimisation procedure represents the so-called model's training. Typically, a portion of the input database is set aside in the training procedure and reserved for further model refinement (validation). Finally, the network test is performed on a third portion of the input data set, called the test set. We refer to the original work [22] for more details on TFTs and related issues.

Exploiting its prediction capability, TFT can detect possible anomalies or unexpected events by inspecting how much the observed targets deviate from the predicted ones. Once the TFT has been trained on a set of non-anomalous data, the prediction $\hat{y}_i(0.5, t, \tau)$ of the i-th target value and the 1st and 99th percentiles $\hat{y}_i(0.01, t, \tau)$ and $\hat{y}_i(0.99, t, \tau)$ are obtained. An anomaly occurs at time $t + \tau$ if the observed value

$y_{i,t+\tau}$ lies outside the confidence interval $[\hat{y}_i(0.01, t, \tau), \hat{y}_i(0.99, t, \tau)]$ predicted by the network.

FE model updating. The experimental dynamic properties obtained via dynamic identification techniques can be used to calibrate an FE model of the structure by calculating some unknown parameters (for example, the mechanical properties of the materials) [12]. The FE model suitably calibrated can be used to compare the experimental and numerical behaviours of the structure subjected to accelerations recorded during a seismic event and to predict its dynamic response to any time–dependent loads.

The FE code NOSA–ITACA [7] developed at ISTI–CNR for the nonlinear analysis of masonry structures allows the integration of ambient vibration tests and numerical modelling. Efficient numerical methods are implemented in NOSA–ITACA to address the modal analysis of linear elastic structures [27] and solve the generalised eigenvalue problem

$$\mathbf{K}\,\mathbf{v} = \omega^2\,\mathbf{M}\,\mathbf{v}, \tag{3}$$

where $\mathbf{K}$ and $\mathbf{M} \in \mathbb{R}^{n\times n}$ are the stiffness and mass matrices of the finite element assemblage, both symmetric and positive definite. The integer n is the total number of degrees of freedom of the system and is generally very large since it depends on the discretization of the problem. Solving (3) provides the first d smallest natural frequencies $f_i = \omega_i/2\pi$ and mode shapes $\mathbf{v}^{(i)}$ of the structure, with $i = 1, ..., d$, $d << n$.

Using experimental modal properties of a structure makes it possible to calibrate its FE model via model updating procedures. The goal of FE model updating is to determine the unknown characteristics of a structure, such as materials' properties and boundary conditions, by matching experimental and numerical frequencies and mode shapes [12].

We assume that the stiffness $\mathbf{K}(\mathbf{x})$ and mass $\mathbf{M}(\mathbf{x})$ matrices of the finite element model depend on a parameters vector $\mathbf{x}$ belonging to the box $\Omega \subset \mathbb{R}^p$, we solve the generalized eigenvalue problem (3) for $\mathbf{K}(\mathbf{x})$ and $\mathbf{M}(\mathbf{x})$ and calculate the frequencies $f_1(\mathbf{x})$,... , $f_d(\mathbf{x})$ and the corresponding eigenvectors $\mathbf{v}_1(\mathbf{x})$,..., $\mathbf{v}_d\mathbf{x})$. We consider the function

$$\phi(\mathbf{x}) = \sum_{i=1}^{d} w_i^2[\hat{f}_i - f_i(\mathbf{x})]^2 + w_{d+i}^2[1 - \gamma_i(\mathbf{x})]^2, \tag{4}$$

which measures the distance between the experimental frequencies $\hat{f}_i$ and mode shapes $\hat{\mathbf{v}}_i$ and the numerical counterparts $f_i(\mathbf{x})$ and $\mathbf{v}_i(\mathbf{x})$. Quantities $\gamma_i(\mathbf{x})$ are the absolute value of the cosine of the angle between the numerical and experimental mode shapes (the square root of the Modal Assurance Criterion defined in [8]). Scalars w_i are the weights that should be given to each frequency and mode shape in the optimization scheme (usually, $w_i = \hat{f}_i^{-1}$, for $i = 1, ..., d$ and $w_i = 0$ or $w_i = 0.1$ for $i = d + 1, ..., 2d$). Then, we minimize the objective function ϕ and calculate the global optimal value of $\mathbf{x}$ in Ω.

The minimum problem we must solve is a nonlinear least square problem, and the numerical procedure implemented in the NOSA–ITACA code to minimize function

ϕ is based on a trust region scheme [19], [21]. By modifying the Lanczos projection scheme used to compute the first (smallest) eigenvalues (and corresponding eigenvectors), we obtain local parametric reduced–order models that, embedded in the trust–region scheme, are the basis for an efficient algorithm that minimizes the objective function ϕ in Ω.

In many applications covered in the literature, the FE code (usually a commercial one) is used as a black–box function and the optimization problem is solved using a general–purpose optimizer. The procedure implemented in NOSA–ITACA is faster than a black–box approach. Moreover, information about the reliability of the minimum point and its sensitivity to noisy experimental data can be obtained from the singular value decomposition of the Jacobian of the residual function (the difference between numerical and experimental frequencies) evaluated at the minimum point [21].

The activities described above have been conducted on the three case studies introduced in the following subsection.

2.1 Three case studies in Lucca

Long–term monitoring campaigns were conducted on three medieval masonry towers in the historic centre of Lucca in collaboration with INGV's Arezzo Seismological Observatory. The towers have been continuously monitored by high–sensitivity seismic stations recording the structures' response to the dynamic actions of the surrounding environment. The San Frediano bell tower (Figure 1 (left)) was monitored from October 2015 to November 2017 [1]. The Clock Tower (Figure 1 (middle)), located in Via Fillungo, was monitored from November 2017 to March 2018 [2]. The Guinigi Tower (Figure 1 (right)), one of the most famous buildings in Lucca for the hanging garden with seven holm oaks on its top, was monitored from July 2021 to August 2022 [3].

The ambient vibration tests were conducted by installing a few seismic stations on the towers according to the given layouts. In particular, tri–axial velocimeters (SARA Electronic Instruments srl, Perugia, Italy) were employed, each equipped with a 24–bit digitizer, a battery and a modem for the internet connection. The velocities time series recorded on the towers were sent to the server hosted at ISTI–CNR in Pisa, where data was stored and processed. The instruments recorded velocities with a sampling frequency of 100 Hz. Two thermo–hygrometers with a sampling time of 60 seconds completed the monitoring system.

Fig. 1 San Frediano bell tower (left), Clock Tower (middle), Guinigi Tower (right).

3 Dynamic Identification and Modal Tracking

Tables 1, 2 and 3 summarize the average values of the first natural frequencies of the three towers calculated with the SSI/Cov method. During the monitoring period, the frequencies are characterized by variations, with relative differences Δ = (Max_{99}-Min_1)/Min_1 (Max_{99} and Min_1 are the 99th and 1st percentiles of the dataset) in the order of 5–6%. The mode shapes do not exhibit significant variations during the entire monitoring period. The tables also report the towers' height h, the average value and the 99th percentile of the dataset of the velocities recorded on their top. The average velocities measured on the towers, sited in a restricted traffic area, are very low. The velocity peaks are in the order of 5 mm/s.

Table 1 San Frediano bell tower, h = 52 m, October 2015 – November 2016

f_1 [Hz] Δ_1 [%]	f_2 [Hz] Δ_2 [%]	f_3 [Hz] Δ_3 [%]	f_4 [Hz] Δ_4 [%]	V_{99} [mm/s]	V_{av} [mm/s]
1.099 5.42	1.382 6.50	3.447 5.44	4.614 5.85	4.99	0.10

Table 2 Clock Tower, h = 48.4 m, November 2017 – March 2018

f_1 [Hz] Δ_1 [%]	f_2 [Hz] Δ_2 [%]	f_3 [Hz] Δ_3 [%]	f_4 [Hz] Δ_4 [%]	V_{99} [mm/s]	V_{av} [mm/s]
1.028 3.65	1.281 3.40	4.052 8.67	4.489 10.68	5.36	0.26

Table 3 Guinigi Tower, h = 44.3, July 2021 – August 2022

f_1 [Hz] Δ_1 [%]	f_2 [Hz] Δ_2 [%]	f_3 [Hz] Δ_3 [%]	f_4 [Hz] Δ_4 [%]	f_5 [Hz] Δ_5 [%]	f_6 [Hz] Δ_6 [%]	V_{99} [mm/s]	V_{av} [mm/s]
1.211 5.93	1.347 6.90	2.640 6.84	3.345 7.03	4.155 7.29	6.344 3.88	1.67	0.31

3.1 The influence of temperature on the towers' frequencies

Long–term dynamic monitoring campaigns showed that natural frequencies depend on environmental parameters like temperature and humidity [33], [9].

The daily variations of the first two natural frequencies of the San Frediano bell tower (from 6 to 8 June 2016) are shown in Figure 2 (a), along with the temperature plot. The curves exhibit an apparent daily periodicity, with the frequencies increasing during the first half of the day (when temperatures increase) and decreasing in the latter half. The frequencies appear to be shifted by about 1–2 hours compared to the temperature trend. This phenomenon is likely due to the tower's thermal inertia and guarantees that the reported effects on the frequencies are not attributable to the experimental apparatus.

The daily variations observed in the frequency values are in the order of 2–3%. Figures 2 (b) and 2 (c) show the dependence of the first two frequencies on temperature. As reported in Table 1, the relative differences Δ of the frequencies in the monitoring period (evaluated on the 1st and 99th percentile) are in the order of 5–6%. The first two frequencies depend almost linearly on temperature. As observed in other long–term vibration monitoring of ancient buildings [28], [15], [32], the frequencies tend to increase with temperature. The thermal expansion caused by positive temperature variations induces a reduction of the micro–cracks inside masonry, thus increasing the global stiffness of the structure.

Figure 3 (a) shows the correlation of the first natural frequency of the Clock tower with air temperature, measured by a sensor located in the Botanical Garden in Lucca's historic centre. The figure confirms the findings of other long–term vibration monitoring campaigns on historical towers, including that carried out on the San Frediano bell tower: frequencies tend to increase with temperature for temperatures greater than zero. Regarding negative temperature values, the figure reveals the opposite trend for the frequency, which increases when the temperature decreases. This phenomenon was mainly observed in the last part of February 2018, when temperatures persistently remained below zero. Correspondingly, Figures 3 (b) and 3 (c), which plot the first two frequencies versus temperature, show the change in the frequency trend. The behaviour below freezing has also been reported for similar weather conditions in other papers [33], [9], where the increase of frequencies when the temperature goes below zero is ascribed to the fact that ice tends to close micro–cracks and then stiffen the masonry. It is also worth noting that, as long as the temperature remains above zero, frequencies respond to temperature variations with a phase shift in time, most likely connected to the thermal inertia of the tower, while, below zero, the frequency and temperature appear to be in phase.

Figures 4 (a) and 4 (b) show the variations of the first and second frequencies of the Guinigi Tower versus time (black line) in January 2021, along with the temperature plot (grey line). Figures 4 (c) and 4 (d) report the plots of the first and second frequencies measured from August 2021 to April 2022 versus temperature. As summarised in Table 3, the relative differences Δ of the frequencies (evaluated on the 1st and 99th percentile) over the monitoring period are at most in the order of 7%. The Guinigi Tower does not exhibit the correlation between frequencies and temperature detected in the two preceding case studies. Figures 4 (c) and 4 (d) show that in the monitoring period, there is a very low correlation between temperature and frequencies, which are relatively sparse. Without a specific explanation of this experimental result, it is worth noting that this scarce correlation also characterizes the Asinelli Tower in Bologna, which, like the Guinigi Tower, is open to the public and visited annually by many people [5].

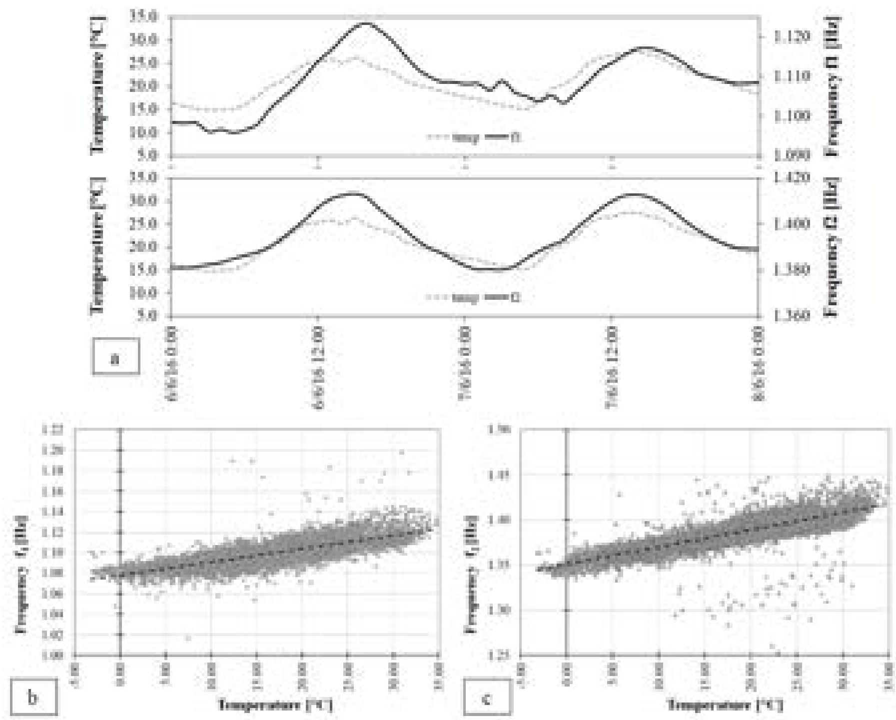

Fig. 2 San Frediano bell tower: first two natural frequencies (black line) and temperature (gray dashed line) versus time (a); first (b) and second (c) natural frequencies versus temperature.

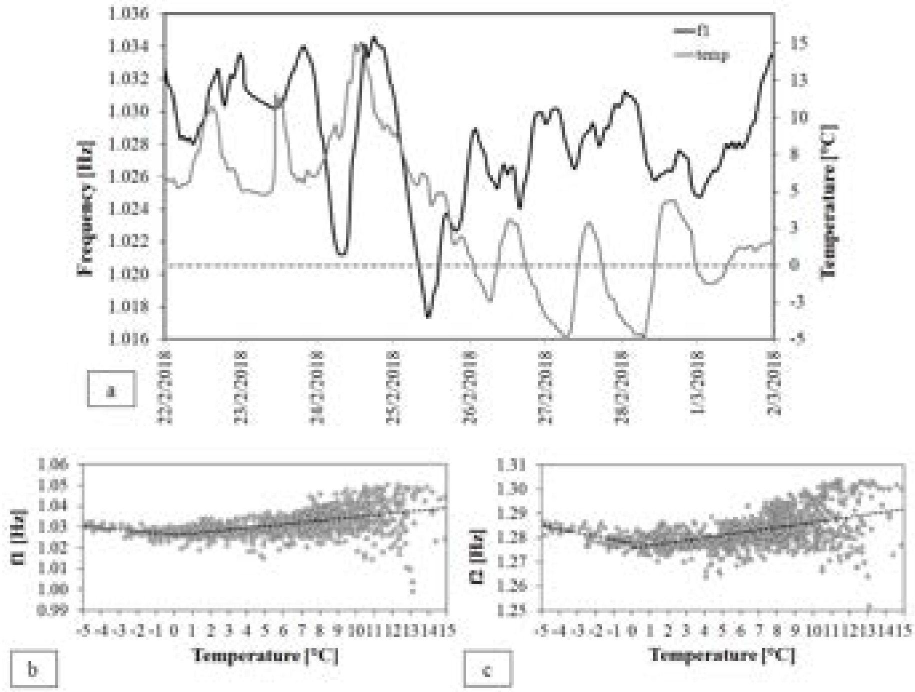

Fig. 3 Clock Tower: first natural frequency (black line) and temperature (grey line) versus time (a); first (b) and second (c) natural frequencies versus temperature.

3.2 Vibration sources: wind, swinging bells, tourists and earthquakes

The principal vibration sources for the three towers in the monitoring period were wind, bells swinging, visitors and some seismic events. Figure 5 shows the maximum velocities per hour recorded atop the San Frediano bell tower (at + 42 m) from 29 October to 31 December 2015. The most relevant values correspond to the swinging of the bells on Saturday and Sunday, with the maximum velocity values in the direction of the bell's swinging (y in the current reference), on the order of 1–1.5 mm/s. Atypical amplification of the tower's movements was recorded in the periods 29 October to 1 November 2015 (Lucca Comics & Games festival), 17–18 November 2015 (celebrations of St Frediano), and 24–25 December (Christmas), up to 3 mm/s. All these events (except Lucca Comics & Games, whose effects on the tower's vibrations were due to the crowd in the square) corresponded to the full swinging motion of the San Frediano bells. The wind affected the tower to a lesser extent, and the vibrations reached relevant values only for relatively high wind velocities, over 50 km/h (for example, on 21 November 2015, the maximum recorded velocity on the tower was on the order of $5 \cdot 10^{-4}$ m/s, against a maximum wind velocity of 60 km/h).

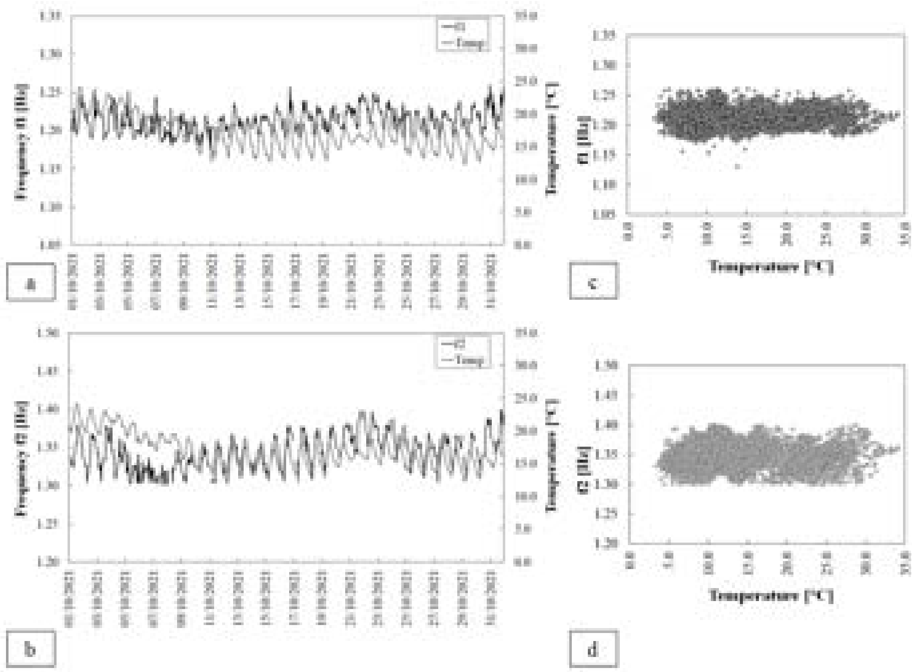

Fig. 4 Guinigi Tower: first (a) and second (b) natural frequencies (black line) and temperature (grey line) versus time in January 2021; first (c) and second (d) natural frequencies versus temperature.

Concerning the environmental parameters that could influence the acceleration levels on the Clock Tower, Figure 6 (a) plots the daily average values of the maximum hourly accelerations in the x (black line) and y (black dashed line) directions from 25 December 2017 to 14 January 2018, together with the daily maximum wind speed (grey dashed line) recorded at Pieve di Compito, about 10 km from the Lucca historic centre (data available at www.sir.toscana.it). The figure clearly shows a correspondence between the peaks in the acceleration levels and those in the wind speed. Figure 6 also reports the correlation between the first (b) and second (c) natural frequencies and the maximum acceleration experimented by the tower and shows that frequencies tend to decrease as the amplitude of acceleration increases. This trend can be attributed to masonry's inability to withstand tensile stresses [18].

Other vibration sources are both local and teleseismic earthquakes [2]. From July 2021 to May 2022, the seismic stations on the Guinigi Tower recorded several earthquakes of magnitude between 3.0 and 4.2 in a circular area centred in the Guinigi Tower with a radius of 108 km. Among them was the Viareggio earthquake (magnitude 3.7), located 20 km from Lucca and occurred on 6 February 2022, which induced the maximum velocity on the top of the tower. The maximum ground velocity recorded at the tower's base was $1.8 \cdot 10^{-3}$ m/s, while the maximum value

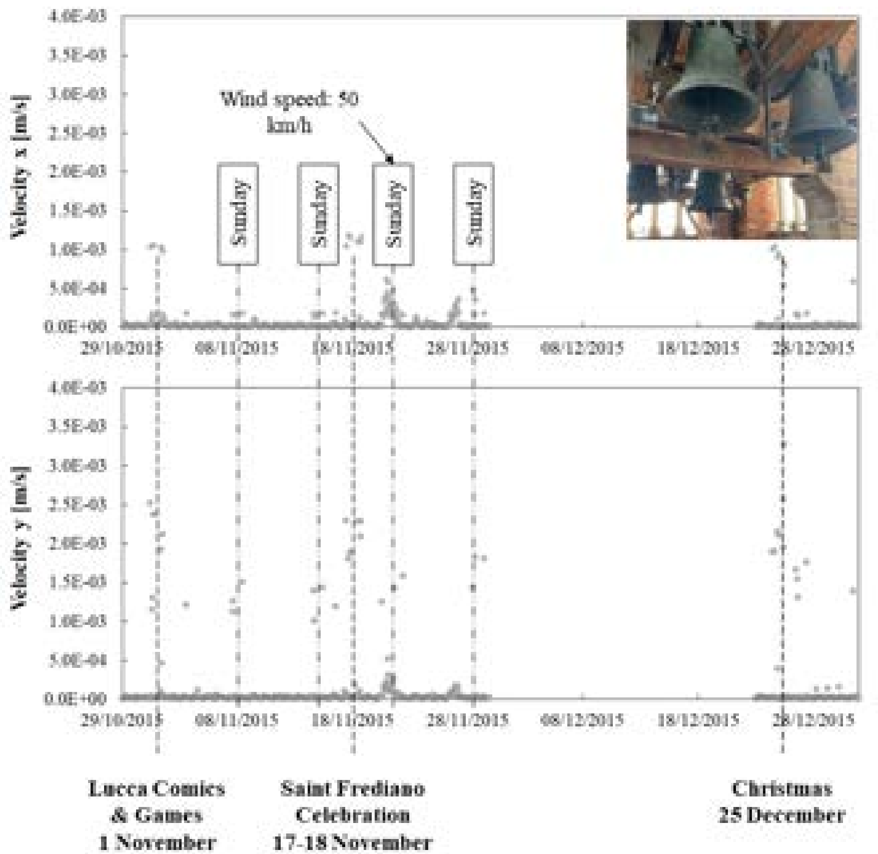

Fig. 5 San Frediano bell tower: maximum absolute values per hour of the velocities recorded by the seismic station on the top (+ 42m) in the x and y directions from 29 October to 31 December 2015.

recorded at the top was $6.3 \cdot 10^{-3}$ m/s. Strong amplification of the signal along the tower's height can be observed, particularly in the horizontal directions, along which the velocity at the top of the tower was more than 3.5 times that recorded at the base. Figure 7 reports the positions of the four seismic stations on the tower and the velocities recorded by the velocimeters 2045 on the underground floor, 2542 at level 0 (about 18 m) and 2896 at level 5 (about 40 m).

People visiting the Guinigi Tower are another source of vibration. Figure 8 (b) plots the maximum velocities per hour recorded on the top of the tower in the x, y and z directions from 5 to 16 April 2022. The trend of the maximum velocities is related to the presence of the visitors in the tower: the tower's entrance is scheduled from 9:30 a.m. to 7:30 p.m. (weekends included). The wind speed reported as a dashed line does not influence the tower's velocities.

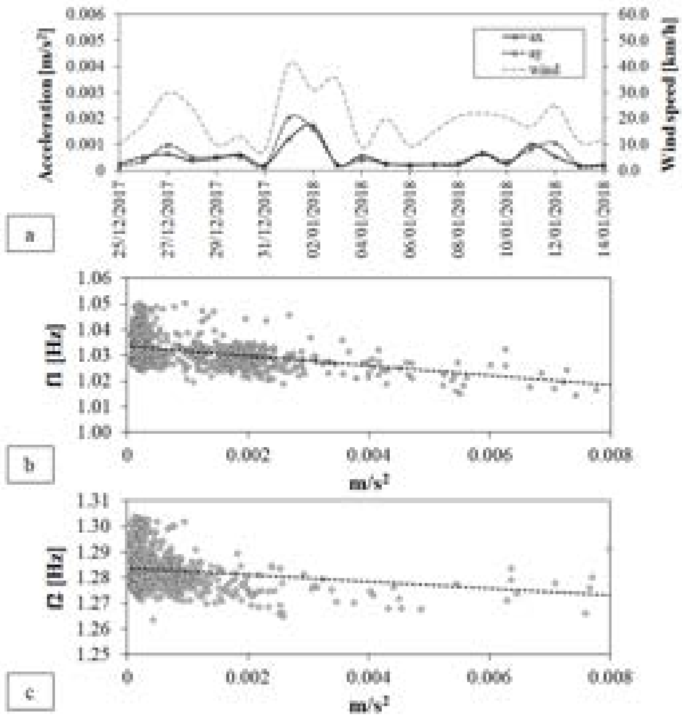

Fig. 6 Clock Tower: daily average of the maximum hourly accelerations measured on the top along the x (black line) and y (dashed line) directions and daily maximum wind speeds (grey dashed line) (a); first (b) and second (c) frequencies versus the maximum accelerations recorded on the tower.

The effects of the visitors moving inside the tower are also highlighted in Figure 8 (c), reporting the spectral amplitudes of the first two frequencies plotted versus time and compared to the number of tickets sold during the day. The figure shows this comparison from 2 to 14 July 2021. The tower's opening to visitors produces a sharp and sudden increase in the two spectral amplitudes, rapidly vanishing at the end of the visiting hours.

In order to compare the effects of people visiting the tower and the Viareggio earthquake on the dynamic behaviour of the Guinigi Tower, Figure 8 (a) shows the spectrogram of the signals recorded from 1 to 7 February 2022 in the x direction. Every day from 9:30 to 19:30, there is an evident increase in the signal's power spectral energy due to the people visiting the tower. In addition, the occurrence of the Viareggio earthquake is visible in the spectrogram, which exhibits an energy peak of about -100 dB/Hz on 6 February at 1:36. It is worth noting that the energy increase due to the visiting people is comparable to that induced by the Viareggio earthquake.

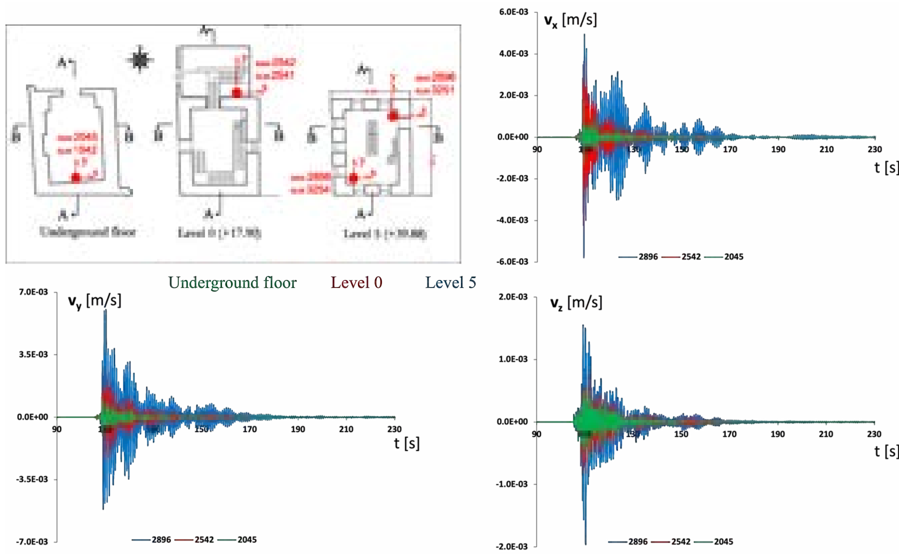

Fig. 7 Guinigi Tower: position of the seismic stations on the tower and seismograms of the Viareggio (LU) earthquake (magnitude 3.7, on 6 February 2022, at about 20 km from the tower), velocities v_x, v_y and v_z (m/s) versus time t (s) recorded by stations 2045 (green, underground), 2542 (red, + 18 m) and 2896 (blue, + 40 m) (colour figure online).

4 Anomaly detection

Data recorded on the San Frediano bell tower and processed via OMA techniques are here used to detect anomalies in the structure's dynamic behaviour.

On 24 August 2016, the signal of the Amatrice earthquake that struck central Italy (magnitude 6.0, about 400 km from Lucca) was detected by the seismic stations installed on the tower, with velocities on the same order as those induced by the swinging of the bells. No significant damage was observed on the tower due to the seismic event.

Figure 9 reports the results obtained with the PCA approach analysing the first three frequencies, with a training period from October 2015 to June 2016 and a validation period from July to October 2016, containing the Amatrice earthquake [1]. In particular, the chart in Figure 9 (top) shows the misfit between the experimental data and data predicted by the model before and after the seismic event. The red horizontal line corresponds to the 95th percentile of the misfit for the training period. The quantity N_{95} is the percentage of points that, after the Amatrice earthquake, exceed the threshold of the 95th percentile. The numerical results confirm that no damage occurred in the tower due to the earthquake.

In the absence of actual damages, the procedure is then applied to a simulated damage scenario, in which the training coincides with the entire monitoring period (blue dots) and validation data coincide with the first three tower frequencies mea-

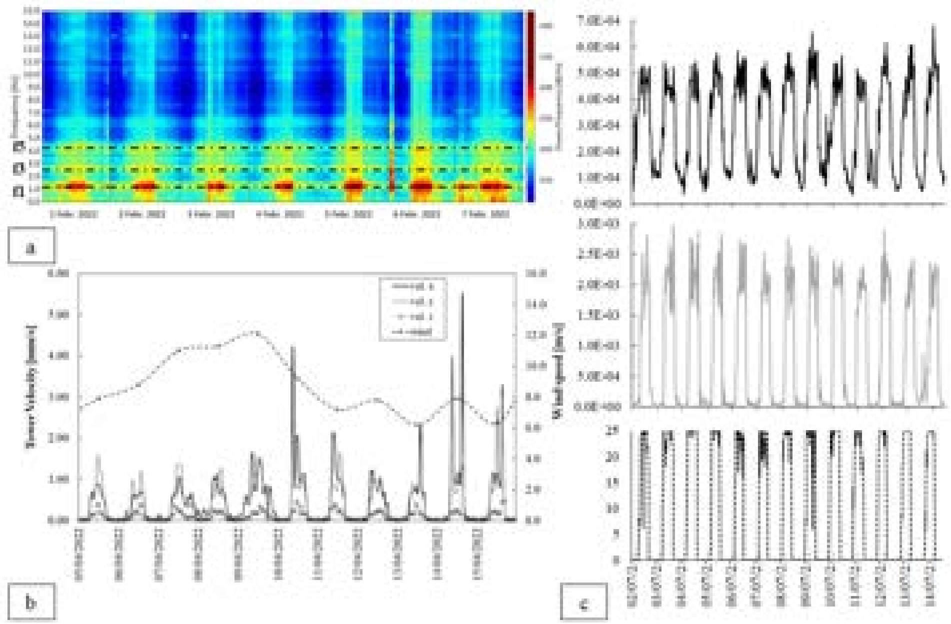

Fig. 8 Guinigi Tower: spectrogram of the signals recorded from 1 to 7 February 2022 in the x direction (a); maximum velocities per hour recorded on the top of the tower in the x, y and z directions from 5 to 16 April 2022 and wind speed (dashed line) (b); spectral amplitudes of the first two frequencies plotted versus time and number of tickets sold during the day from 2 to 14 July 2021 (c).

sured in the training period and reduced by 4%, 2% and 1% (green dots). The results shown in Figure 9 (bottom) and the high value of N_{95} indicate the presence of novelty in the tower's dynamic behaviour, and PCA proves to be an effective tool for damage detection.

An alternative approach to anomaly detection is based on the TFT networks introduced in Section 2, whose results are described in [10] and summarised in the following.

The natural frequencies of the bell tower and other environmental parameters (temperature, humidity, et cetera) measured on the tower or in its proximity (*www.sir.toscana.it*) constitute the input database on which the TFT algorithm has been trained, validated and tested.

As for the PCA, the Amatrice earthquake is considered to test the sensitivity of the TFT algorithm to potential anomalies. Figure 10 shows the anomaly detection results when the TFT network (with $\tau = 1$ in equation (2)) is tested over a period containing the earthquake. The green line represents the measured (experimental) frequencies, the continuous red line is for the 50th percentile predicted by TFT, and the two red dashed lines represent the predicted confidence interval between the 1st and 99th percentiles. According to the damage detection criterion introduced at the end of Section 2, an anomaly occurs when at least one experimental frequency

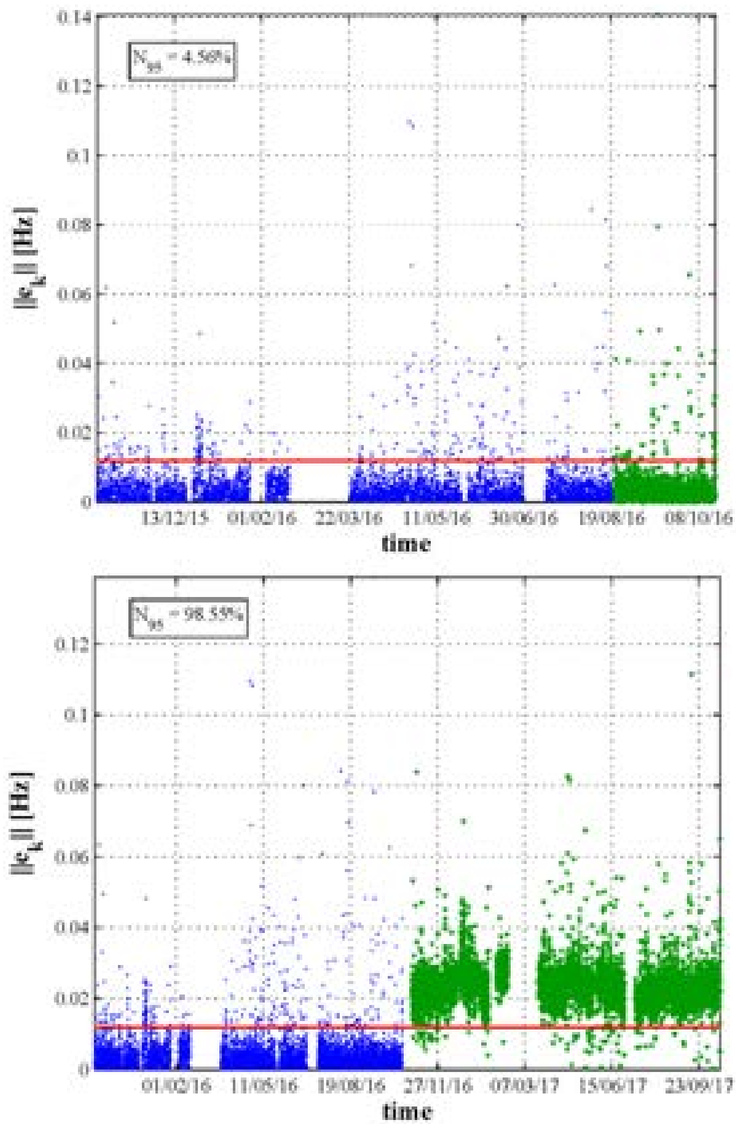

Fig. 9 San Frediano bell tower: misfit of PCA trained with the data measured before the Amatrice earthquake (top); misfit of PCA for the simulated damage scenario (bottom).

exceeds this predicted interval. The network can capture the Amatrice earthquake as an anomaly. In particular, the seismic event affects only the first two frequencies.

The algorithm can also detect the San Frediano bell tower vibrations induced by the swinging bells. This anomaly involves the second frequency (related to the swinging direction) and corresponds to the main religious ceremonies held in the

Cathedral, particularly on Saturday (20 August, h 17:00) and Sunday (21 August, h 10:00).

It is worth noting that the frequencies of the San Frediano bell tower exhibit a very marked oscillatory behaviour over the day; this behaviour is due to the daily temperature variations and is very well predicted by the TFT network.

Several open issues concern anomaly and damage detection tools. Further investigations are needed to confirm the good performance and reliability of the TFT method. Possible future activities include the application of the TFT algorithm to different damage indicators and velocity times series, a comparison between the anomaly detection techniques used in the literature and the TFT model, further tests of the TFT algorithm using artificial damage scenarios, and the automatic classification of the anomalies.

5 Experimental investigations and numerical modelling

This section presents the results of the dynamic analysis of the Guinigi Tower subjected to the Viareggio earthquake of 6 February 2022, recorded by the instruments installed on the tower (Figure 7).

The Guinigi Palace and its tower, shown in Figure 11, have been modelled using the NOSA–ITACA code [7]. The model updating procedure recalled in Section 2 was used to determine the Young's modulus of the palace (in blue) and the Young's moduli and mass densities of the portion of the tower contained within the palace (in red) and the remaining free portion (in brown).

The masonry constituting the tower was modelled as a nonlinear elastic material with zero tensile strength, adopting the constitutive equation of masonry–like materials described in [24]. The structure is subjected to its weight and the acceleration history recorded at the tower's base during the Viareggio earthquake (underground floor, Figure 7). The numerical response of the structure to the dynamic excitation was compared to that recorded on the tower by the seismic station 2896, placed at 40 m. Figure 11 shows the experimental velocity in the y direction (cyan line) and the numerical counterpart calculated by NOSA–ITACA (black dashed line). The numerical simulations, described in detail in [3], show a good agreement between numerical and experimental results.

6 The digital twin paradigm

The integration of SHM within the digital twin (DT) paradigm framework has a crucial role in the maintenance of engineering structures [30]. The natural evolution of the methods and tools described in this chapter is a digital twin platform for SHM of historical buildings. Such a platform should be characterised by

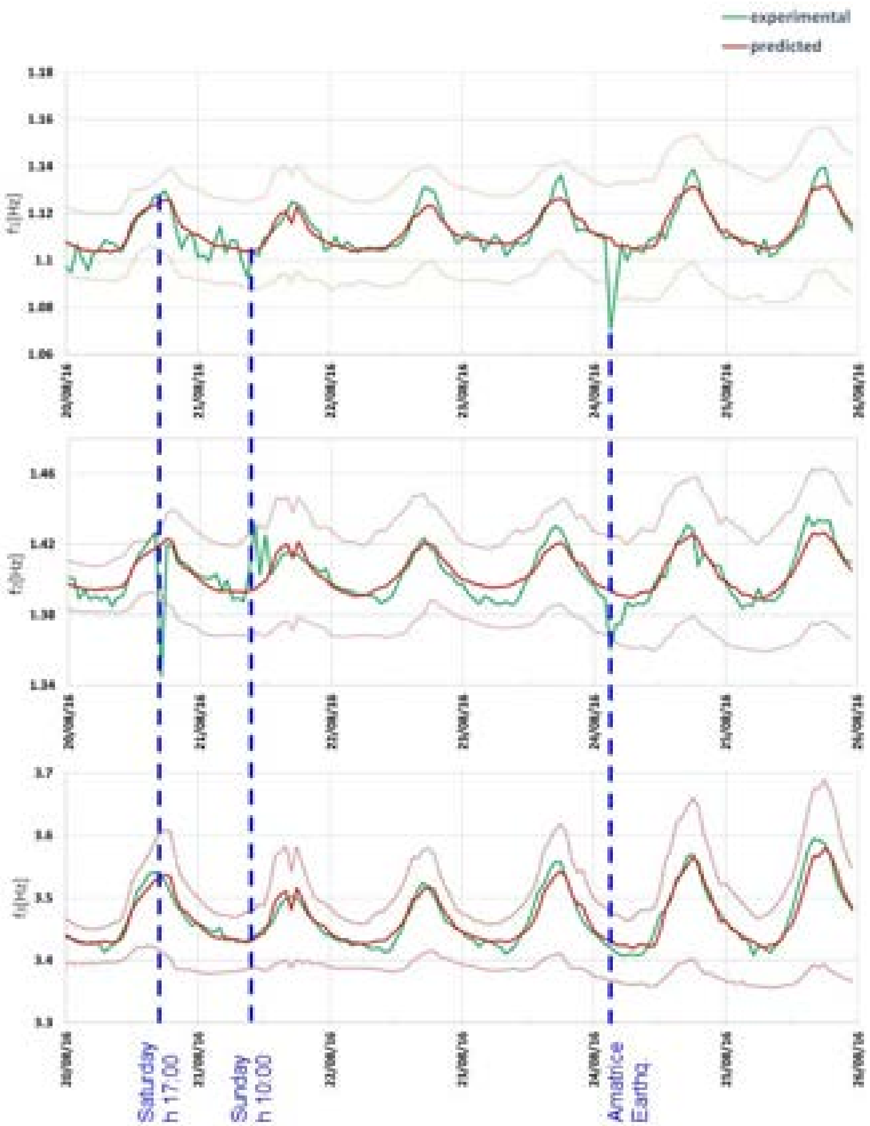

Fig. 10 San Frediano bell tower, Amatrice earthquake (24 August 2016, 3:36 UTC). First three predicted (red line) and experimental frequencies (green line). The dashed lines represent the 1st and 99th percentiles predicted by the model.

- Flexible and efficient tools for 3D digitization and CAD modelling of complex buildings.

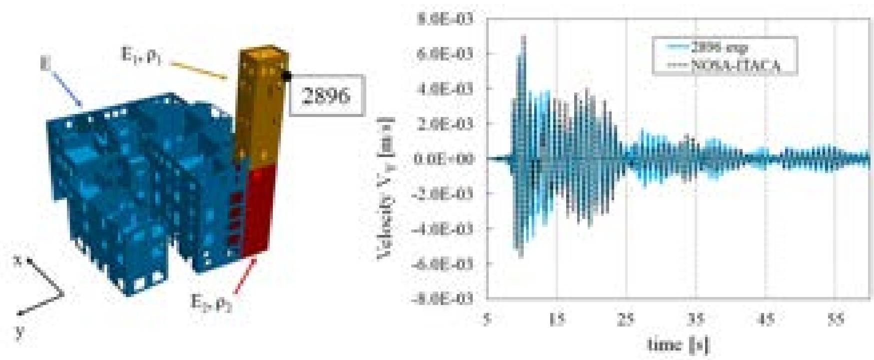

Fig. 11 Guinigi Tower: FE model of the Guinigi structure (left); experimental velocity in the y direction (cyan line) recorded by the seismic station 2896 and its numerical counterpart (black dashed line).

- Integration of data measured by the monitoring system and data provided by advanced numerical simulations; numerical tools for predictive assessments and support the decision process.
- Algorithms for detecting damages induced by the environmental impact, human activities and seismic actions and highlighting anomalies in the dynamic behaviour of the structure under examination.

The project REVOLUTION, conducted by the authors and funded by CNR, aims to design and develop a DT platform by integrating the numerical tools described in this chapter. Figure 12 shows the architecture of the DT platform. The platform's core is NOSA–ITACA [7], [20], which combines the FE solver NOSA and SALOME, an open–source platform for pre/and post–processing operations. REVOLUTION aims to equip the NOSA–ITACA platform with new tools and algorithms for storing and processing data from the sensors installed on the structure, performing numerical simulations and damage detection.

7 Conclusions

This chapter describes the results of the dynamic monitoring campaigns conducted on three historical towers in Lucca from 2015 to 2023, focusing on the crucial role of SHM and its components, including experimental activities (in which dynamic and environmental data are recorded), data processing, anomaly detection and FE numerical simulations.

The vibrations of the San Frediano bell tower, the Clock Tower and the Guinigi Tower were continuously monitored by high–sensitivity seismic stations installed on the structures to record their response to the dynamic actions of the surrounding

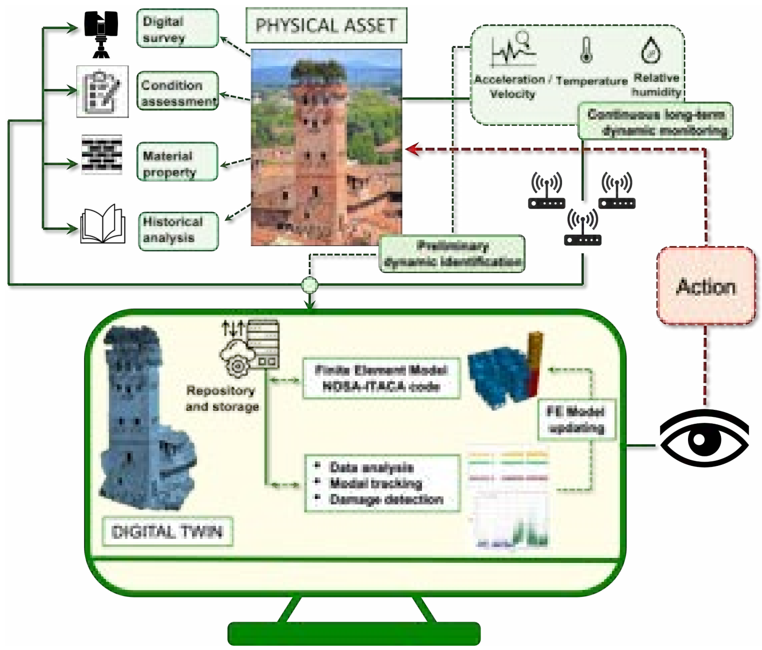

Fig. 12 Digital twin framework for historic buildings.

environment. The main results of the experimental campaigns on the three towers can be summarised as follows:

- Continuous long–term dynamic monitoring allows for collecting information regarding the vibration levels and the vibration sources, the evolution of the dynamic properties of the towers over time, and the structural response to earthquakes and exceptional loadings.
- The average velocities measured on the towers, sited in a restricted traffic area, are very low. The velocity peaks are in the order of 5 mm/s.
- The most important vibration sources are the wind, the bells swinging (for the San Frediano bell tower), people moving around the structures and the tourists accessing the structure (for the Guinigi tower).
- The instruments on the towers can detect earthquakes at an epicentral distance of up to hundreds of kilometres and teleseismic sequences in the low–frequency range.
- Natural frequencies depend on temperature. The towers' first frequencies exhibit a variation in the order of 5–6% during the monitoring periods.
- The correlation between frequencies and temperature is positive for the San Frediano and Clock Tower. For the Guinigi tower, the experimental data recorded in the monitoring campaign exhibits a relatively low correlation. The presence of tourists strongly influences the building's dynamic and makes it impossible

to evaluate the effects of the environmental parameters on the tower's modal properties.

The dynamic behaviour of the towers was also investigated to detect novelties and anomalies that occurred during the monitoring period, adopting the PCA and TFT approaches. The application of the TFT method to historic buildings is recent and needs further investigation. In particular, open issues about damage detection concern the choice of damage indicators and the automatic classification of anomalies.

It is essential to underline that despite the fundamental issues addressed in the chapter (experimental campaigns, data processing, dynamic identification, model updating, numerical modelling), several problems in SHM remain open and relevant aspects must be deepened. Regarding the experimental campaigns, collections of records measured on ancient buildings during long seismic sequences and over the years are still rare, and the availability of large datasets is crucial for an effective SHM of heritage buildings and infrastructures, like railway and road bridges that are in urgent need of monitoring and maintenance. SHM of bridges will be dealt with in future activities focusing on novelty detection techniques.

Regarding the dynamic identification of structures, numerical approaches that can provide satisfactory results when removing the white noise hypothesis on unknown environmental excitations should be investigated. Lastly, the NOSA-ITACA software adopted for model updating and structural analysis and representing an original, non-commercial contribution to the numerical modelling of historic structures should be further developed for stronger integration between experiments and mathematical models. In particular, a further challenging open issue is developing a DT platform oriented to historical buildings and infrastructures based on NOSA–ITACA.

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