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Published Version:
Zonzini, F., Testoni, N., Palermo, A., De Marchi, L., Mennuti, C., Augugliaro, G., et al. (2024). Green Wireless Sensing Network for Structural Health Monitoring: A Vertical Approach. Piscataway : IEEE [10.1109/mn60932.2024.10615586].

Availability:
This version is available at: https://hdl.handle.net/11585/977295 since: 2024-08-08

Published:
DOI: http://doi.org/10.1109/mn60932.2024.10615586

(Article begins on next page)

Green Wireless Sensing Network for Structural Health Monitoring: a Vertical Approach

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***Abstract*—Decentralized monitoring systems rely on the coalescence between hardware/software resource exploitation. Green Wireless Sensing (GWS) network can fulfill such requirement in a sustainable manner by offering a more efficient allocation of the communication protocol, power units, and computing scheme. Following this vision, we present a vertical approach to GWS for Structural Health Monitoring at two different levels. On a hardware viewpoint, we present a novel version of a wireless accelerometer sensor compatible with sensor-near vibration analysis based on System Identification (SysId). To improve the energy autonomy and achieve GWS, the board has been equipped with a solar energy harvester and advanced power managing functionalities allowing for a battery duration major than $330\,\mathrm{h}$ neglecting the power of the solar cell. Secondly, we propose an original method, called SysId2FDD, for the reconstruction of complex mode shapes from local SysId estimations. The architecture has been deployed on a truss structure and tested in multiple defective configurations, scoring a modal fitting above 94% and effective damage detection.**

***Index Terms*—Green Wireless Sensing, Structural Health Monitoring, System Identification, Vibration analysis**

I. Introduction

Green Wireless Sensing (GWS) is one of the driver of the newborn Green IoT paradigm, i.e., a novel hardware-software framework which aims at optimizing the energy provision, energy transfer, and energy efficiency of a sensor system by means of sustainable network infrastructures [1]. To do so, it relies on the application of power-profitable energy harvesting, the exploitation of more efficient communication hardware and protocols, and the better usage/distribution of the computing capabilities of edge and far-edge devices [2]. GWS technologies and power-friendly computational approaches are attracting particular interest within the Structural Health Monitoring (SHM) community since inspection procedures are constantly challenged by three main issues [3]: i) long-term functionalities versus low-power consumption and energy supply, ii) data management, storage, and volume versus network bandwidth, iii) clock synchronization versus durability, stability, and sensitivity of electronic components. Following this trend, the current approach in SHM is to distribute the diagnostic process between multiple computing resources, eventually charging the peripheral sensing units with pre-processing functionalities essential to reduce the data burden. Ultimately, this sensor-near computing perspective influences positively the energy transmission cost which is the most critical entry in the system power budget. Despite being advantageous from a hardware-viewpoint, the most critical aspect of decentralized networks relates to the possibility of retrieving full-scale damage sensitive features from local estimates. Standalone data processing frameworks, based on which each sensing unit pre-elaborates structural parameters and transmits them in place of the raw time series, are intrinsically affected by a loss of cross-information between sensors. This is the main reason limiting the widespread applicability of distributed architectures, especially when vibration monitoring applications are tackled. In these cases, in fact, the inspection process usually passes through the reconstruction of global structural features, such as the natural modes of vibration and their mode shapes, which can only be obtained from the analysis of cross-power spectral distributions. The described scenario highlights the necessity to develop coalescent approaches which can comprehensively tackle the specificity of all layers of the monitoring architecture, paving the way to more sustainable SHM installations.

This research work aims at bypassing some of the crucial issues above by proposing a vertical approach to GWS basing on the following novel aspects:

This research was partly funded by PNRR – M4C2 – Investimento 1.3, Partenariato Esteso PE00000013 – “FAIR – Future Artificial Intelligence Research” – Spoke 8 “Pervasive AI”, funded by the European Commission under the NextGeneration EU programme. This work has also been supported by the project “DS2: Digital Smart Structures”, funded by INAIL (Italian Workers’ Compensation Authority), BRIC 2021.

1) We propose, for the best of the authors' knowledge, the first method (SysId2FDD) for global mode shape reconstruction (phase and amplitude) from decentralized System Identification (SysId)-based vibration inspection without requiring extra data transfer between sensors for cross-correlation;
2) We present a prototype wireless sensor supporting such distributed approach by implementing GWS thanks to its advanced power management, harvesting functionalities, and embedded processing capabilities;
3) We extensively validate the proposed architecture for the monitoring of a truss structure under different damage scenarios, reaching a modal fitting always greater than 94.60% and effectiveness in frequency shift detection.

The rest of the paper is organized as follows. In Section II, SysId is firstly presented while the core of the SysId2FDD method is introduced in Section III. The hardware architecture of the novel wireless acceleration sensor is described in Section IV. An experimental validation conducted on a truss structure in lab environment is discussed in Section V, opening to final remarks and future outlooks.

II. SysId for decentralized vibration characterization

SysId based on autoregressive models offers a suitable solution for vibration analysis [4]. The idea behind SysId is that the dynamics of a structural system can be encapsulated in a set of parameters, also called as model parameters, which can be seen as the taps of a linear time invariant filter whose frequency response function (FRF) reflects the spectral profile of the observed structure. To achieve this goal, SysId postulates a mathematical model on the signal and computes, according with some heuristics, the set of parameters that best approximates the input-output relationship. SysId typically involves complex mathematics and linear algebra operations, which are barely compatible with hardware-oriented integration. Nevertheless, researchers have recently proposed an embedded variant running on low-end devices equipped with 32-bit microcontroller architectures [5], [6] along with its parallelization on a multi-core and ultra-low-power computing platform [7]. The importance of deploying SysId in a sensor-near manner is that, opposite to alternative edge algorithms for vibration characterization, it allows to reach a deeper level of optimization while preserving the accuracy of the diagnostic process. This is due to the fact that, since all the dynamics is collapsed in a very reduced batch of parameters (less than 20 to 30 parameters are sufficient to model even the most complicated structural signatures), it appears as a potent means for data compression, network payload reduction, and power efficiency [5].

To be applicable in the context of data compression, the computation of SysId models is inherently performed in a sensor–driven manner. Conversely, the structural assessment process must be accomplished globally to provide a comprehensive overview of the overall integrity of the facility. This is fundamental for the reconstruction of mode shapes, which are spatial dependent quantities whose profile is determined by the relative position of the sensors with respect to the modal response of the structure at each modal component [8].

However, the estimation of mode shapes from output-only[1] SysId models is, implicitly, an ill–posed problem due to the lack of a shared reference signal necessary to normalize each local estimation with respect to a common ground. Consequently, the relative temporal shifts between each sensing unit and the reference one, corresponding to as many phase rotations in the phase diagram of the local FRF, are lost, irrespective of the physical relationship between each measured vibration response and the modal components. Ultimately, such drawback hampers the possibility to retrieve the sign of the mode shapes but has no effect on the magnitude of the FRF since phase rotations are phasors of unitary value; this defining feature ensures proper reconstruction of the mode shape amplitude.

III. Global mode shape reconstruction from local SysId parameters: the SysId2FDD algorithm

To fill the gap above, this work presents the SysId2FDD algorithm as a suitable strategy for the retrieval of the complex mode shapes (both sign and amplitude) from local SysId estimates. The name comes from the fact that it combines the superior spectral properties of SysId (namely its achievable compression ratio and spectral resolution) with the feature aggregation capability of the Frequency Domain Decomposition (FDD) method. FDD is a commonly adopted strategy for structural characterization which identifies natural frequencies and mode shapes by computing time correlations between vibration data [9].

The algorithm involves the steps depicted in Fig. 1 assuming that P vibration modes are to be identified from N_s sensors:

1) *SysId parameter estimation* (Step 1): SysId parameters Θ_i are estimated by each peripheral node i and wirelessly transmitted to the aggregating unit where the remaining steps are implemented.
2) *FRF retrieval* (Step 2.1): N_s FRF complex quantities $H_i(f)$, one per sensor node, are computed according with the selected autoregressive model.
3) *CPSD matrix estimation* (Step 2.2): for each pair of sensors (i, j) the N-sample Cross Power Spectral Density (CPSD)
$$S_{i,j}(f) = H_i(f)H_j(f)^H \tag{1}$$
is computed directly in the frequency domain as the product between the individual FRF (superscript ^{H} stands for the complex conjugate operator). Every $S_{i,j}(f)$ profile can be seen as an entry of a tri-dimensional matrix $S(f) \in \mathbb{R}^{N_s \times N_s \times N}$. Elements in

[1]Output-only refers to broad category of practical monitoring scenarios in which diagnostic is performed on the measured system responses without knowing the true input stimulus.

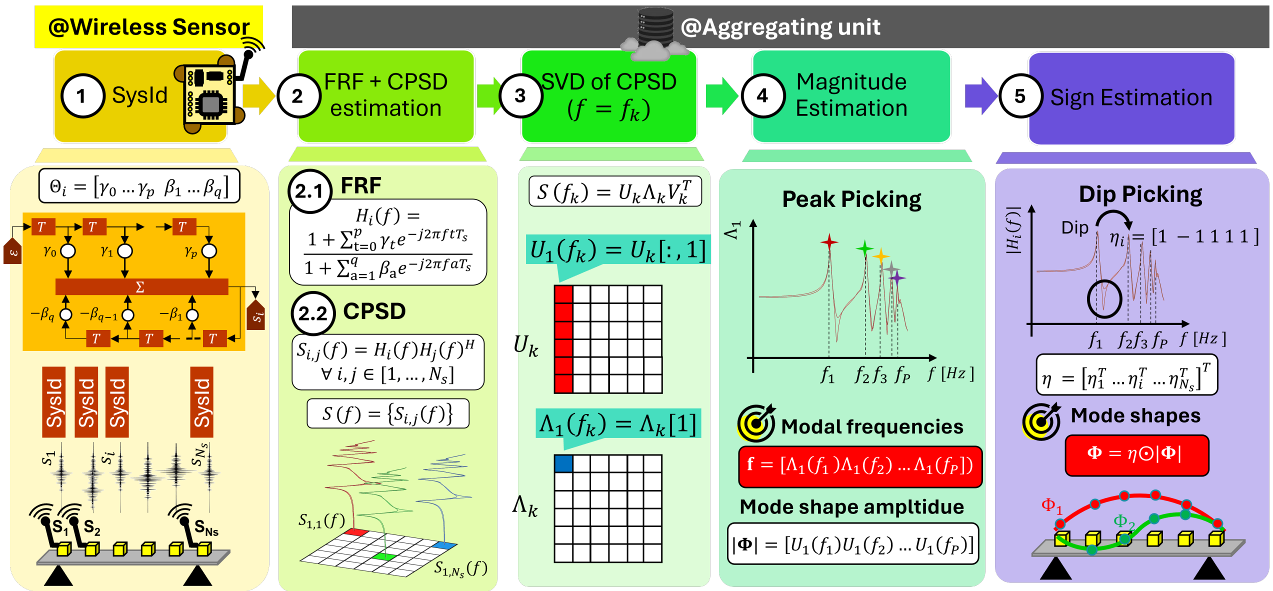

Fig. 1. Workflow of the SysId2FDD algorithm: local SysId estimates can be computed in a fully-decentralized manner by an intelligent wireless sensor, while the reconstruction of the complete mode shapes is demanded to an aggregator implementing the remaining steps.

the main diagonal correspond to the autocolleration functions ($i = j$), while the off-diagonal quantities represent the cross distributions.

4) *CPSD decomposition* (Step 3): for each frequency component $f_k \in [0, \dots, f_{N-1}]$, the Singular Value Decomposition (SVD) of $S(f_k)$ is obtained such that

$$U_k \Lambda_k V^T = S(f_k) \tag{2}$$

with U_k (V_K) and Λ_k being the matrix of left (right) singular values and singular values, respectively, at that frequency (^{T} is the transpose operator). Since most of the signal energy is carried by the first singular element, only the first singular value $\Lambda_1(f_k) = \Lambda_k[1]$ and first singular vector $U_1(f_k) = U_k[:, 1]$ are preserved for each frequency. Spanning over all frequencies, the matrix $U_1(f) = [U_1(0) \dots U_1(f_{N-1})] \in \mathbb{R}^{N_s \times N}$ and the N-long vector $\Lambda_1(f) = [\Lambda_1(0) \dots \Lambda_1(f_{N-1})]$ are obtained.

5) *Magnitude estimation* (Step 4): the P most energetic peaks in $\Lambda_1(f)$ can be identified via the peak picking algorithm such that $\mathbf{f} = [\Lambda_1(f_1) \dots \Lambda_1(f_P)]$; the indexes of the peaks are used to select the associated P left singular vectors in $U_1(f)$, which correspond to the mode shape at that frequency [9]. Since Λ_1 quantities are real elements, such procedure only allows for the retrieval of the amplitude of the mode shapes, i.e., $|\mathbf{\Phi}| = [U_1(f_1) \dots U_1(f_P)]$.

6) *Sign estimation* (Step 5): the sign can be reconstructed in a sensor-wise manner by adopting the Dip Picking (DP) algorithm. DP probes for phase changes in a FRF profile by looking for the presence of antiresonant frequencies [10], i.e., frequencies whose vibration amplitude is theoretically null.

If $\Phi_i = [\Phi_{1,i}, \dots, \Phi_{P,i}]$ represents the row vector of P modal coordinates identified for node i at different modes, a phase change among two successive modal coordinates $\Phi_{p,i}$ and $\Phi_{p+1,i}$ is identified if a dip in the spectrum is present between the peak spectral values f_p and f_{p+1}. Therefore, the sign η_i of the mode shapes for this sensor can be expressed as a row–wise antipodal vector containing, for each entry $\eta_{p,i} (p \geq 2)$, a value equal to -1 or 1 depending on whether or not a dip is revealed. The method assumes $\eta_{1,i} = 1$ for all the sensor locations, hence it is applicable for structures whose first peak spectral value correspond to a clear bending mode. The sought mode shape matrix is finally computed as:

$$\mathbf{\Phi} = \eta \odot |\mathbf{\Phi}| \tag{3}$$

where $\eta = [\eta_i^T \dots \eta_{N_s}^T]^T \in \mathbb{R}^{N_s \times}$ and $\odot$ indicates the point–wise Hadamard product.

While step 1 and 5 are totally original, procedures 2.2 to 4 are in common with the standard FDD approach. Importantly, there are two crucial differences. The former is that the CPSD matrix is computed by SysId2FDD from single FRF representations directly in the frequency domain rather than by applying the Fourier transform to the time cross-correlation between the raw time series. This is paramount since it reduces also the computational complexity at the edge, becoming equivalent to that of a simple QR decomposition [5], while all the remaining and more involved tasks are demanded to the more powerful aggregating unit. The second is that FRFs are estimated in an analytical way such that the frequency resolution can be tuned depending on the richness of the spectral profile at different sensing locations. Consequently, the SysId2FDD allows to adapt the number of parameters in a sensor-wise manner, while preserving the same spectral resolution.

IV. Wireless sensor node

Performing SysId computation at the edge requires a careful allocation of the computing and storage resources, necessary to make it compatible with real-time and low-power functionalities. A preliminary sensor node compatible with such requirements and hosting the eSysId library [6] has been proposed in [11], showing promising results. Here, to further reduce the impact of cabling, shorten the network installation time, and increase energy autonomy, a wireless version of the former sensor is presented together with its newly designed power management logic.

To fully exploit the advantages of a wireless installation, the updated sensor node can be operated both by battery and by monocrystalline solar cells: two IXOLAR™ SM351K09TF capable of $138.3\,\mathrm{mA}$ and $5.02\,\mathrm{V}$ at maximum power-point are installed on top of the sensor node, as shown in Fig. 2. They charge a PCB protected 3.7V 2600mAh LI-ION 18650 battery pack through a Solar Power management module based on the STMicroelectronics ultra-low power energy harvester and battery charger SPV1050. To insulate the whole circuitry, including the solar cells, the sensor node is housed inside a polycarbonate semitransparent IP67 box.

To reduce the power consumption to the minimum, an STM32 Nucleo-144 development board with STM32L496ZG MCU, supporting Arduino, ST Zio and Morpho connectivity has been used. This device is an ultra-low-power microcontroller based on the high-performance Arm® Cortex®-M4 32-bit RISC core operating at a frequency of up to 80 MHz, capable of down to $2.86\,\mu\mathrm{A}$ in Stop 2 while keeping the RTC active. At the same time, a twin accelerometer architecture is used on the sensor path: a $3\,\mu\mathrm{A}$ high-performance LIS2DH12 three-axis linear accelerometer detects accelerations events through its activity/inactivity recognition function, waking up the MCU and a $200\,\mu\mathrm{A}$ and ultra-low noise density ($20\,\mu\mathrm{g}/\sqrt{\mathrm{Hz}}$), low 0 g offset drift, ADXL355 three-axis MEMS accelerometer which is responsible for the actual data collection. This device [12] can measure accelerations up to $\pm 8\,\mathrm{g}$ and offers a tunable output data rate from $4\,\mathrm{Hz}$ to $4\,\mathrm{kHz}$: these features make it a suitable candidate for the majority of civil and industrial vibration diagnostic applications. The data collection length is programmable, up to $15\,\mathrm{ksa}$.

A Digi XBee 3 PRO, $2.4\,\mathrm{GHz}$, 802.15.4 module is employed in pin-sleep, transparent mode to establish and maintain the link between each sensor node and the gateway. These modules have already been field tested in many relevant industrial and civil scenarios, proving that effective data communication up to $18\,\mathrm{kbps}$ over $1200\,\mathrm{m}$ distance in outdoor/RF line-of-sight conditions are possible, with a transmit current of $32\,\mathrm{mA}$ and a receive current of $14\,\mathrm{mA}$ at a power supply of $3.3\,\mathrm{V}$. The communication protocol of the star network is an extension of what has been presented in [13]: the radio modules efficiently and transparently substituted all the wired connections.

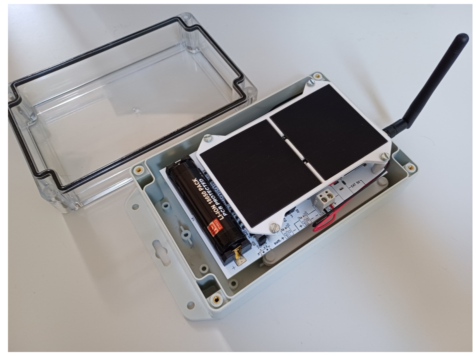

Fig. 2. Prototype of the designed wireless sensor node for SysId implementation with GWS capabilities.

Due to a sleep current of only $8\,\mathrm{mA}$, this module becomes very attractive by implementing an awake/sleep cycle, trading-off network availability for power consumption reduction. In the current realization, a periodic $8\,\mathrm{s}$ radio sleep followed by a $2\,\mathrm{s}$ active listening period, independent of the data collection and processing activity, allows for a battery life of $337.6\,\mathrm{h}$, neglecting the power provided by the solar cells. Since, at maximum power-point, each of the two solar cells is single-handedly capable of both powering the sensor node and charging the battery, the proposed node achieves GWS network capabilities.

V. Experimental validation

The effectiveness of the proposed SHM system has been tested pursuing two main objectives: i) prove the applicability of the entire architecture for damage detection purposes, and ii) verify the mode shape reconstruction capability of the SysId2FDD method versus fully centralized techniques.

A. Case study: a laboratory truss structure

Vibration responses collected for a metallic truss structure at the research labs of the Department of Civil Engineering of the University of Bologna, Italy, have been collected. The structure comprises 70 aluminum beams arranged in five cubic blocks measuring 1m x 1m x 1m each, as illustrated in Fig. 3. These beams feature a circular section with an inner diameter of $0.036\,\mathrm{m}$ and an outer diameter of $0.042\,\mathrm{m}$ for an overall cross-sectional area of $3.67 \cdot 10^{-4}\ \mathrm{m}^2$. Quasi-spherical nodes are employed at the terminal sections to ensure moment-free connections, while metal pads firmly connected to the ground maintain the structure in fixed position.

This structure represents one of the pillar test–beds of the DS2 project focusing on the realization and monitoring of digital smart structures. A chain of six accelerometer sensors, all of them deployed along one column of the frame, has been installed in correspondence of the junction elements, one per floor. This installation allows to properly capture the truss global lateral bending modes.

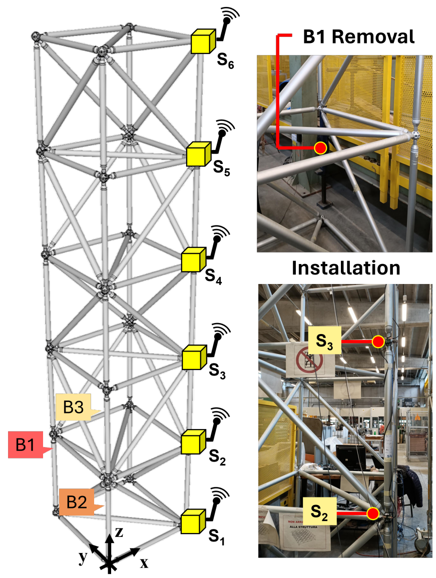

Fig. 3. Schematic of the aluminum truss structure and insights from the experimental campaign.

B. Methods

1) Network configuration and testing protocol: A sampling frequency $F_s = 500\,\mathrm{Hz}$ has been selected allowing up to the sixth vibration mode to be inspected with enough spectral resolution. $N = 8192$ samples have been used for the computation of the CPSD matrix to ensure sufficient spectral resolution. Time series were acquired continuously with a fixed batch size of 2000 samples along each axis. However, only horizontal displacements have been considered in the analyses, given the interest in reconstructing only lowest structure bending modes. In order to replicate operative scenarios, a fan motor simulating the effects of wind was used to excite the structure. This motivates the choice of a full-scale range equal to $\pm 2\,\mathrm{g}$ for the accelerometer unit. Beside tests in nominal condition, defective configurations have been simulated by removing and re-inserting, in order, beams B1, B2, B3, one at a time. The primary effect of this action is to induce an asymmetric mass distribution and a loss in the mechanical stiffness, which causes significant mode decoupling and frequency shifts in the spectral content of the truss. For each structural configuration, ten different measurements were registered to enlarge the pool of observations.

Concerning the SysId parameters, the Autoregressive with Moving Average (ARMA) model has been selected as candidate autoregressive method from the SysId suite given its superior performances for output-only characterization [5]. A total amount of 32 model parameters have been extracted from each sensing location; this quantity has been estimated by means of the Bayesian Information Criterion (BIC), which is widely adopted procedure in the field. $H_i(f)$ can be computed, for ARMA, as reported in Step 2.1 of Fig. 1.

2) Performance metric: The relative percentage reduction

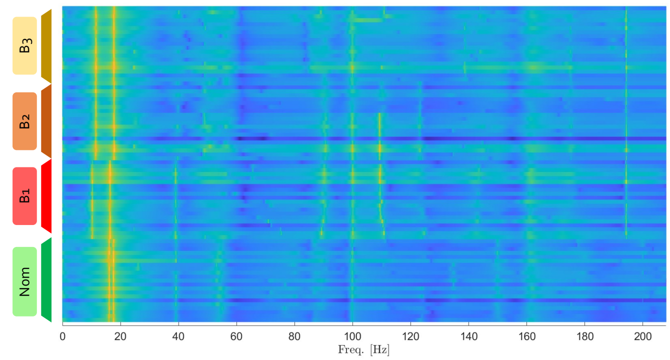

Fig. 4. Color–map of the waterfall plot obtained from the cascade of CPSD spectra computed by ARMA parameters in different structural configurations.

$$\Delta f_{p,\%} = \left(1 - \frac{f_p^{B_b}}{f_p^{Nom}}\right) \tag{4}$$

has been introduced to quantify the frequency reduction in the nominal modes of vibration for the different damaged scenarios (b stands for the removed beam index) compared to the nominal case. Alongside, the Modal Assurance Criterion (MAC) has been employed to measure the level of superimposition between the mode shapes $\mathbf{\Phi}^{(S)}$ retrieved by the SysId2FDD approach and those $\mathbf{\Phi}^{(F)}$ returned by the standard FDD technique, serving as a benchmark approach, applied to the ensemble of measured data. The MAC can be computed for each p-th mode of vibration as [14]:

$$\mathrm{MAC}_p = \frac{\left|\sum_{i=1}^{N_s} \Phi_{p,i}^{(S)T} \Phi_{p,i}^{(F)H}\right|^2}{(\Phi_p^{(S)T}\Phi_p^{(S)H})(\Phi_{p,i}^{(F)T}\Phi_{p,i}^{(F)H})} \tag{5}$$

and can be interpreted as an indicator of the square correlation between two modal vectors: in case of perfect matching, MAC = 1 (viz, 100%) is scored, while MAC proximal to zero indicates orthogonality (i.e., zero fitting) between the two mode shape vectors.

C. Results

1) Damage detection: The waterfall plot of Fig. 4 shows the variation over time (vertical axis) of the CPSD ($\Lambda_1(f)$) of the frame as a color-map: yellow regions correspond to high energy bands in which most of the structural energy concentrates, while those in blue are associated with non-informative portions of the spectrum. The figure suggests that six modal components are present below $120\,\mathrm{Hz}$: their evolution over time is summarized in Table I, which reports the frequency values (averaged over the ten data logs) taken after peak identification of the waterfall distribution. As can be seen, a consistent drop characterizes the first vibration mode, which moves from almost $16.22\,\mathrm{Hz}$ to $10.19\,\mathrm{Hz}$ as beam B1 is removed, corresponding to a 37% of frequency reduction. Similar reductions in frequency occur also after the removal of the other two structural elements. The frequency

TABLE I

First six modal frequencies and relative percentage variation computed via SysId2FDD in different structural configurations.

Conf	f_1	$\Delta f_{1,\%}$	f_2	$\Delta f_{2,\%}$	f_3	$\Delta f_{3,\%}$	f_4	$\Delta f_{4,\%}$	f_5	$\Delta f_{5,\%}$	f_6	$\Delta f_{6,\%}$
Nom	16.22	-	17.68	-	39.10	-	86.53	-	100.06	-	110.45	-
B1	10.19	37.17	16.43	7.07	39.10	0	85.70	0.96	99.44	0.62	110.24	0.19
B2	11.65	28.18	17.89	-1.19	39.94	-2.15	86.11	0.49	100.27	-0.21	110.03	0.38
B3	11.65	28.18	17.68	0	40.14	-2.66	86.53	0	100.69	-0.63	110.03	0.38

TABLE II

Average MAC percentages (μ_p) and standard deviation (σ_p) between FDD and SysId2FDD.

	Φ_1		Φ_2		Φ_3		Φ_4		Φ_5		Φ_6	
Conf	μ_1	σ_1	μ_2	σ_2	μ_3	σ_3	μ_4	σ_4	μ_5	σ_5	μ_6	σ_6
Nom	99.60	0.02	98.60	0.34	97.94	1.19	95.64	0.74	98.08	0.53	97.53	1.80
B1	99.29	0.10	98.49	0.07	98.31	0.39	88.51	2.41	97.14	0.70	94.60	2.27
B2	99.58	0.12	98.97	0.12	98.35	0.87	42.83	35.61	98.02	0.44	95.29	1.03
B3	99.62	0.07	99.06	0.06	97.96	1.80	43.31	30.95	98.64	0.21	95.28	1.02

shift is less pronounced for the remaining modal components, which undergo variations in the order of a couple of Hertz, hence leading to variations below 1%. Interestingly, the effect of B2 and B3 is almost equivalent: this is proven both by the numbers in Table I and by a qualitative analysis of Fig. 4. It could depend on the fact that both beams are contiguous and located along the same side of the frame compared with B1.

2) Mode shape reconstruction: Average MAC percentages (μ_p) and their standard deviation (σ_p) over the ten measurements per structural conditions are reported in Table II. MAC values always above 94% demonstrate that, apart from the isolated case related to the fourth modal component, for all the remaining modes and irrespective of the structural configuration, mode shapes from SysId2FDD superimpose remarkably to the ones provided by FDD. The quality of the results is further corroborated by the low standard deviation among the different tests, which remains stably beneath 2.5%.

VI. Conclusions and future perspective

In this work, a vertical approach to GWS for decentralized vibration-based SHM applications has been presented and thoroughly validated for the inspection of a tall truss building. Novelties have been introduced at two different levels. The hardware component consists of a wireless accelerometer sensor integrating all the circuitry necessary for smart data sensing, on-board data processing and transmission, and sustainable energy supply via a solar energy harvester. From a software perspective, the SysId2FDD algorithm has been proposed as an effective strategy to reconstruct complex mode shapes from local estimates returned by the wireless sensor. Experimental results demonstrate that the method can reach a modal fitting greater than 94% and proper damage detection while reducing at a large extent the data volume. Future efforts will be dedicate to the analysis of the robustness with respect to synchronization issues as well as entail larger monitoring scenarios.

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