Wiley
Advances in Civil Engineering
Volume 2024, Article ID 4447739, 17 pages
https://doi.org/10.1155/2024/4447739

WILEY

Research Article

Identification of Natural and Forcing Frequencies through Noisy Measurements Acquired in Operational Conditions on a Hospital Building

C. Rinaldi,[1] **A. Talebi**,[1] **M. D'Alessio**,[1] **F. Potenza**,[2] **and V. Gattulli**[1]

[1]*Department of Structural and Geotechnical Engineering, Sapienza University of Rome, Via Eudossiana 18, Rome 00184, Italy*
[2]*Department of Engineering and Geology, University "G. d'Annunzio" of Chieti-Pescara, Viale Pindaro 42, Pescara 65127, Italy*

Correspondence should be addressed to C. Rinaldi; cecilia.rinaldi@uniroma1.it

Received 25 March 2024; Revised 4 June 2024; Accepted 28 June 2024

Academic Editor: Chao Zou

Operational modal analysis is a robust and practical approach to structural health monitoring which assumes white noise as input. Therefore, the accuracy of this method can be compromised when dealing with colored unknown excitations, in which, for example, harmonic loads induced by the operation of mechanical equipment, may affect the modal parameter estimation. This study aims to address the challenge of identifying both natural and forcing frequencies of a complex building by exploiting the potentiality of both the spectral kurtosis analysis and stochastic subspace identification technique. The first one is based on the evaluation of a statistical quantity characterized by low values when data are stationary and Gaussian and high values when specific frequencies and nonstationarity are present in the signals. It allows the detection of harmonics, transients, and repetitive impulses in the frequency domain. Its combined use with the stochastic subspace identification technique enables us to effectively identify and separate harmonic-induced vibrations from structural response to ambient white noise. This approach can lead to a more accurate modal parameter estimation that has been investigated in this work through numerical and experimental analyses carried out on the Cardinal Massaia hospital building in Asti, Italy. An experimental daily dynamic campaign has been carried out to acquire accelerations in operational conditions including disturbances due to machinery like elevators and air conditioners. The combined use of kurtosis analysis and stochastic subspace identification techniques has been used to process a large dataset of noisy measurements acquired in operational conditions. Five different measurement setups have been implemented, each one composed of 14 sensors. Notwithstanding the complexity of the case study under investigation for both the structural configuration and difficulties in the experimental data acquisition, this approach allowed to distinguish natural from forcing frequencies, highlighting its accuracy and robustness.

1. Introduction

In vibration-based structural health monitoring, the measurement of the dynamic response under ambient excitation allows to identify modal parameters of structures through operational modal analysis (OMA) procedures [1, 2]. The assumption of OMA testing techniques is that the excitation has white noise characteristics, and its energy is distributed over a wide frequency spectrum [3]. Modal parameter estimation, particularly OMA, proves to be a practical and reliable approach for both understanding the dynamic behavior of the structures and monitoring their modal properties for a damage-sensitive estimation, without the need of measuring the input signals. While these methods are powerful and efficient for analyzing dynamic behavior, for model updating and damage detection purposes [1, 4, 5], they often rely on assumptions, such as replacing unknown ambient loads with a zero-mean stationary signal as input [5]. In some cases, the operational loading conditions cannot be considered as white noise, and the process of structural identification becomes more difficult [6]. Hence, the presence of harmonic excitation can disrupt the assumption on the input of zero-mean stationary signal leading to errors like false mode detection especially in the case of forcing frequencies close to natural frequencies associated to their own modes.

A simple approach to detect the harmonic content in measured signals is based on the identification of modes with extremely low damping. Nevertheless, the existence of harmonic frequencies in the external excitation close to natural frequencies determines bad convergence results in the identification process, as discussed in [7] in relation to the application of the polyreference least-square complex exponential method in cases where the harmonic excitation part has frequencies close to structural eigenfrequencies. The challenges associated with OMA techniques in the presence of harmonic excitation sources have been faced by different approaches. Gres et al. [8] proposed a Kalman filter-based subspace identification for modal analysis under unmeasured periodic excitation. In their three-step approach, they used stochastic subspace identification (SSI) and a sequence of nonsteady Kalman filters to estimate the periodic subsignal from periodic modes and reject them from the data. Kang et al. [9] used a nonstationary signal decomposition technique to remove the harmonic response in the OMA of time-varying structures. The study described in [10] has been based on joint use of the statistical parameter of entropy and output-only procedure based on the Hilbert transform properties, while Maamar et al. [11] developed a method based on transmissibility measurements. To identify the modal parameters even when harmonic excitation frequencies were close to the natural frequencies, the approach proposed by Sadeqi and Moradi [12] exploits the singular value decomposition (SVD) of the response Hankel matrix to find and remove the components associated with steady-state response and noise. They used a transient response to identify the observability matrix and modal parameters. Several other studies address this problem using SSI and Enhanced Frequency Domain Decomposition (EFDD) [13, 14]. Also, machine learning (ML) approaches have been investigated for harmonic detection aims. In the field of structural mechanics, ML is applied to various tasks including structural health monitoring, damage detection, optimization, and reliability, and it continues to expand its applications [15, 16, 17, 18, 19]. The core of these approaches is the utilization of trained data, where ML algorithms learn patterns and relationships from dynamic measurements to estimate the modal parameters. Using trained data, ML models can provide a remarkable ability to recognize anomalies in structural dynamics, nonlinear behaviors, the influence of harmonics, or the presence of noise in experimental data. Some of these studies utilize time series data to extract system properties or forecast future outputs. Peng et al. [20] implemented three methods, the piecewise linear least squares, a fully connected neural network, and a long short-term memory neural network for structural dynamic response under the condition of periodic, impact and seismic loads, and the achieved results show how the last method is the more promising. Also, Birky et al. [21] used an artificial neural network (ANN) to predict the dynamic response of the structures. Worden and Green [22] proposed an ML approach for nonlinear modal analysis. Liu et al. [23] used a deep neural network for modal estimation in output-only modal identification. A multistage clustering algorithm for automated OMA to health monitoring was developed by Civera et al. [24] testing their approach performance with different levels of noise. As a matter of fact, health monitoring and fault detection require high-quality signals, while experimental data often include environmental and/or measurement noise. A novel denoising method based on deep residual U-Net to mitigate noise in the vertical vibration signals of elevator cabins is proposed in [25]. The method is based on a convolutional neural network that can automatically learn the potential mapping between noisy and clean signals. In [26] an experimental campaign was carried out to investigate the elevator-induced building vibrations which were statistically separable from other ambient vibration components in both the time and frequency domains with the need to measure elevator position or elevator counterweight vibrations. To eliminate harmonic components in the modal identification process, Jacobsen et al. [27] proposed a method based on EFDD, and Modak [28] presented a method by using random decrement of the response to realize different frequencies, while Devriendt et al. [29] suggested a technique based on transmissibility measurements.

Spectral kurtosis (SK) analysis is also used for characterizing nonstationary signals and detecting frequencies related to harmonic loads. This approach consists of the combination of statistical and spectral information computing kurtosis from spectral data [30, 31]. An optimized SK analysis is proposed in [32] to distinguish structural modal responses from periodic excitation frequencies related to rotor dynamics without assumptions on the periodic excitation. Unlike other methods based on SK, in [32], first, the temporal signal is filtered in the time domain with a series of sharp passband filters (PBF), and second, the kurtosis is computed from the filtered temporal signals for each central frequency of PBF.

SK is a robust signal processing tool that has gained attention for its ability to enhance the detection of non-Gaussian and transient features in the frequency domain. This capability makes it particularly useful for identifying natural and forcing frequencies in noisy environments, such as operational conditions of industrial or hospital buildings. Therefore, this study aims to explore the effectiveness of an SK-based approach in the identification process of the modal properties of the complex structure of a large hospital, where the operation of several equipment induces both noise and harmonic contents in vibration measurements, demonstrating its potential in distinguishing between mechanical vibrations from machinery and the building's structural responses. When the experimental response is acquired under ambient vibration excitation and harmonic loads, a more accurate modal identification can be pursued by distinguishing harmonic from natural frequencies. For this purpose, the output-only modal analysis technique SSI is applied, and, afterward, harmonic frequencies are identified by estimating the kurtosis parameter [30]. The kurtosis spectra can be obtained by calculating the kurtosis parameter for the frequency bins and time windows within the time and frequency range of the measurements. The accuracy of the procedure is evaluated starting from a simple numerical case study (a 2D frame structure) and then carrying out both numerical and experimental investigations on the Cardinal Massaia hospital, in

Asti (Italy). The identification strategy pursued to detect natural and harmonic frequencies, based on SSI and kurtosis spectra, is described in Section 2. Section 3 shows the numerical simulations performed on both the 2D frame structure and the hospital building, and Section 4 reports the experimental campaign carried out on the Cardinal Massaia hospital and the corresponding results of the identification of both natural and forcing frequencies. Finally, conclusions are drawn in Section 5. This study endeavors to explore the feasibility of detecting modes resulting from harmonic loads and highlighting them with respect to the structural modes. The procedure is meant to enhance the accuracy of modal feature identification and facilitate the understanding of the structural dynamics of complex structures in their operating conditions influenced by external noise sources, for structural health monitoring tasks aiming to contribute to their safety and resilience.

2. Adopted Methodology

In this section, the role of the unmeasured periodic harmonic and random excitation in a general state-space representation of a dynamic system will be highlighted .

2.1. State-Space Formulation for Stochastic and Periodic Excitation. The differential equation governing a linear time-invariant (LTI) dynamic system representative of a structure can be expressed as in the following Equation (1):

$$\mathbf{M}\ddot{\mathbf{q}}(t) + \mathbf{C}\dot{\mathbf{q}}\,(t) + \mathbf{K}\mathbf{q}(t) = \mathbf{f}(t), \tag{1}$$

where **M**, **C**, and **K** are the mass, viscous, and stiffness matrices, respectively, while the vectors **q** and **f** contain the degrees of freedom of the system and the forces applied to the structure both depending on the time t.

State-space models are well-suited for LTI systems, and they can be rewritten through first-order continuous differential equations (state-space formulation). However, practical and experimental scenarios often involve discrete-time data, and so, for a better analysis of the methodology, a conversion of the system into discrete form is needed. The time steps with specific samples can be defined as $t = k\tau$, where k indicates the number of the steps while τ is the sample time.

Considering m degree of freedom in a structural system, the model order in the state-space formulation will be $n = 2 \times m$. Moreover, hypothesizing that the state-space vector x_k contains, in general, displacements and velocities, the state-space model, at the kth instant, can be written as follows:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{w}_k \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k + \mathbf{v}_k, \end{aligned} \tag{2}$$

where the **A** and **C** are the state-space matrices while the vectors **w** and **v** are used to introduce noise in the dynamical system and output (i.e., the vector **y**). These two latter key variables will be considered as zero-mean white noise signals with the following covariance definition:

$$\boldsymbol{E}\left(\begin{bmatrix} \mathbf{w}_k \\ \mathbf{v}_k \end{bmatrix}\begin{bmatrix} \mathbf{w}_k & \mathbf{v}_k \end{bmatrix}\right) = \begin{bmatrix} \mathbf{Q} & \mathbf{S} \\ \mathbf{S}^T & \mathbf{R} \end{bmatrix}\delta_{kl}, \tag{3}$$

where δ_{kl} is the Kronecker delta. As well-known, the SSI technique aims to identify the unknown state-space matrices (**A** and **C**) but also the matrices **Q**, **S**, and **R** defined in Equation (3). In particular, once the matrix **A** is identified, it is possible to obtain the natural frequencies and the corresponding modal shapes from its eigenvalues and eigenvectors.

In the previous formulation, the dynamical system is subject only to stochastic excitation modelled as white noise. If some harmonics are introduced, as input, in the model, its form will change as follows:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{B}u_k + \mathbf{w}_k \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k + \mathbf{D}u_k + \mathbf{v}_k, \end{aligned} \tag{4}$$

where the scalar variable u_k includes the harmonic components and it is allocated through the state-space matrices **B** and **D**. Such an input can be thought as sum of n periodic harmonics:

$$u_{\boldsymbol{k}} = \sum_{\boldsymbol{i}=\mathbf{1}}^{n} a_{\boldsymbol{i}} \sin\,(\omega_i t + \theta_i), \tag{5}$$

where a_i is the amplitude of the i-th component while ω_i and θ_i are the corresponding frequencies and phases, respectively.

Based on this new formulation, the target of the procedure will be an accurate identification and separation of the frequencies owned by the system and the ones belonging to the harmonic input.

2.2. SSI. In this subparagraph, the main step of the identification procedure carried out by SSI will be illustrated briefly. It aims to solve the following inverse problem: "given the measured input sequence $\mathbf{U}_i$ and the output sequence $\mathbf{Y}_i$ defined as $\mathbf{U}_i = [\mathbf{u}_i, \mathbf{u}_{i+1}, \ldots, \mathbf{u}_{i+j-1}]\,\varepsilon\Re^{mxj}$ and $\mathbf{Y}_i = [\mathbf{y}_i, \mathbf{y}_{i+1}, \ldots, \mathbf{u}_{i+j-1}]\,\varepsilon\Re^{lxj}$ with $j \longrightarrow \infty$, determine the unknown system matrices $\mathbf{A}\varepsilon\Re^{nxn}$, $\mathbf{B}\varepsilon\Re^{nxm}$, $\mathbf{C}\varepsilon\Re^{lxn}$, $\mathbf{D}\varepsilon\Re^{lxm}$ and the noise covariance matrices $\mathbf{Q}\varepsilon\Re^{nxn}$, $\mathbf{S}\varepsilon\Re^{nxn}$, $\mathbf{R}\varepsilon\Re^{lxl}$ defined in the previous section".

The first step is to group the measured input and output into block Hankel matrices for both measurements, respectively, $\mathbf{H}^{\mathbf{U}}_{0|2i-1}$ and $\mathbf{H}^{\mathbf{Y}}_{0|2i-1}$ defined as follows:

$$\mathbf{H}^{\mathbf{U}}_{0|2i-1} = \frac{1}{\sqrt{j}} \begin{bmatrix} u_0 & u_1 & u_2 & \dots & u_{j-1} \\ u_1 & u_2 & u_3 & \dots & u_j \\ \dots & \dots & \dots & \dots & \dots \\ u_{i-1} & u_i & u_{i+1} & \dots & u_{i+j-2} \\ u_i & u_{i+1} & u_{i+2} & \dots & u_{i+j-1} \\ u_{i+1} & u_{i+2} & u_{i+3} & \dots & u_{i+j} \\ \dots & \dots & \dots & \dots & \dots \\ u_{2i-1} & u_{2i} & u_{2i+1} & \dots & u_{2i+j-2} \end{bmatrix} = \begin{bmatrix} \mathbf{H}^{\mathbf{U}}_p \\ \mathbf{H}^{\mathbf{U}}_f \end{bmatrix}, \tag{6}$$

$$\mathbf{H}^{\mathbf{Y}}_{0|2i-1} = \frac{1}{\sqrt{j}} \begin{bmatrix} y^{\mathrm{ref}}_0 & y^{\mathrm{ref}}_1 & y^{\mathrm{ref}}_2 & \dots & y^{\mathrm{ref}}_{j-1} \\ y^{\mathrm{ref}}_1 & y^{\mathrm{ref}}_2 & y^{\mathrm{ref}}_3 & \dots & y^{\mathrm{ref}}_j \\ \dots & \dots & \dots & \dots & \dots \\ y^{\mathrm{ref}}_{i-1} & y^{\mathrm{ref}}_i & y^{\mathrm{ref}}_{i+1} & \dots & y^{\mathrm{ref}}_{i+j-2} \\ y_i & y_{i+1} & y_{i+2} & \dots & y_{i+j-1} \\ y_{i+1} & y_{i+2} & y_{i+3} & \dots & y_{i+j} \\ \dots & \dots & \dots & \dots & \dots \\ y_{2i-1} & y_{2i} & y_{2i+1} & \dots & y_{2i+j-2} \end{bmatrix} = \begin{bmatrix} \mathbf{H}^{\mathbf{Y}}_p \\ \mathbf{H}^{\mathbf{Y}}_f \end{bmatrix}, \tag{7}$$

where the upper, $\mathbf{H}^{\mathbf{U}}_p$ and $\mathbf{H}^{\mathbf{Y}}_p$ (highlighted in red), and the lower half, $\mathbf{H}^{\mathbf{U}}_f$ and $\mathbf{H}^{\mathbf{Y}}_f$, are known as the past and future reference output and input submatrices, respectively. It is important to highlight that *ref* inserted as apex in the upper part of the output Hankel block matrix is referred to as the reference-based procedure. Indeed, since during an experimental dynamic test, some sensors could be placed in nodal points of the modal shapes (i.e., zero-modal) or near boundaries, the selection of "best" sensors (i.e., the related measurements) should be chosen to implement the upper part of the output Hankel block matrix. Subsequently, the key step of the method regards the oblique projection of the row space of $\mathbf{H}^{\mathbf{Y}}_f$ onto the joint row space of $\mathbf{H}^{\mathbf{U}}_p$ and $\mathbf{H}^{\mathbf{Y}}_p$ in the direction of the row space of $\mathbf{H}^{\mathbf{U}}_f$ giving the following projection matrix:

$$\Theta_i = \mathbf{H}^{\mathbf{Y}}_f / \mathbf{H}^{\mathbf{U}}_f \begin{bmatrix} \mathbf{H}^{\mathbf{U}}_p \\ \mathbf{H}^{\mathbf{Y}}_p \end{bmatrix}, \tag{8}$$

where the symbol / is the projection operator. After that, based on the main theorem of the subspace identification, it is possible (considering that $j \longrightarrow \infty$) to be equal to the projection matrix Θ_i, just defined in Equation (8), to the product $\Gamma_i \mathbf{X}_i$ where Γ_i is the observability matrix while $\mathbf{X}_i$ is the vector containing, in general, displacements and velocities (defined in Equation 2) to the i-th step. Moreover, the estimation of the two matrices Γ_i and $\mathbf{X}_i$ is based on the evaluation of the SVD of the projection matrix $\Theta_i = \mathbf{U}_i \Sigma_i \mathbf{V}_i^{\mathrm{T}}$. They will be obtained by the following formulations:

$$\Gamma_i = \mathbf{U}_i \Sigma_i^{1/2} \quad \mathbf{X}_i = \Sigma_i^{1/2} \mathbf{V}_i^{\mathrm{T}}. \tag{9}$$

Subsequently, once the matrices Γ_i and $\mathbf{X}_i$ have been estimated (together with $\mathbf{X}_{i+1}$ simply iterating at $i+1$), the state-space matrices can be extracted by the following formulation through the least-square solution.

$$\begin{bmatrix} \widehat{\mathbf{A}} & \widehat{\mathbf{B}} \\ \widehat{\mathbf{C}} & \widehat{\mathbf{D}} \end{bmatrix} = \begin{bmatrix} \widehat{\mathbf{X}}_{i+1} \\ \mathbf{Y}_{i|i} \end{bmatrix} \begin{bmatrix} \widehat{\mathbf{X}}_i \\ \mathbf{U}_{i|i} \end{bmatrix}^{\dagger}, \tag{10}$$

the subscript $i|i$ is the subscript of the first and last element in the first column of the block Hankel matrix (i.e., only one block row), and the symbol "$\widehat{\ }$" indicates that the obtained matrices are an estimate, while the symbol "†" is related to the pseudo-inverse procedure. Once the state-space matrices are achieved (especially the state-space **A**), it is possible to estimate the eigenproperties of the system some of which will correspond to the modal frequencies and shapes of the real system. According to this procedure, the size of the Hankel matrix is related to the order of the identified system. In the case of processing of dynamic measurements acquired on real civil structures, it is quite difficult to predict the order that best fits the experimental data. Therefore, it could be convenient to iterate the modal parameter estimation for several models with decreasing order, fixing a conservative high-order starting point, and continuing until an optimal synthesis is achieved, according to a user-defined balanced criterion of sufficient representativeness and minimal order. The identified modal frequencies can be simultaneously represented in the so-called stabilization diagram to evidence those that maintain similar values (stability) for increasing order models.

2.3. Improvement Investigation of Harmonic Identification by Kurtosis Spectra. In the frequency domain, harmonic components appear as sharp peaks, and sometimes they contain higher energy levels compared to the structural modal response. This can be a problem for OMA algorithms which are not able to realize the difference, and they aim to identify the most energetic components in a signal. The detection and potential removal of harmonic components from response measurements can be pursued through the use of algorithms that rely on estimating kurtosis within a narrow band of the measured data, as, for example, is the case of the harmonic detection method implemented in the ARTeMIS software. By sliding this frequency band across the entire frequency range, a frequency domain kurtosis diagram is generated. Typically, modal responses follow a Gaussian distribution, which results in kurtosis values around 3. The frequencies where harmonic components are stronger than structural frequencies show peaks and drop points in the kurtosis spectra. By defining a threshold, the algorithm automatically identifies possible harmonic components. This information is important to remove data from regions dominated by harmonic components for structural identification tasks. In this paper, the ability of kurtosis analysis in detecting harmonic components is investigated for vibration signals acquired on a large hospital building affected by the operation of several equipment. Such an

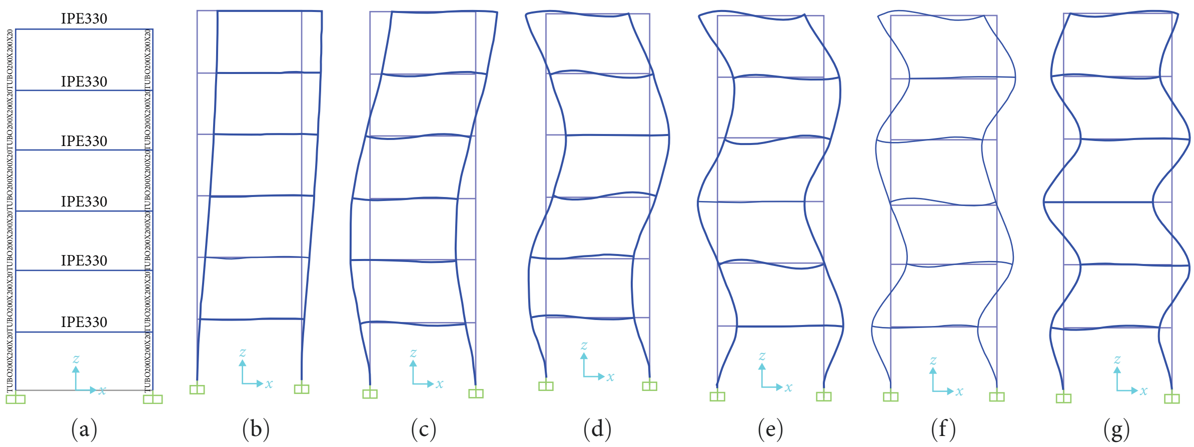


FIGURE 1: Numerical investigations on 2D frame structure: FEM model (a) and numerical modal analysis results from mode 1 (b) to mode 6 (g). (b) 2.71 Hz, (c) 8.52 Hz, (d) 15.22 Hz, (e) 22.59 Hz, (f) 29.86 Hz, and (g) 35.43 Hz.

identification process has been implemented using both the specific ARTeMIS tool "Harmonic Detection and Removal" (HDR) and the MatLab function "SK". The HDR tool is based on two algorithms; one removes fitted sine waves from the measured data by nonlinear Gauss–Newton minimization, and the other one uses an orthogonal projection technique, where a time series with only the harmonic parts of the measured response is detected. Then, the original measured response is projected orthogonally onto this harmonic time series, which can result in a new response data time series with no harmonic components. Regarding the SK function implemented in MatLab, it is based on the evaluation of the spectral moments. For each signal, this algorithm generates spectrograms, which result in a temporal-frequency representation, and then, it calculates spectral moments to find the SK. This parameter is the critical indicator for finding possible harmonic components in the measured data. By observing the values for this parameter in the frequency domain and finding sharp peaks, the algorithm can estimate identified harmonic frequencies, and this is because the values of this parameter can deviate from the expected Gaussian distribution which usually is reported in the modal response.

3. Numerical Investigation

Numerical investigations using synthetic signals are a common technique in signal processing to test methods. Therefore, in this study, synthetic signals (i.e., artificially generated white noise and harmonics signals) to evaluate the efficacy of kurtosis as a statistical parameter for detecting harmonics in structural dynamic responses have been tested before conducting tests on real dynamic measurements.

In structural dynamics, a crucial aspect is the identification of structural natural modes. Thus, in this case, the synthetic signal is applied as input to the structure, and the measured response by the numerical model represents the signal to be processed to identify harmonics and natural modes. As shown in this section, such numerical investigation revealed that the most significant factor affecting mode detection is the ratio of white noise to the signal containing harmonics (where the total amplitude is mainly constituted by the ones of each harmonic component), named signal-to-noise ratio (SNR) defined as

$$SNR_{\mathrm{dB}} = 10 \log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right), \tag{11}$$

where

$$\begin{aligned} P_{\mathrm{signal,dB}} &= 10 \log_{10}(P_{\mathrm{signal}}) \\ P_{\mathrm{noise,dB}} &= 10 \log_{10}(P_{\mathrm{noise}}). \end{aligned} \tag{12}$$

The numerical tests were conducted through the following steps:

(1) Modal analysis of the structure in a finite element model (FEM) environment (Sap2000);
(2) Generate noisy signals (including white noise and harmonics) with different SNRs;
(3) Use the generated signal as input for time history analysis through the FEM model and extract time history response output;
(4) Process the output data through the harmonic detection algorithm based on SK;
(5) Compare the real input harmonics and SNR with the identified detected natural modes and harmonics.

The natural modes identified with a difference of less than 5% with respect to the modal analysis results are considered as identified modes.

3.1. D Frame Structure. To understand the effect of the periodic excitation in a stochastic identification, numerical investigations have been conducted on a 2D frame structure (Tube 20 × 20 × 2 mm columns, IPE30 beams, 3-m interstory, 18 m high and 4 m width) modeled with one-dimensional elements with a FEM approach.

First, the modal parameters of this structural system have been determined with a classical modal analysis (eigenvalue solution based on the stiffness and mass matrices), and the first six modes are considered (Figure 1). Then, an excitation

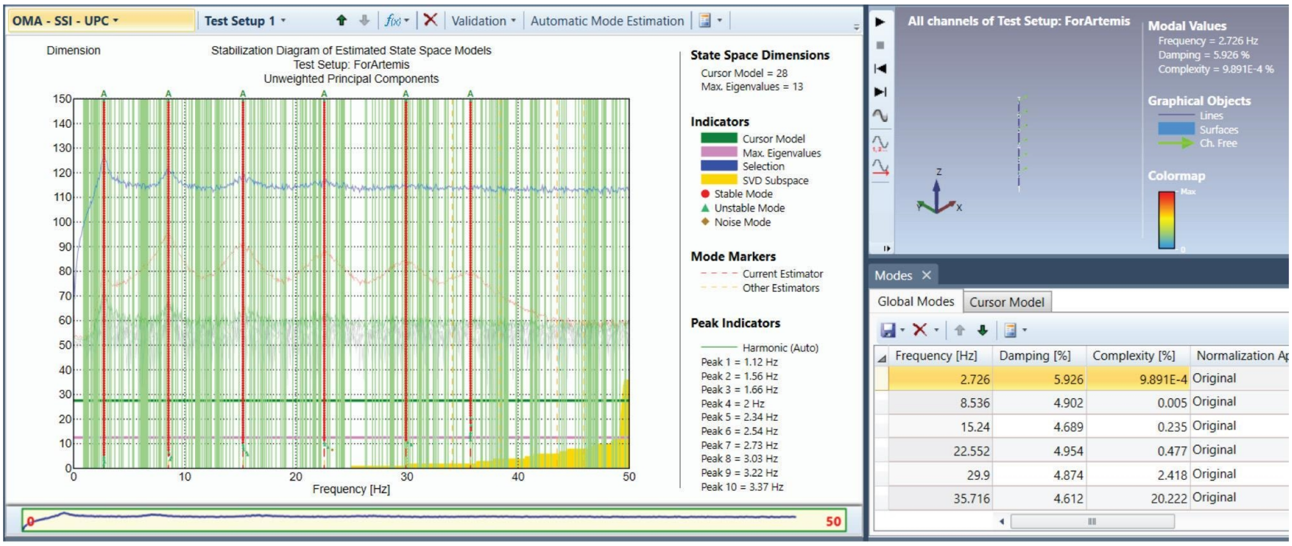


FIGURE 2: Stochastic subspace identification with harmonic detection: stabilization diagram for SNR = −200 db.

including a white noise signal and six harmonics with equal amplitude (at 2, 5, 10, 20, 25, 32 Hz) has been applied to the structure. The frequency values have been selected close to the natural frequencies of the structure to test the performance of the method in unfavorable conditions. The data processing of these outputs (structural response under random input, i.e., a zero-mean white noise) should provide the pseudoidentification of the natural modes. The dynamic identification by only output data has been done by SSI and kurtosis analysis (Figure 2). The effectiveness of the pursued approach has to be evaluated not only by the accuracy of identified natural frequencies but also by the minimization of the false-positive detected frequencies. Therefore, the effect of SNR ratio in the identification of natural and harmonic frequencies is evaluated and shown in Figure 3, where the number of detected modes is plotted with varying SNRs. In this figure, the blue points represent the number of structural modes detected in the signal, with the corresponding SNR as input.

Conversely, the red points indicate the number of detected harmonics. The size of these bubbles represents the accuracy of these modes; larger sizes indicate lower root mean squared error (RMSE) in the detected modes. It's important to note that only values with less than 5% error, compared to the real modes, have been considered as detected modes. As shown in this figure, for the input acceleration with SNR equal to 100 db, the best estimation for harmonic detection is achieved. All the frequencies that were included in the generated signal were detected with the lowest RMSE which shows high accuracy in the detection. On the other hand, from six possible structural modes, only two were detected. The dashed lines in Figure 3 illustrate the linear regression of the data. The figure itself presents the accuracy and number of the identified natural and harmonic modes in the corresponding SNR, and the accuracy of each point based on the RMSE of the identified frequencies is shown by its size. On the other hand, the dashed lines show that with higher SNR, the number of identified natural frequencies using SSI decreases,

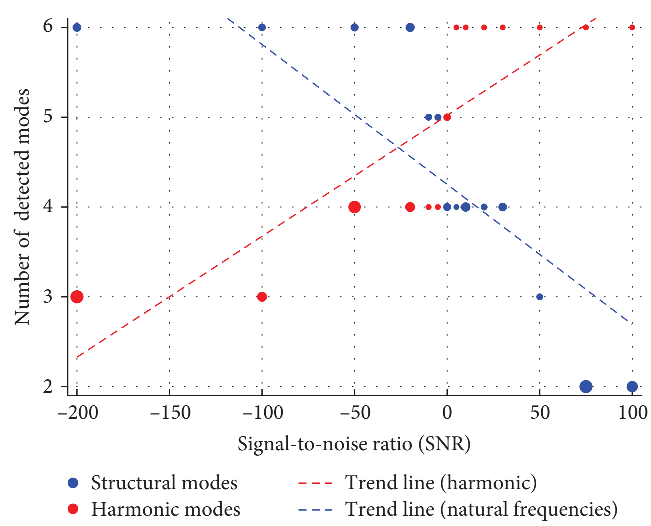


FIGURE 3: Numerical investigations on 2D frame structure: number of detected modes varying signal-to-noise ratio.

while the number of identified harmonic frequencies increases. However, by increasing the SNR, the number of detected frequencies of harmonics increases, and their accuracy also increases. The opposite happens for the natural modes. This is because, with lower SNR, it means the white noise part is dominating in the input or excitation of the structure, and this is an expected result from a correct detection algorithm. In order to understand which external frequency is detected, the SK of one signal is evaluated and reported in Figure 4, where peaks at 2, 5, and 10 Hz can be observed.

3.2. A Computational Model for the Prediction of the Hospital Building Dynamic Response. As in the case of the 2D case, numerical investigations have been conducted on a 3D frame structure modeled with a classical FEM approach, that it has been constructed to simulate the dynamic response of a hospital building under environmental conditions strongly

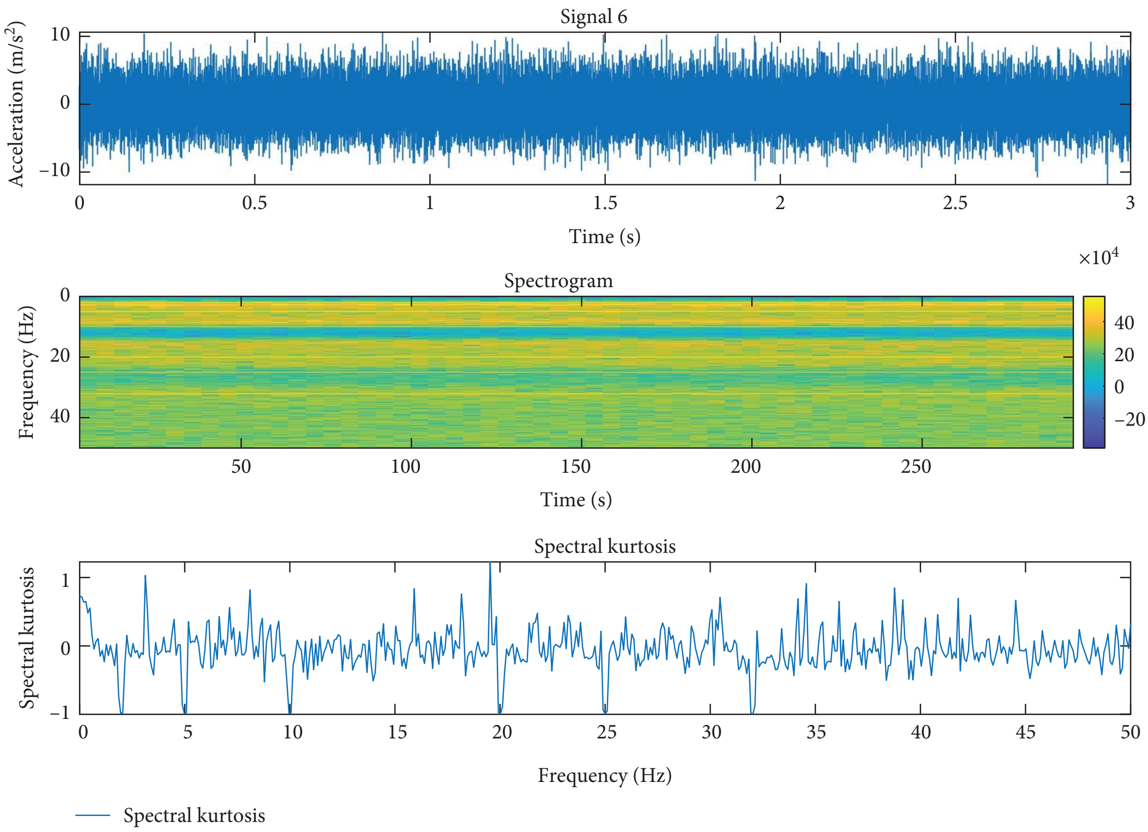


Figure 4: Spectral kurtosis of the sixth floor acceleration of the 2D frame structure.

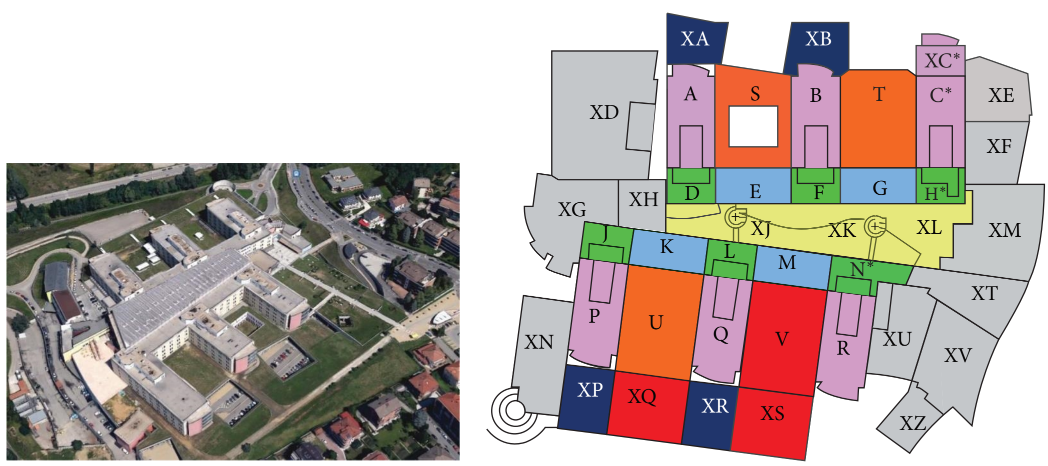


Figure 5: Cardinal Massaia hospital in Asti (Italy): aerial view (a) and classification of the blocks in eight groups (b).

characterized by the presence of different machinery. Due to their complex services and heterogeneous nature, hospitals are one of the most difficult groups of public buildings to monitor and maintain [33]; these are large buildings that run around the clock employing medical equipment that needs a variety of services, including air conditioning, refrigeration, source of noise, and vibration, making structural identification procedures more challenging. The selected case study is the "Cardinal Massaia" hospital (Figure 5) in Asti, northwestern Italy, inaugurated as a part of the national health system in 2003. The original structural layout of the project involved the division of the entire building into 41 blocks, classified for structural configuration in eight groups (distinguished by different colors in Figure 5(b)) and constructively separated by 5-cm thick structural joints. The total area provided by all the blocks is about 140,000 m^2 distributed over eight levels. Some blocks are connected by wooden beams on the roof level; it can be noted in Figures 6 and 7 that

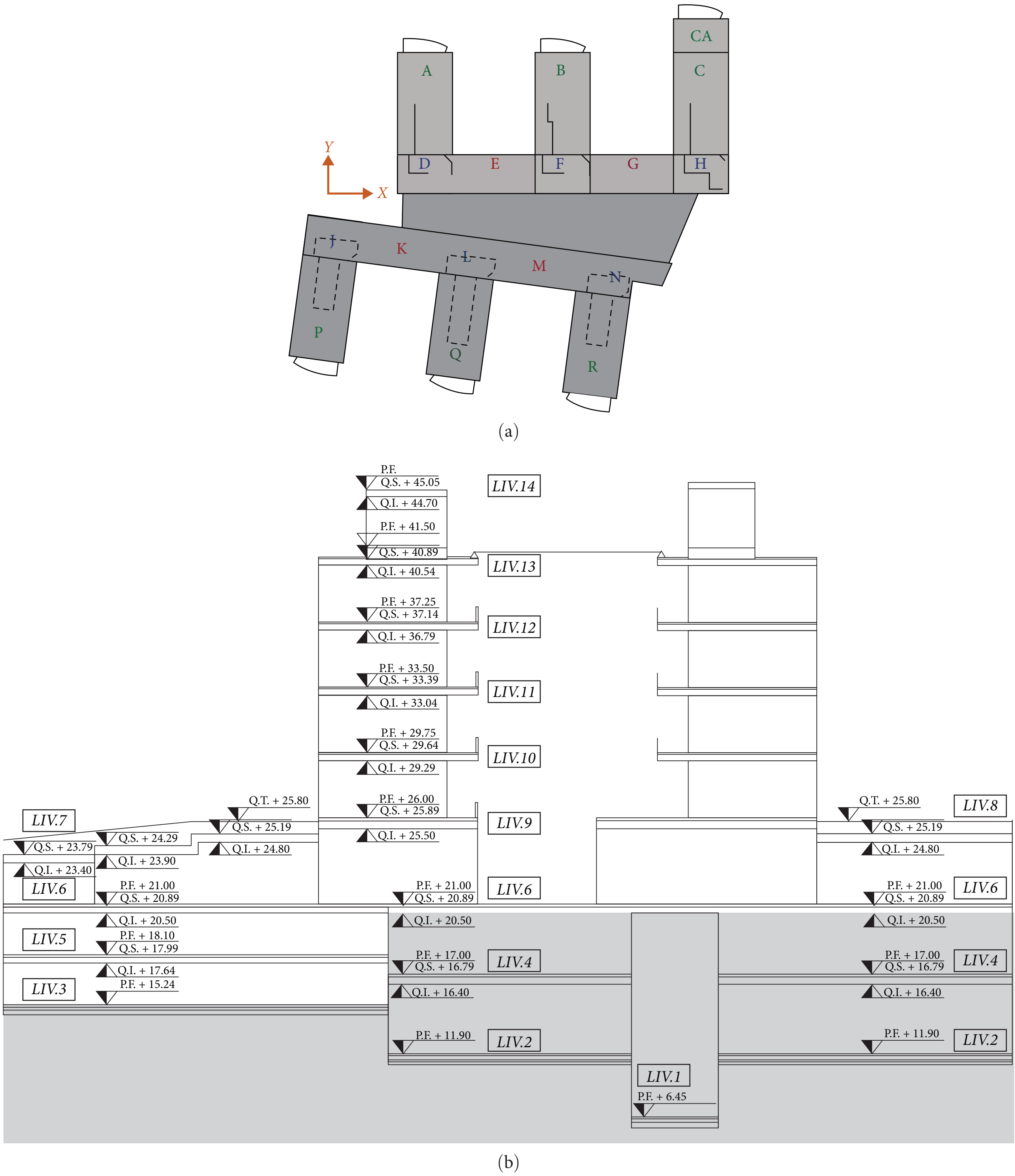


Figure 6: Cardinal Massaia hospital: plan view of roof level (a) and elevation view in (y, z) plane (b).

blocks K, L, M, and N are connected to blocks D, E, F, G, and H. On lower levels, some blocks are connected by walkways (Figure 7). The structures of the hospital are supported by deep plinth foundations in reinforced concrete with some piles or with direct foundations on continuous reinforced concrete beams. The vertical structures are mainly made of reinforced concrete, and the floors are prefabricated reinforced concrete slabs.

For the computational model of the whole structure, concrete and wooden beams have been modeled by frame

(a) (b)

Figure 7: Inside view of the Cardinal Massaia hospital: wooden beams (a) and walkway (b) connecting the blocks K, L, M, and N to blocks D, E, F, G, and H.

elements (11,500 frame elements); the overall behavior of the blocks has been considered including the connections among them by short concrete beams in adjacent joints, by the wooden beams on the roof level, and by the walkways (modeled by rigid diaphragm) on the lower level.

Following the same approach of the previous section, four natural modes have been determined and depicted in Figure 8 from modal analysis results. An excitation including a white noise signal and four harmonics with equal amplitude (at 1.5, 2, 3, and 3.5 Hz) has been applied, and the effect of SNR parameter in detecting harmonic and natural frequencies using kurtosis is presented in Figure 9, showing the same trend encountered for the 2D case, while SK for SNR = 100 is plotted in Figure 10. The selected harmonic frequencies and high value of SNR have been chosen to see clearly if the algorithm can detect only harmonics (or if it also includes natural modes or false detected modes) for a complex structure, like the hospital in Asti. As a result, all the pick points happen in the range of the mentioned signals and close to those frequencies, and no other detected frequencies, including higher natural frequencies, were observed. The simulation has permitted to validate the proposed procedure for a more complex case, and even if it has been exploited in a numerical environment, it has been necessary to approach the difficulties which come from treating signals acquired on the real building as it has been explained in the following section.

4. Experimental Investigation

Experimental investigations concerning the identification of natural and forcing frequencies through noisy measurements acquired in operational conditions have been carried out at the Cardinal Massaia hospital, described in the previous section. The experimental setup and the identification procedure based on kurtosis analysis to detect natural modes and forcing frequencies related to elevator and/or air conditioning systems are described in this section.

4.1. Test Campaign and Experimental Setups. To understand the dynamic behavior of the hospital building, an experimental campaign has been carried out consisting of dynamic tests based on the acquisition of acceleration structural response in operation conditions. An acquisition system composed of 14 wireless Lunitek uniaxial and triaxial accelerometers (model SentinelM), equipped with low-noise micro-electromechanical system (MEMS) sensors, 32 GB memory, and a Global navigation satellite systems (GNSS) receiver for synchronizing recordings between different units, has been employed setting the sampling rate at 250 Hz. Other main technical characteristics include sensitivity of 1,350 mV/g, spectral density noise of 7 $\mu g/\sqrt{Hz}$, and dynamic measurement of ± 2 g pk, with frequency range (bandwidth) from DC to 50 Hz, and electric connections are 62 GB-12E12-10SN. Most of the accelerometers have been installed on the parapets and columns (Figure 11) of the roof level (level 13, 24 m high from the foundation level) and others on level 12 (Figure 12). Considering the large dimensions of the building, the measurement procedure has been subdivided into five different setups implemented over 2 days with an acquisition duration of around 1 hr for each. In this sense, the employed wireless sensor network has been effective in implementing the dynamic experimental tests of this case study. All measurement points considered in the five setups are shown in Figure 12. To merge the data coming from different setups and to obtain the global mode shapes, the acquired data have been normalized by taking a reference sensor fixed for each setup. In this case, the accelerometer in position 1 has been considered as a reference sensor.

4.2. Dynamic Measurements in Operational Condition. For a preliminary evaluation of the dominant frequencies and for investigating the effectiveness of the block interaction due to wooden beams on the roof level and pedestrian bridges on lower levels, for data coming from sensors installed in nodes 1, 2, 3, and 4, the power spectral density (PSD) has been evaluated, showing most observed peak points in the ranges 2–3 Hz and 8–9 Hz. In the y-direction (the same direction of the wooden beams), the same peak values visible for node 1 can be found in node 2, and the same accord can be observed for node 3 and node 4 (Figure 13). These findings confirm the effectiveness of connection among the blocks. Furthermore, using the SSI-unweighted principal component (UPC) [34], three modes have been identified in the frequency range

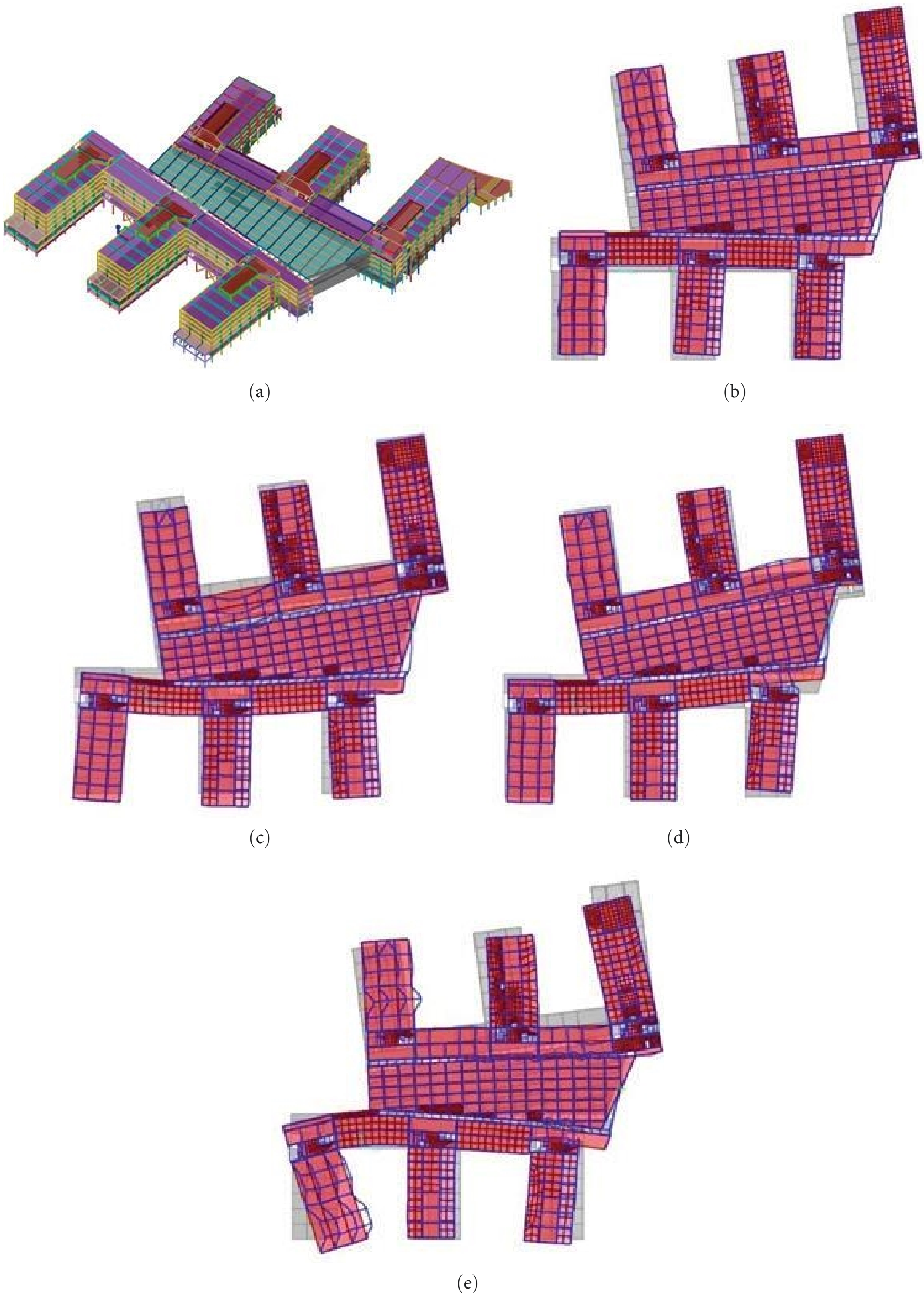


FIGURE 8: Numerical investigations on 3D frame structure of Cardinal Massaia hospital: FEM model (a) and numerical modal analysis results from mode 1 (b) to mode 4 (e). (b) 2.18 Hz, (c) 2.25 Hz, (d) 2.37 Hz, and (e) 2.72 Hz.

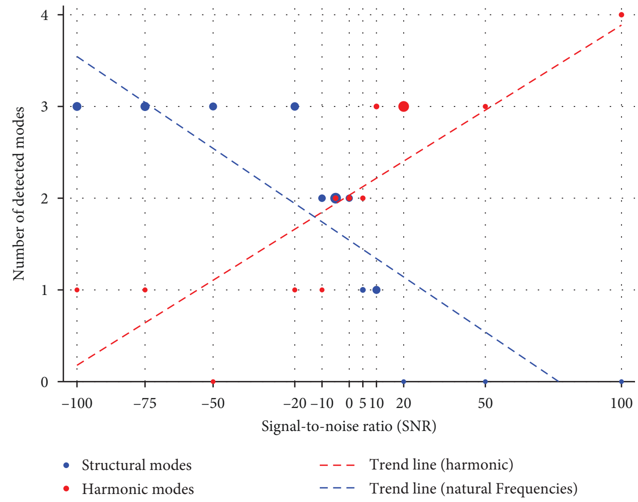


FIGURE 9: Numerical investigations on 3D frame structure of Cardinal Massaia hospital: number of detected modes varying signal-to-noise ratio.

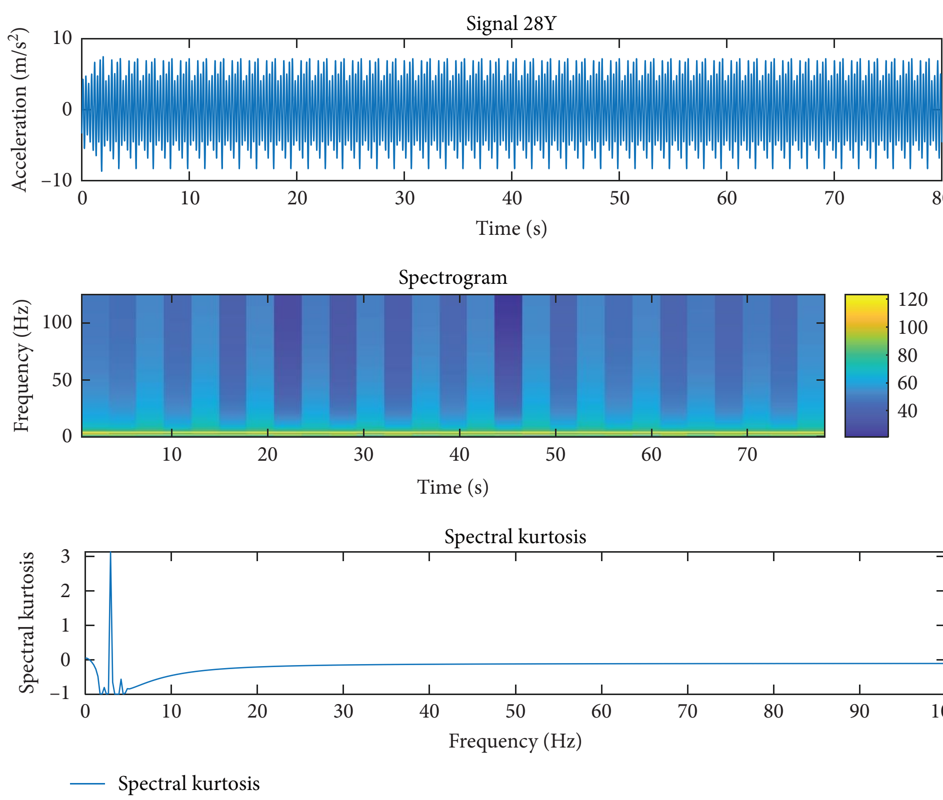
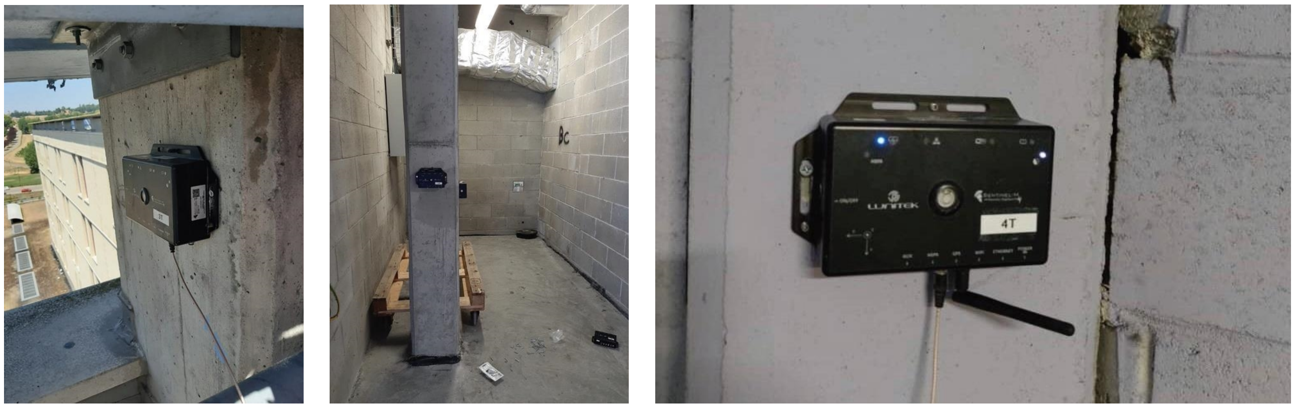


FIGURE 10: Spectral kurtosis of an acceleration signal in y-direction of the hospital building.

2–4 Hz. The identification of such natural modes, through the stabilization diagram (Figure 14(a)), has been driven by considering the numerical modes depicted in Figure 8 confirming the usefulness of the FEM model and its ability in describing the dynamical behavior of the complex structure. In particular, the three experimental modes correspond, respectively, to the first, the third, and the fourth numerical mode. These identification results have also been confirmed by the natural modes identified by the frequency domain decomposition (FDD) [35] technique plotted in Figure 14(b) and summarized in Table 1. To provide further tools to distinguish natural frequencies from forcing frequencies aiming to automatize the natural mode selection, the SK has been evaluated for all the measurement points. First, the harmonic detection was performed for all test setups, identifying harmonic frequencies around 10, 20, 25, 32, and 40 Hz (Figure 15). Then, the SK has been evaluated for each acceleration measurement (separated) allowing for a



(a) (b) (c)

Figure 11: Sensor installation on the parapets (a) and on the columns (b and c).

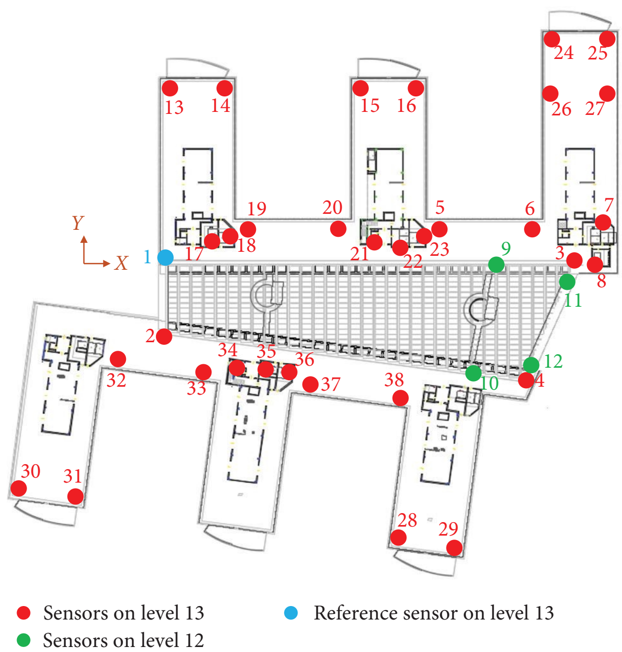


Figure 12: Sensor layout including all measurement points considered in the five experimental setups.

better understanding of the peculiarity of each signal. The main results are reported in Figure 16 where it can be noted that for signals acquired far from the elevator (node 2) the kurtosis values are very low, with a max value of around 6, if compared to the ones of signals acquired close to it (node 35), with a max value around 30. For node 2, kurtosis peaks are found around 10, 20, and 35 Hz; for node 35, peaks with low values are found around 10 and 20 Hz while high values from 35 to 50 Hz and 70 Hz.

5. Discussion

The pursued procedure for the interpretation of the dynamic identification results of the Cardinal Massaia hospital building allowed for detecting the frequency content related to harmonic excitation, probably induced by hospital equipment, such as air conditioning systems or elevators. According to the results, the natural frequencies range from 2 to 3 Hz, while forcing frequencies are found around 10, 20, and 35–50 Hz. Through the SK analysis evaluated for the data acquired from all test setups (Figure 15), a clear identification of harmonics has been obtained. Furthermore, the evaluation of SK for each signal (Figure 16) showed higher values of the peaks for signals acquired close to the elevator (node 35), leading to correlations such as harmonic excitation to elevator equipment. Such a hypothesis is supported by an observation of the continuous wavelet transform of node 35, showing the frequency variation in time, during the time the elevator was in operation close to the sensor. In the wavelet transform reported in Figure 17(a), magnitude variation in time is observed for frequencies around 10

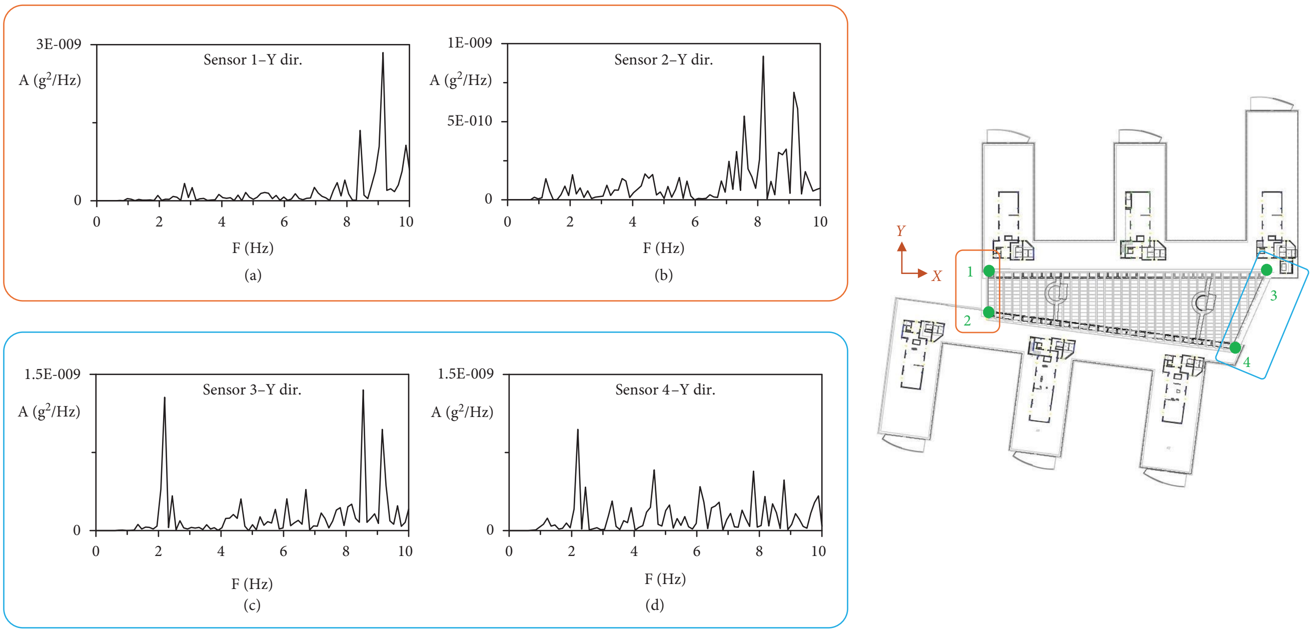
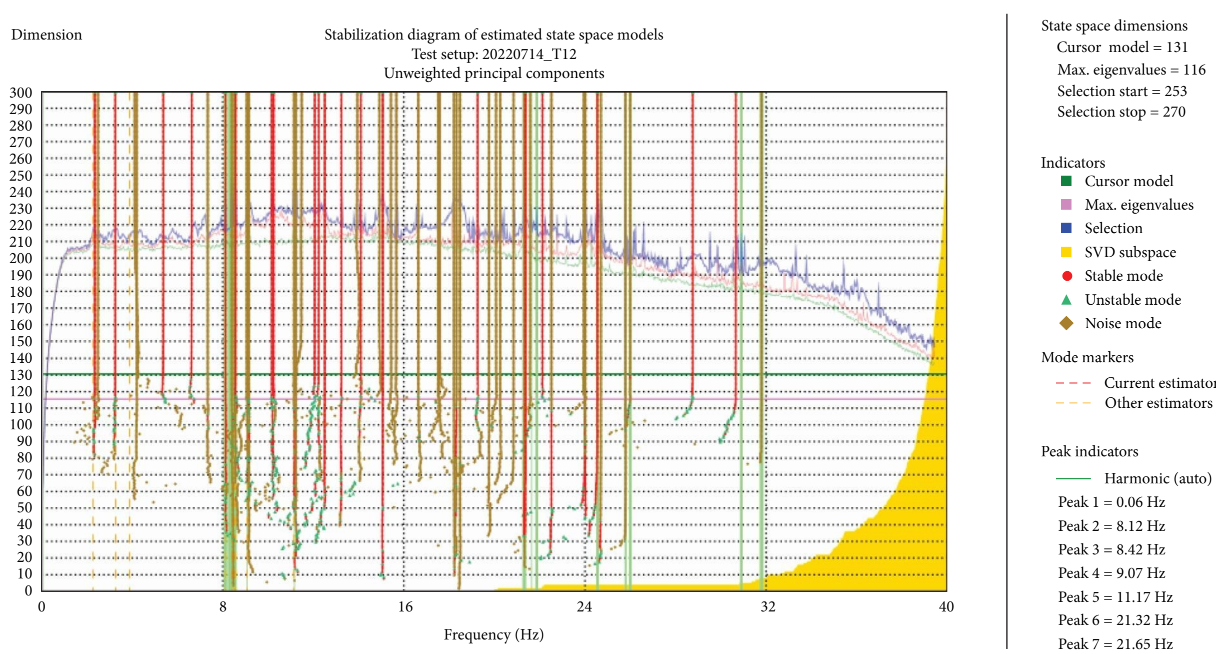
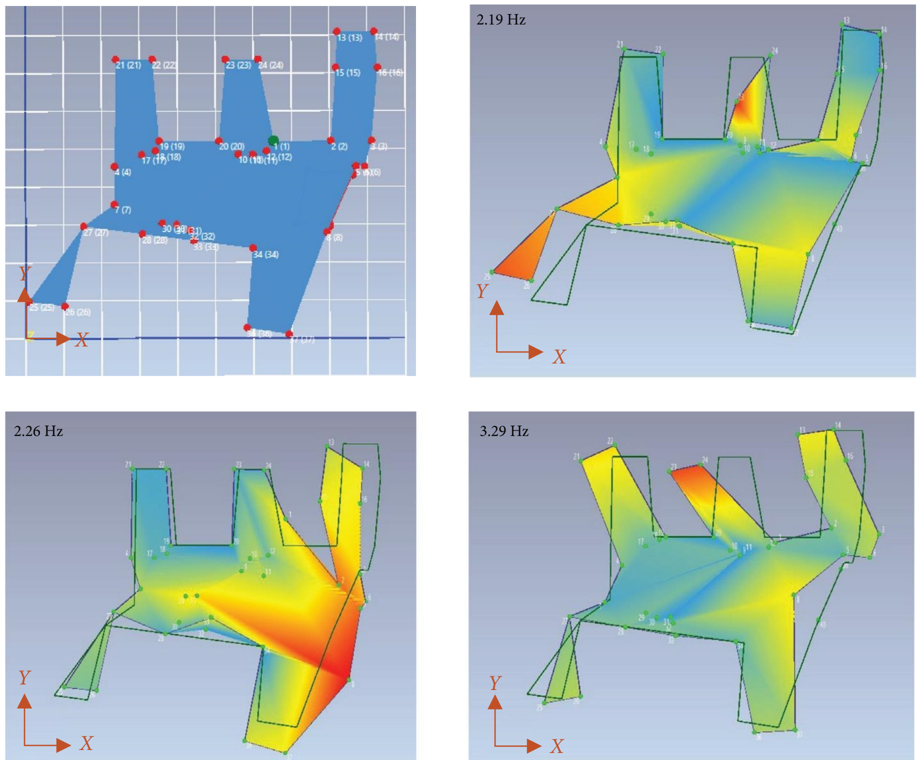


Figure 13: Investigation on block interaction through the comparison of the spectral power density of signal 1 (a), with signal 2 (b), and signal 3 (c), with signal 4 (d).



(a)

Figure 14: Continued.



(b)

Figure 14: Experimental natural frequencies and mode shapes identified by SSI and stabilization diagram (a) and FDD (b).

Table 1: Comparison with numerical results of natural frequencies (in Hz) identified by SSI and FDD.

Mode	Numerical	Identified (SSI)	Identified (FDD)
Mode 1	2.18	2.35	2.19
Mode 2	2.25	—	—
Mode 3	2.37	2.49	2.26
Mode 4	2.72	3.26	3.29

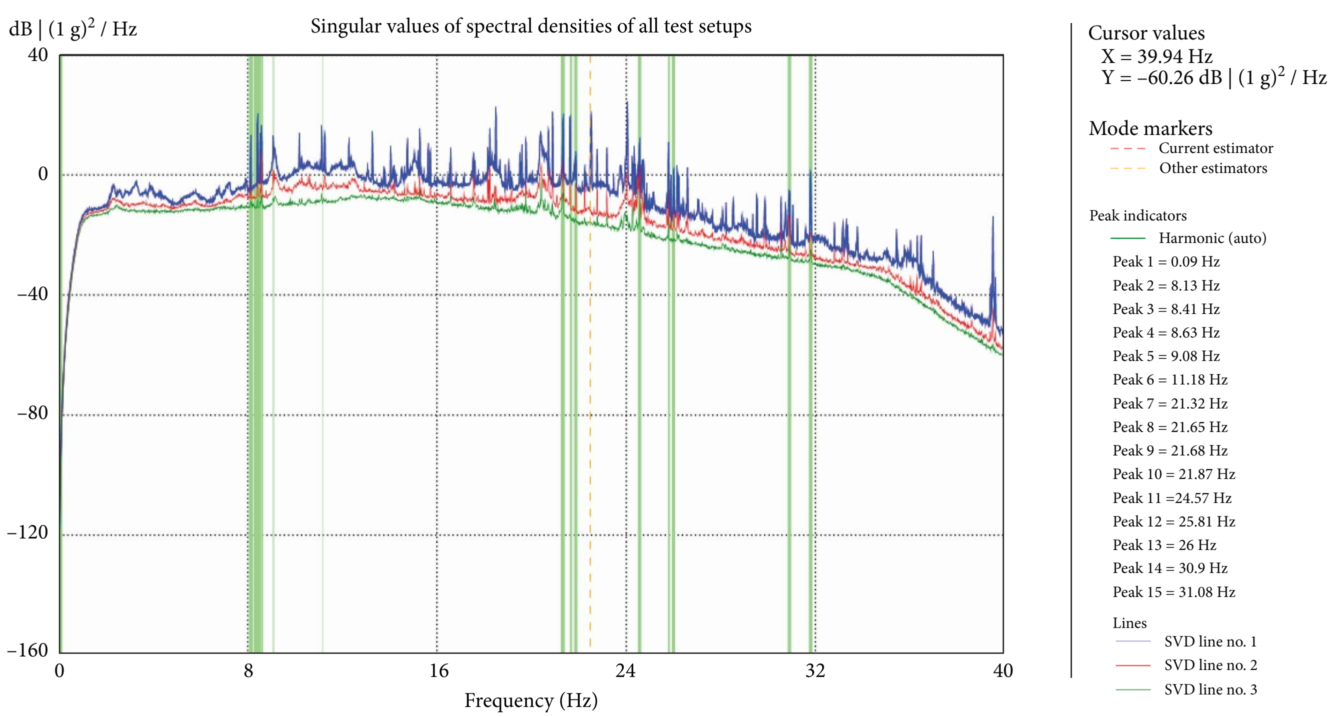


Figure 15: Harmonic detection by kurtosis in signal measurements of Cardinal Massaia hospital responses.

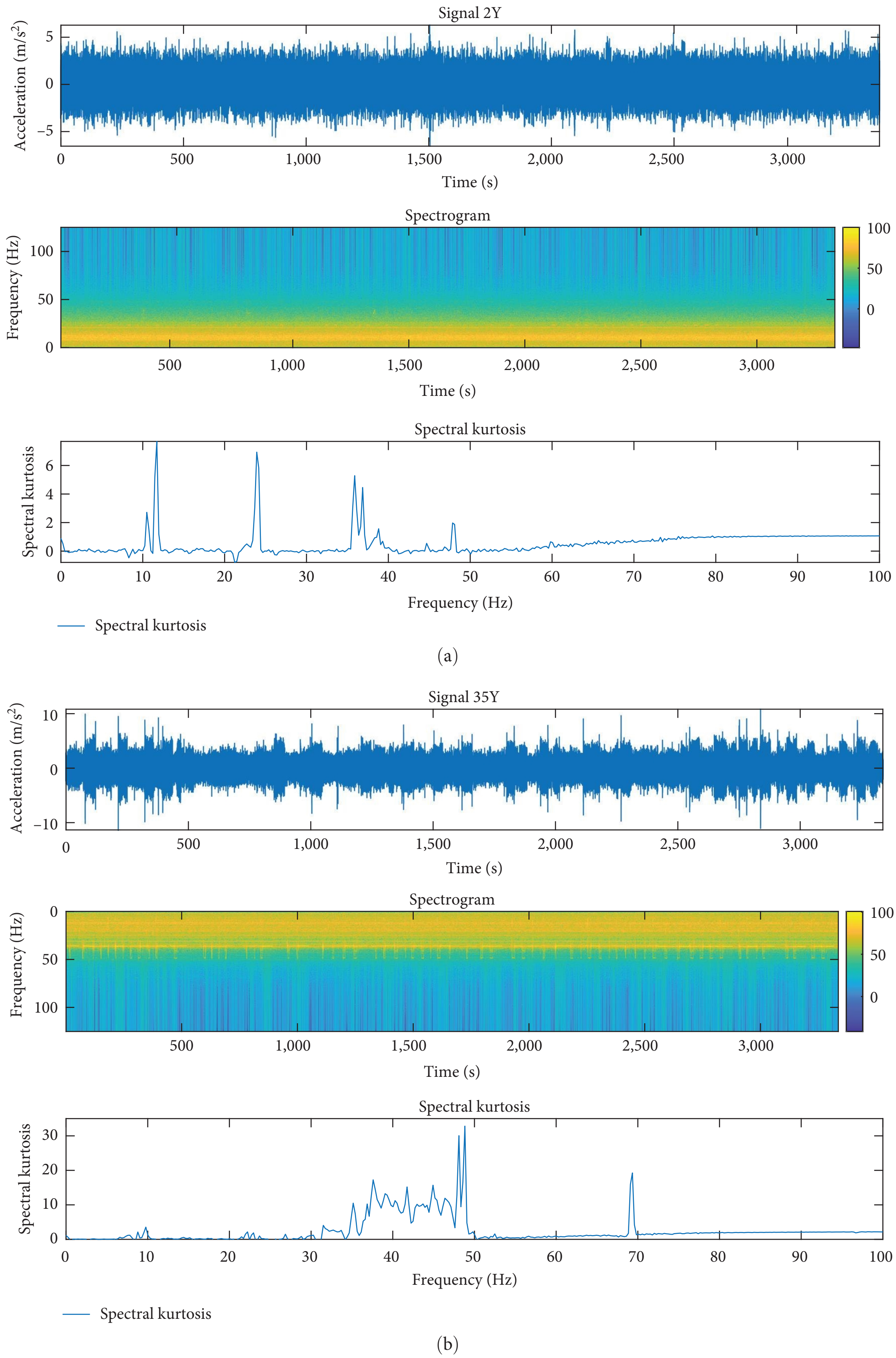
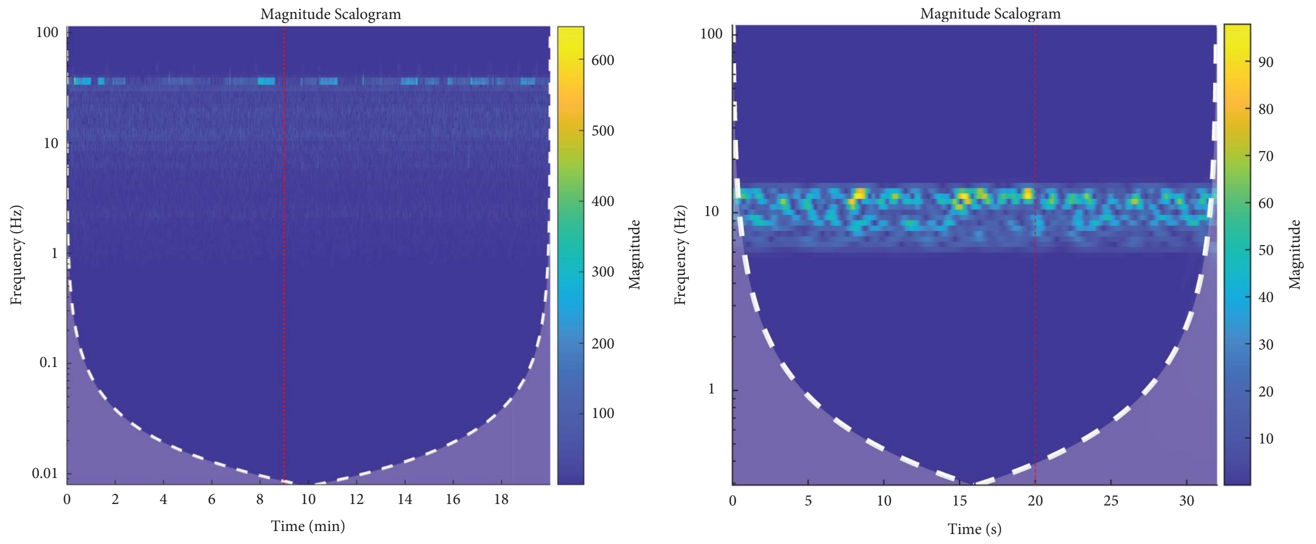


FIGURE 16: Spectral kurtosis of experimental acceleration signal of node 2 (a) and node 35 (b), respectively, far and close to the elevator, in y-direction for Cardinal Massaia hospital.



(a) (b)

FIGURE 17: Continuous wavelet transform of node 35 in y-direction for the acquired (a) and filtered (b) signal. The red line indicates the activation time of the elevator.

and 40 Hz (values that coincide with the detected harmonics); the first one can be observed more clearly when using the signal filtered between 6 and 13 Hz, as shown in Figure 17(b), where a higher magnitude is found at the activation time of the elevator, indicated by the red line.

6. Conclusion

This paper describes the structural identification procedure pursued to identify the natural frequencies of a hospital building in operating conditions, acquiring its structural response under white noise and harmonic loads induced by the operation of mechanical equipment. The identification strategy combines the SK analysis with operational modal analysis techniques, and it has been tested with numerical and experimental investigations. Experimental data have been acquired in operational conditions including disturbances due to machineries like elevators and air conditioners. The pursued procedure for the interpretation of the dynamic identification results of the hospital building allowed for detecting the frequency content related to harmonic excitation. Furthermore, the evaluation of SK for each signal showed higher values of the peaks for data acquired close to the elevator, leading to correlations such as harmonic excitation to elevator equipment. Of course, subsequent in-depth analysis will be oriented to a correct evaluation of the effect of the harmonic periodic frequencies and possible triggers of damage. To do this, a fusion of information coming from other technologies (coupled with the vibration ones) will be needed.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure

This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgments

The authors gratefully acknowledge ASL AT—Azienda Sanitaria Locale di Asti. This research was in part sponsored by the NATO Science for Peace and Security Programme under grant ID. G5924. This study was carried out within the MOST—Sustainable Mobility National Research Center (Spoke 7, WP4) and received funding from the European Union NextGenerationEU (PNRR—MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1033 17/06/2022, CN00000023). The authors kindly acknowledge the Research Project "AIDSTRU AgeIng and Degradation in the performances of STRUctures: model- and data-driven tools embedded in digital-twins" funded by the Italian Ministerial grant PRIN 2022 n. 2022X9TETW.

References

[1] V. Gattulli, A. Cunha, E. Caetano, F. Potenza, A. Arena, and U. Di Sabatino, "Dynamical models of a suspension bridge driven by vibration data," *Smart Structures and Systems*, vol. 27, no. 2, pp. 139–156, 2021.

[2] A. Talebi, F. Potenza, and V. Gattulli, "Interoperability between BIM and FEM for vibration-based model updating of a pedestrian bridge," *Structures*, vol. 53, pp. 1092–1107, 2023.

[3] C. Ventura and R. Brincker, *Introduction to Operational Modal Analysis*, Wiley, 2015.
[4] C. Rinaldi, M. Lepidi, F. Potenza, and V. Gattulli, "Cable-stayed bridge model updating through analytical formulation, finite element model and experimental measurements," in *Dynamics and Aerodynamics of Cables. ISDAC 2023*, V. Gattulli, M. Lepidi, and L. Martinelli, Eds., vol. 399, Lecture Notes in Civil Engineering, Springer, Cham, 2024.
[5] M. Crognale, F. Potenza, and V. Gattulli, "Fatigue damage identification by a global-local integrated procedure for truss-like steel bridges," *Structural Control and Health Monitoring*, vol. 2023, Article ID 9594308, 23 pages, 2023.
[6] V. Gattulli, E. Lofrano, A. Paolone, and F. Potenza, "Measured properties of structural damping in railway bridges," *Journal of Civil Structural Health Monitoring*, vol. 9, no. 5, pp. 639–653, 2019.
[7] P. Mohanty and D. J. Rixen, "Operational modal analysis in the presence of harmonic excitation," *Journal of Sound and Vibration*, vol. 270, no. 1-2, pp. 93–109, 2004.
[8] S. Greś, M. Döhler, P. Andersen, and L. Mevel, "Kalman filter-based subspace identification for operational modal analysis under unmeasured periodic excitation," *Mechanical Systems and Signal Processing*, vol. 146, Article ID 106996, 2021.
[9] J. Kang, L. Liu, Y.-P. Shao, and Q.-G. Ma, "Non-stationary signal decomposition approach for harmonic responses detection in operational modal analysis," *Computers & Structures*, vol. 242, Article ID 106377, 2021.
[10] A. Agneni, G. Coppotelli, and C. Grappasonni, "A method for the harmonic removal in operational modal analysis of rotating blades," *Mechanical Systems and Signal Processing*, vol. 27, no. 1, pp. 604–618, 2012.
[11] A. Maamar, M. Abdelghani, T.-P. Le, V. Gagnol, and L. Sabourin, "Operational modal identification in the presence of harmonic excitation," *Applied Acoustics*, vol. 147, pp. 64–71, 2019.
[12] A. Sadeqi and S. Moradi, "A new SVD-based filtering technique for operational modal analysis in the presence of harmonic excitation and noise," *Journal of Sound and Vibration*, vol. 510, Article ID 116252, 2021.
[13] M. Xu, F. T. K. Au, S. Wang, and H. Tian, "Operational modal analysis under harmonic excitation using Ramanujan subspace projection and stochastic subspace identification," *Journal of Sound and Vibration*, vol. 545, Article ID 117436, 2023.
[14] N. J. Jacobsen, P. Andersen, and R. Brincker, "Using enhanced frequency domain decomposition as a robust technique to harmonic excitation in operational modal analysis," in *Proceedings of ISMA2006: International Conference on Noise & Vibration Engineering*, Katholieke Universiteit, 2006.
[15] H. Yu and B. M. Wilamowski, *Levenberg–Marquardt Training, in Intelligent Systems*, pp. 11-12, CRC Press, 2018.
[16] A. C. Neves, I. González, R. Karoumi, and J. Leander, "The influence of frequency content on the performance of artificial neural network-based damage detection systems tested on numerical and experimental bridge data," *Structural Health Monitoring*, vol. 20, no. 3, pp. 1331–1347, 2021.
[17] B. Xu, Z. Wu, G. Chen, and K. Yokoyama, "Direct identification of structural parameters from dynamic responses with neural networks," *Engineering Applications of Artificial Intelligence*, vol. 17, no. 8, pp. 931–943, 2004.
[18] C. S. Huang, S. L. Hung, C. M. Wen, and T. T. Tu, "A neural network approach for structural identification and diagnosis of a building from seismic response data," *Earthquake Engineering & Structural Dynamics*, vol. 32, no. 2, pp. 187–206, 2003.
[19] M. De Iuliis, C. Rinaldi, F. Potenza, V. Gattulli, T. Toullier, and J. Dumoulin, "Ambient vibration prediction of a cable-stayed bridge by an artificial neural network," in *Data Driven Methods for Civil Structural Health Monitoring and Resilience*, pp. 242–257, CRC Press, 2023.
[20] H. Peng, J. Yan, Y. Yu, and Y. Luo, "Time series estimation based on deep Learning for structural dynamic nonlinear prediction," *Structures*, vol. 29, pp. 1016–1031, 2021.
[21] D. Birky, J. Ladd, I. Guardiola, and A. Young, "Predicting the dynamic response of a structure using an artificial neural network," *Journal of Low Frequency Noise Vibration and Active Control*, vol. 41, no. 1, pp. 182–195, 2022.
[22] K. Worden and P. L. Green, "A machine learning approach to nonlinear modal analysis," *Mechanical Systems and Signal Processing*, vol. 84, pp. 34–53, 2017.
[23] D. Liu, Z. Tang, Y. Bao, and H. Li, "Machine-learning-based methods for output-only structural modal identification," *Structural Control and Health Monitoring*, vol. 28, no. 12, 2021.
[24] M. Civera, V. Mugnaini, and L. Zanotti Fragonara, "Machine learning-based automatic operational modal analysis: a structural health monitoring application to masonry arch bridges," *Structural Control and Health Monitoring*, vol. 29, no. 10, 2022.
[25] P. Xie, L. Zhang, M. Li, S. F. S. Lau, and J. Huang, "Elevator vibration signal denoising by deep residual U-Net," *Measurement*, vol. 225, Article ID 113976, 2024.
[26] J. H. Baek, M. Hansen, R. Nigbor, and S. Tileylioglu, "Elevators as an excitation source for structural health monitoring in buildings," in *Proceedings of the 4th World Conference on Structural Control and Monitoring*, pp. 11-12, Los Angeles, CA, USA, July 2006.
[27] N. Jacobsen, *Aalborg Universitet Eliminating the Influence of Harmonic Components in Operational Modal Analysis Eliminating the Influence of Harmonic Components in Operational Modal Analysis Brüel & Kjær Sound & Vibration Measurement A/S*, NOVI Science Park, Niels Je, 2007.
[28] S. V. Modak, "Separation of structural modes and harmonic frequencies in operational modal analysis using random decrement," *Mechanical Systems and Signal Processing*, vol. 41, no. 1-2, pp. 366–379, 2013.
[29] C. Devriendt, G. De Sitter, S. Vanlanduit, and P. Guillaume, "Operational modal analysis in the presence of harmonic excitations by the use of transmissibility measurements," *Mechanical Systems and Signal Processing*, vol. 23, no. 3, pp. 621–635, 2009.
[30] J. Antoni, "The spectral kurtosis: a useful tool for characterising non-stationary signals," *Mechanical Systems and Signal Processing*, vol. 20, no. 2, pp. 282–307, 2006.
[31] V. Vrabie, P. Granjon, and C. Serviere, "Spectral kurtosis: from definition to application," 2006, [Online]. Available: https://hal.science/hal-00021302.
[32] J.-L. Dion, I. Tawfiq, and G. Chevallier, "Harmonic component detection: optimized spectral kurtosis for operational modal analysis," *Mechanical Systems and Signal Processing*, vol. 26, pp. 24–33, 2012.
[33] I. M. Shohet, "Key performance indicators for maintenance of health-care facilities," *Facilities*, vol. 21, no. 1/2, pp. 5–12, 2003.
[34] P. Van Overschee and B. De Moor, *Subspace Identification for Linear Systems—Theory, Implementation, Applications*, Kluwer Academic Publishers, 1996.
[35] R. Brincker, L. Zhang, and P. Andersen, "Modal identification of output-only systems using frequency domain decomposition," *Smart Materials and Structures*, vol. 10, no. 3, pp. 441–445, 2001.