Structural Health Monitoring and Prognostic of Industrial Plants and Civil Structures: A Sensor to Cloud Architecture

Published Version:
Zonzini F., Aguzzi C., Gigli L., Sciullo L., Testoni N., De Marchi L., et al. (2020). Structural Health Monitoring and Prognostic of Industrial Plants and Civil Structures: A Sensor to Cloud Architecture. IEEE INSTRUMENTATION & MEASUREMENT MAGAZINE, 23(9), 21-27 [10.1109/MIM.2020.9289069].

Availability:
This version is available at: https://hdl.handle.net/11585/791048 since: 2023-03-21

Published:
DOI: http://doi.org/10.1109/MIM.2020.9289069

(Article begins on next page)

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The deployment of Structural Health Monitoring (SHM) systems is a natively interdisciplinary task involving joint research contributions from sensing technologies, data science and civil engineering. The capability to assess, also from remote stations, the working conditions of industrial plants or the structural integrity of civil buildings is widely requested in many application fields. The technological development aims at continuously providing innovative tools and approaches in order to satisfy these demands. As a first instance, reliable monitoring strategies are needed to detect structural damages while filtering out environmental noise. Ongoing solutions to tackle these topics are based on the exploitation of highly customised sensing technologies, such as shaped transducers for Acoustic Emission (AE) testing or Micro-Electro-Mechanical System (MEMS) accelerometers for Operational Modal Analysis (OMA) [1]. On the other hand, effective data acquisition and storage techniques must be employed in order to cope with the heterogeneity of the sensing devices and with the amount of data produced by collecting raw measured signals. Finally, damage detection and prediction tasks should be computed via data-driven algorithms that can complement the model-based alternatives traditionally used in civil engineering. Layered SHM architectures [2] represent straightforward approaches to address the system complexity originated by this interdisciplinary design; however, few real-world implementations have been presented so far in literature. In this paper, we overcome these limitations by presenting an Internet of Things (IoT)-based SHM architecture for the predictive maintenance of industrial sites and civil engineering structures and infrastructures. The proposed cyber-physical system includes a monitoring layer, consisting of accelerometer-based sensor networks, a data acquisition layer, built on the recent W3C Web of Things standard [3], and a data storage and analytics layer, which leverages distributed database and Machine Learning (ML) tools. We extensively discuss the hardware/software components of the proposed SHM architecture, by stressing its advantages in terms of device versatility, data scalability and interoperability support. Finally,

the effectiveness of the system is validated on a real-world use-case, i.e. the monitoring of a metallic frame structure located at the SHM research labs of the University of Bologna within the MAC4PRO project [4].

State of the art and related works

A close analogy can be established between SHM tasks and those performed by healthcare systems in the sense that they require a perfect coordination among the sensing, the communication and the cognitive/decision subsystems to achieve a timely and reliable diagnosis. To be effective, an SHM architecture must chase the optimal combination between the required hardware (HW) resources for signal recording and the associated software (SW) infrastructure in charge of data management, data analytics and structural assessment. Coherently with this joint HW-SW optimization, SHM platforms can be considered as cyber-physical systems, in which the intrinsic capability of smart devices to measure, pre-elaborate and forward physical data to virtual aggregating units is exploited [5]. From a HW standpoint, the selection of the specific sensors to be deployed and their relative positioning strictly depend on the characteristics of the structure to be inspected, the complexity of which may demand the combination of different sensing technologies, as well as several diagnostic approach (AE, OMA, others).

At higher abstraction levels, considerable research efforts have been made to (*i*) enhance the reliability in retrieving and sharing structural information collected at multiple locations, (*ii*) increase the quality of the extracted structural parameters while reducing the computational latency, and (*iii*) bridge the gap between human and computer-aided prognostics about the remaining structural life cycle prediction, possibly combining them with dedicated interfaces [6]. In this paper, we focus on the vast and highly critical field of vibration engineering. In fact, among the many different SHM systems, the implementation of those devoted to vibration monitoring is particularly challenging because it is usually based on dense sensor networks, characterized by high sampling frequencies and heavy duty cycles.

Sensor networks built on MEMS accelerometers have recently drawn a considerable attention [1], due to their capability of precisely capturing acceleration signals in a cost-effective manner. The structural characterization is then performed by computing a set of damage-sensitive parameters embedded in vibration data. However, the data retrieving and processing tasks are strictly application-dependent; thus, apart from general recommendations [7], no precise standardization has been formalized yet.

Operational Modal Analysis (OMA) is a widely adopted strategy to extract meaningful features from vibration data and it can be performed when the structures are in operation and the loading conditions (traffic, wind, seismic events, etc.) are unknown [8]. OMA procedures are fed with vibration-related signals (e.g. accelerations, rotation), and output the so called "modal parameters". These features may comprise natural frequencies (i.e. the frequency components carrying most of the total structural energy), damping factors and modal shapes, namely the specific spatial patterns of vibrations exhibited by the monitored structure at the different natural frequencies.

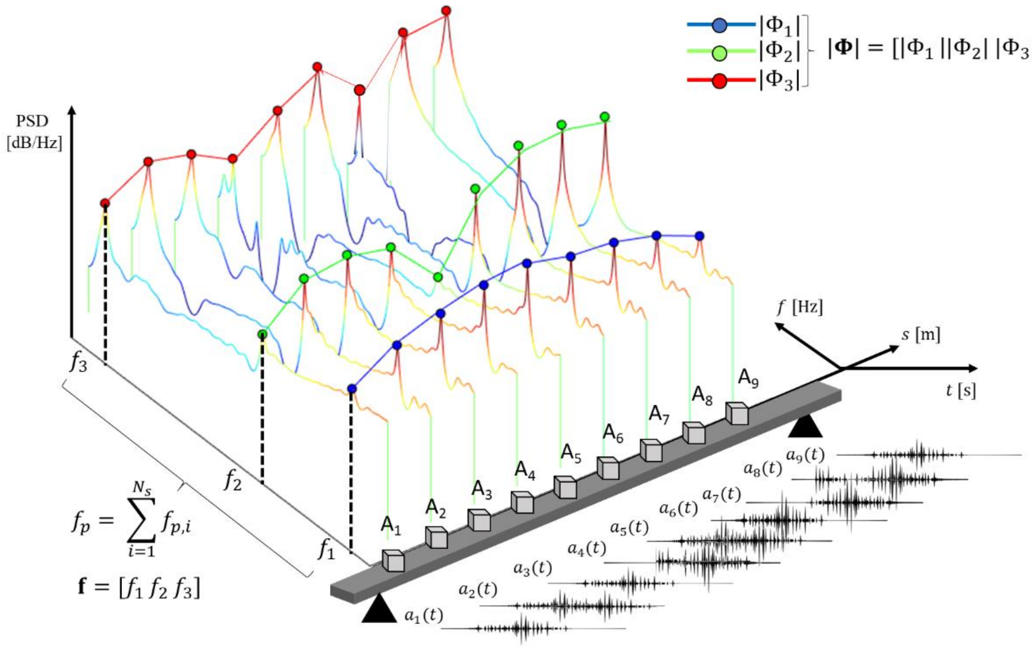


Fig. 1. Time-Frequency-Spatial domain representation of a typical OMA-based processing flow

A schematic overview of a typical OMA-based processing flow is depicted in Fig. 1, illustratively comprising a monitoring application with $N_s = 9$ accelerometers and $P = 3$ natural frequencies and as many identified modal shapes.

Vibration signals ($a_i(t),\ i = 1 \dots N_s$) acquired at individual sampling positions (A_i) are the only input required by the system. As it can be observed, the set $\mathbf{f} = [f_1 \dots f_P]$ of P natural (modal) frequencies is identified from the collection of P dominant peaks appearing in the Power Spectral Density (PSD) profile of gathered signals. A global estimation of the cumulative vibration frequencies is commonly obtained as a point-by-point average of the peak frequency values estimated at each sensor of the network. Alongside, the absolute value of the p-th modal shape vector $|\mathbf{\Phi}_p| \in \mathbb{R}^{N_s \times 1}$, corresponding to the equally-indexed modal frequency f_p, can be trivially reconstructed by interpolating in spatial domain the previously computed peak spectral magnitudes. Once all the P modal shape vectors have been estimated, they can be vertically arranged as columns of the modal shape matrix $|\mathbf{\Phi}| = [|\mathbf{\Phi_1}| \dots |\mathbf{\Phi_P}|] \in \mathbb{R}^{N_s \times P}$. Through conventional spectral analysis tools, just the absolute value of the modal shape can be extracted; therefore, more advanced techniques have been developed to reconstruct the actual modal curve such as eigenvector-based algorithms or Blind Source Separation (BSS) strategies [8].

Proposed SHM Architecture

Even if there is a growing number of SHM solutions presented in literature [6], still two main difficulties hamper their wide adoptions, i.e.: (i) the lack of standard sensing solutions and estimation methods and (ii) the need for adequate data management tools to aggregate, process and analyse the possibly big-data volume produced by the sensor devices for fine-grained predictive maintenance applications. The issues discussed above are tackled within the MAC4PRO project [4], where a reference SHM architecture which integrates the traditional components of multi-source structural monitoring with data management and analysis is proposed. Specifically, three functional requirements have been considered during the design and deployment of the HW/SW elements: (1) *scalability*, i.e. the possibility to cope with large sensor installations likely producing high data volumes; (2) *heterogeneity*, namely the need to support multi-type sensor devices (e.g. MEMS and piezoelectric transducers) with different data formats, required estimation procedures and outputs; (3) *extendibility*, i.e. the seamless support for the dynamic adding of new sensors and/or their remote configuration updating. The proposed architecture consists of three main layers, as shown in Fig. 2; in the following, the enabling technologies of each architectural level are discussed, while an integrated validation on an SHM use-case is presented in Section 3.

Data measure Layer

The measuring layer consists in a sensor network composed of low-power, light weight and small footprint accelerometer sensor nodes [9]. Each of them features an ST Microelectronics STM32F303 32bit, 3.3 V low-power microcontroller unit (MCU) embedding Digital Signal Processing (DSP) functionalities and a floating-point unit (FPU). The sensing element consists of a 6 Degree-of-Freedom (DoF) system-in-package LSM6DSL device, a MEMS-based inertial measurement unit (IMU) capable to simultaneously provide triaxial accelerations and as many angular velocities. Admitted values for the output data rate (ODR) span from 1.6 Hz to 6.664 kHz, whereas the minimum linear and angular sensitivity per Least-Significant Bit (LSB) correspond to $0.598 \cdot 10^{-3}$ m/s^2 and $0.074 \cdot 10^{-3}$ rad/s respectively. Multiple devices can be joined in a daisy–chain fashion by means of a multidrop Sensor Area Network (SAN) bus, which exploits data–over–power (DoP) communication leveraging the EIA RS-485 standard. This protocol can be used effectively over long distances and in electrically noisy environments, such as industrial sites. A wired connection was preferred over a wireless one in order to grant the user the possibility to acquire data from the structure at high data-rates while preserving data confidentiality from external attacks. Moreover, this choice led to the design of lighter nodes, which did not require the presence of a battery.

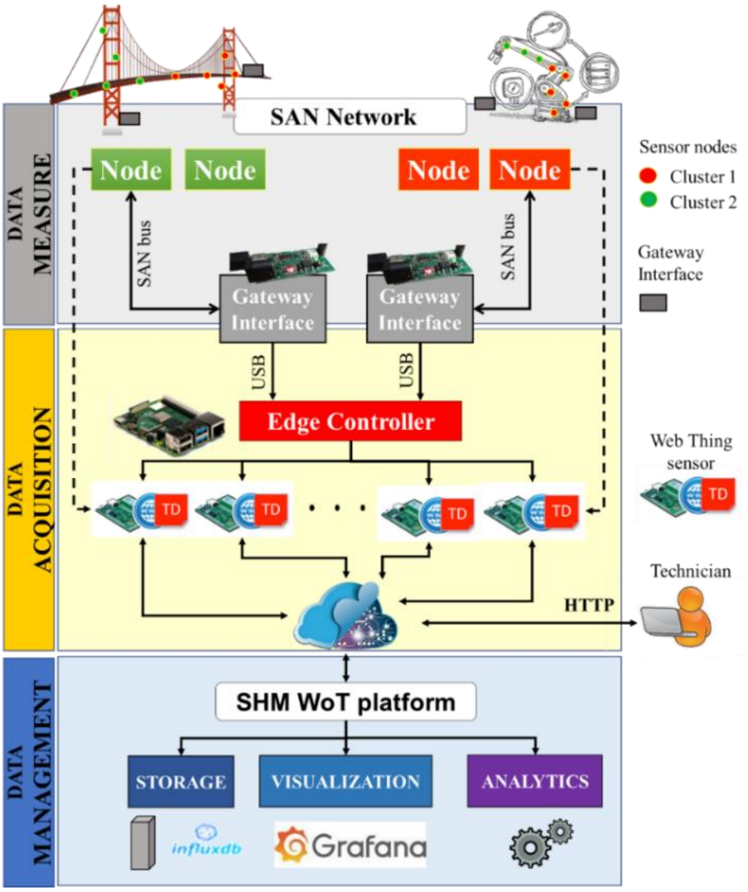


Fig. 2. Proposed layered architecture for structural health monitoring and data analysis

Meaningful information sensed by each device is transmitted to an Edge Controller (EC) through a companion Gateway (GW) network interface (see Fig. 2), which can orchestrate up to 64 nodes at a time. Nonetheless, it should be mentioned that the maximum number of sensors per GW could be arbitrarily increased by means of repeater nodes. During acquisition, signals are collected simultaneously by each sensor node. A unique time-stamp is provided by means of an internal 32bit high-speed hardware counter, clocked at 64MHz; once every hour a 32bit low–speed software counter is updated. The cycle–to–cycle jitter of the internal high-speed clock system is 300 ps whereas its accuracy for soldered parts working in the $-10°C$ to $85°C$

temperature range is -1.9% to 2.3% with respect to the nominal value. Measurements taken on the implemented sensor network showed cycle–to–cycle jitter of 239.5 ps, a minimum deviation of -0.069% and a maximum deviation of 0.026% over a time period of 2400 s. The synchronisation algorithm exploited in this work is based on a software implementation of the classical three-way handshake adopted by the RFC 793 Transmission Control Protocol, according to which the reception of each data packet must be acknowledge by the receiver before the next packet is sent by the transmitter. The maximum divergence between the sensor nodes' clocks, which is due to inherent clock's drift, was reduced to 4.7 ms by issuing the synchronization command once every 5 s. The obtained value is acceptable for vibration-based structural inspection [10]. The sensor-to-GW data transmission is performed sequentially, in packets, by exploiting a proprietary lossless encoding technique.

Data acquisition Layer

The Edge Controller in Fig. 2 is configured to gather the measurements produced by each sensor of the monitored structure, consequently presenting them towards a remote cloud. To cope with sensor heterogeneity while minimizing the need for manual configuration and intervention, a software layer was specifically added to each EC in order to virtualize the sensor operations by making them accessible and discoverable from a remote client. Following this design, we leveraged the Web of Things (WoT) paradigm [3], a recent standard promoted by a W3C working group that enables mutual interworking of different IoT eco-systems and devices by means of web technologies. More in details, the WoT architecture identifies the concept of a Thing as a physical or a virtual entity whose interfaces are described by a WoT Thing Description (TD). The TD includes a list of machine-understandable meta-data that specify –among others- the list of properties (e.g. state variables), actions and events exposed by a Thing as well as its communication strategies (protocol bindings). Hence, the TD does not define the implementation of the IoT physical devices but rather its services and the way they can be accessed by other software components by means of a uniform and well-defined interface. To this aim, the TD is usually encoded in JSON-LD language and likely annotated with semantic labels providing a machine-understandable knowledge representation of each property/action/event. An example of such annotations can be found in [11] and [12], where two of the most popular semantic ontologies for the SHM domain are described. In our case, each sensor is represented by a dedicated Web Thing (WT); the properties that can be read from a remote Web client include, for instance, the raw sensing values (e.g. 3-axial accelerometer values) and the aggregated features extracted from the raw signal (e.g. min/max peak values).

A small subset of the TD associated to each accelerometer sensor of Section 2.1 is sketched in Table 1.

Type	Name	Description
Property	`acceleromenter_sample`	Last 3-axial accelerometer measurement
Property	`accelerometer_vector`	Last 3-axial accelerometer vector of samples
Property	`accelerometer_threshold`	Accelerometer threshold for event detection
Action	`start/stop`	Activate/deactivate the sensor monitoring
Event	`onOverThresholdEvent`	Trigger the event when the accelerometer sample is greater than the threshold value

Table 1. Subset of the TD associated to each SHM sensor (machine-understandable format)

Data management Layer

In [13], we proposed the WoT Store, a novel software platform supporting the dynamic management of Web Things on generic WoT environments. The platform has been installed on a private cloud and customized for the SHM domain by enabling the following functionalities: (1) *device discovery*, i.e. it is possible to monitor the Things/sensors available in the current WoT deployment; (2) *device interaction*, i.e. it is possible to interact with each Thing through a Web dashboard, e.g. reading or setting a sensor property; (3) *service management*, i.e. it is possible to execute external software modules that store and process data produced by each Thing/sensor. Regarding point (2), we highlight the extendibility of the WoT-SHM platform: since the Web dashboard is dynamically generated by reading the TD of the registered Things, the insertion of new sensors is automatically supported and does not require any manual configuration. Dealing with point (3), three software modules were designed for the SHM data storage, processing and visualization purpose. The storage module issues periodic queries to each available SHM sensor/Thing (the up-to-date list is provided by the device discovery) and saves the measurements on a distributed database implemented in InfluxDB (https://www.influxdata.com). The query period is configurable according to the requirements of the monitoring application. The visualization module, instead, enables to plot the stored time-series of each sensor/Thing on the Grafana (https://grafana.com) tool. Finally, the data analytics module (currently under development) will implement machine-learning and signal-processing techniques for structural risk assessment, anomaly detection and remaining life-cycle prediction.

Validation and discussion

The proposed SHM architecture will be extensively validated by the MAC4PRO project [4] for the monitoring and predictive maintenance of industrial sites and civil engineering structures. Here, the preliminary project's results are reported, concerning the monitoring of a metallic frame structure located at the research labs of the Department of Civil Engineering of the University of Bologna. More specifically, the facility consists of a high-rise five-story frame composed by five identical cubic modules with nominal height of 1 m. This structure was instrumented with a double chain of six accelerometers fixed in correspondence of the junction elements. The rationale behind the selection of one out of two GW units concerns the idea to minimize the total electrical consumption while exploiting the beneficial multi-drop capabilities of the SAN network. Indeed, the practical limit about the total number of connected sensors per GW is dictated by the power budget admitted by the chosen GW-to-EC connection bus.

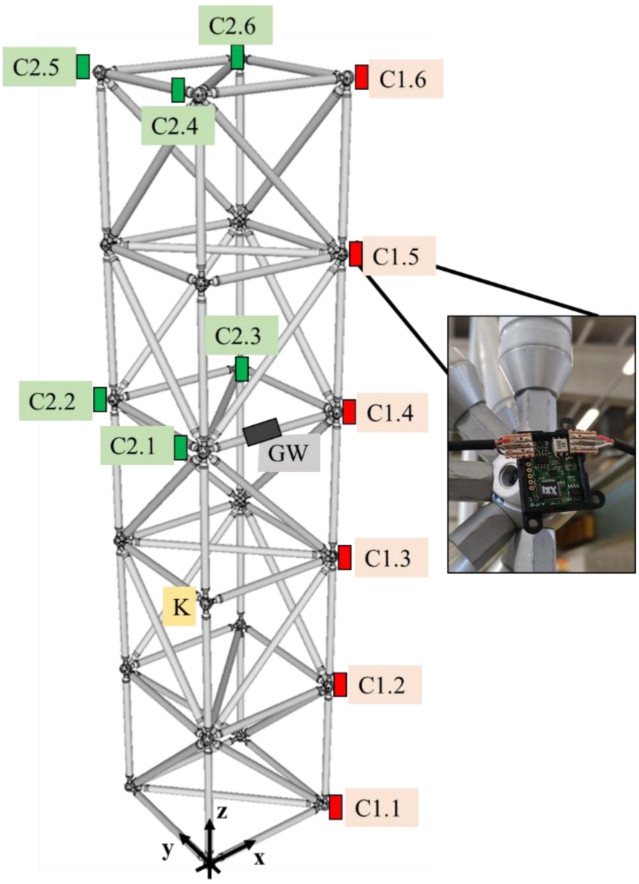


Fig. 3. Sensor installation plan over a 5-story frame

During this experimental campaign, a USB 2.0 cable with a nominal power output of 500 mA has been employed. As a result, taking into consideration the power drawn by the GW itself and that associated to the sensor node (which amounts to 8 mA and 40.8 mA respectively), a network density of 12 nodes simultaneously connected is achievable. Furthermore, a favourable deployment strategy was followed in order to halve the electrical load seen by the GW device concurrently allowing the torsional modes, which are expected to characterize the dynamic response of this structure, to be reconstructed. The final installation plan is sketched in Fig. 3 where the two clusters of sensors have been differentiated with red (cluster 1, label C1) and green (cluster 2, label C2) colours, while the GW unit is identified by the grey rectangle drawn at the mid-span of one bar on the third floor. Noteworthy, the geometrical rigidity of the elements imposes quite a stiffened dynamic behaviour. Thus, a sampling frequency $f_s = 833$ Hz was selected (among the available ones) to extend the spectral analysis in a frequency range compatible with the high-order modes of vibration, which are more suited for damage detection. Time series were acquired continuously with a fixed batch size of 2000 samples for each DoF.

Offline data retrieval

A sample dataset collected at point C1.3 after a one-shot knocking excitation of the frame (hammer shaking at point K along the y direction-see Fig. 3) is displayed in the upper panels of Figure 4 on top of the relative frequency content. These cloud data were accessed from a host PC remotely connected via the HTTP port and retrieved for further off-line processing.

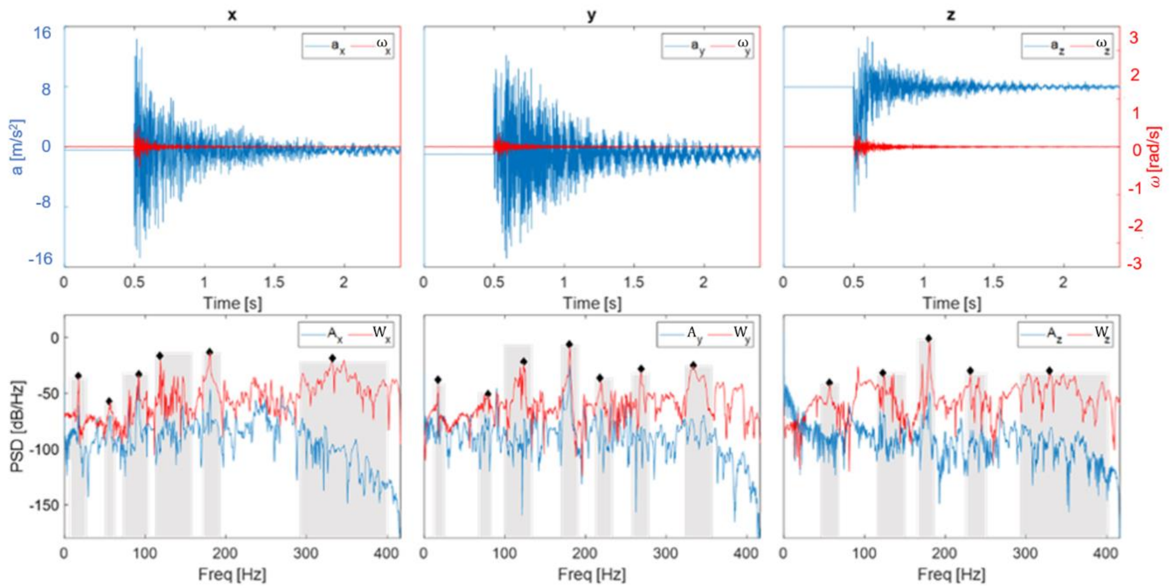


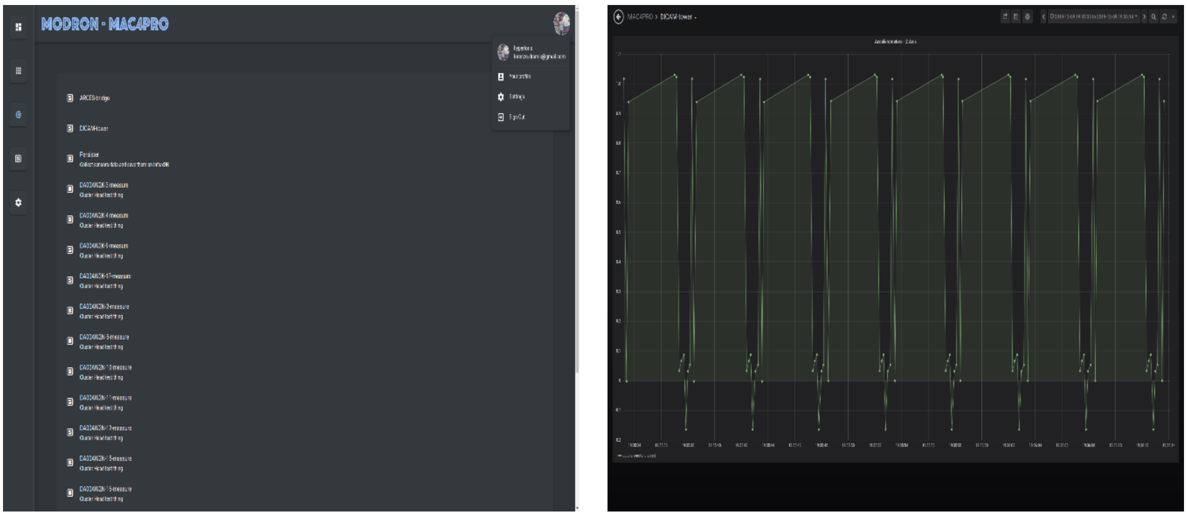
Figure 4. Signals collected at sensing position C1.3 along the three axes: time domain (upper panels) and frequency domain (lower charts) representation of acceleration and rotational data (blue and red line style, respectively). Regions evidenced with grey colour identify the frequency band associated to the most energetic spectral peaks.

The observed accelerations/angular velocities are coherent with the adopted spatial reference system, since the bending mechanism forces the structure to vibrate along the vertical axis, hence favoring highly lateral displacements while minimizing the vertical and rotational ones. As such, a richer and sharpner frequency distribution is expected along the x and y directions, a prediction which is proven by the denser and more localized number of harmonics appearing in the A_x/W_x and A_y/W_y spectra. Conversely, a flatter frequency profile characterizes the A_z/W_z response lying on the latitudinal plane. Moreover, the structural complexity causes the presence of tighthly coupled components, a condition which makes the modal identification problem more challenging. To stress this result, regions in grey background colour are drawn to evidence the frequency bands where most of the structural energy tends to concentrate after merging together the information inherent in linear and angular measurements. As it can be seen, the shape and the width of the identified spectral peaks broaden the higher the frequency.

Performing a cumulative evalutation, it may be argued that the spectral signature of the frame is substantially defined by several well-resolved components spread in the interval from 17 Hz to 200 Hz, the cardinality of which varies according to the specific axis each of them is likely to manifest on. In spite of that, a common dominant mode is present and located nearby 180 Hz. By monitoring how this frequency distribution varies over time, the health assessment procedure can be effectively performed.

Online data retrieval

In Fig. 5, evidence of the operations of the Data Acquisition and Data Management layers over the same scenario are provided. In detail, Fig. 5.a shows a screenshot of the Thing registration/discovery dashboard: the list of the sensors installed on the metallic structure and currently active is returned. By clicking on any sensor/Thing of the list, its TD is rendered; the users can read/update the values of the properties, execute an action or be notified of the occurrence of an event. The measurements of the active Things are gathered and stored in a database by the storage module executed in background on the private cloud. Besides, a screenshot of the Grafana tool with long-term x-accelerometer time-series are displayed in Fig. 5.b.



(a) (b)

Fig. 5. WoT-SHM framework during nominal working conditions: (a) list of active sensor/Things displayed by the, (b) accelerometer time-series values of Fig. 4 displayed by the Grafana tool

Conclusions

The WoT-SHM architecture thoroughly described in this work discloses a promising and innovative paradigm for the real-time and continuous health assessment of structures, such as industrial sites and civil buildings. The resulting system stands out for its scalability, heterogeneity, and extendibility, consequently supporting the diagnostics and prognostics phase which are meant as challenging but crucial phases in every monitoring process. In fact, by combining the advantages of smart sensing devices with the potentialities of the WoT standard, the network demonstrated to be performative and effective for the real structural evaluation of a tall 5-story frame. Future works will include the design and testing of data-analytics solutions for event detection and prediction, simultaneously implementing advanced and innovative signal processing techniques for the extraction of modal shapes, which are considered more effective for damage localization purposes. In terms of hardware equipment, a consistent up-scale of the network will be made effective, both considering the network density and the sensor heterogeneity by including MEMS and acoustic emission detectors. In parallel, the implementation of mobile and Web data visualization dashboards will be tackled. All these steps onwards will provide a tangible response to the need of real-time and continuous structural assessment required by 4.0 industrial applications.

Acknowledgement

This work has been funded by INAIL within the BRIC/2018, ID = 11 framework, project MAC4PRO ("*Smart maintenance of industrial plants and civil structures via innovative monitoring technologies and prognostic approaches*").

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Authors' bio

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