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Published Version:
Zyrianoff, I., Forlesi, M., Gigli, L., Kamali, S., Testoni, N., Mennuti, C., et al. (2024). Digital Smart Structure: Engineering a Sensor-to-Cloud Structural Health Monitoring Pilot. New York : IEEE [10.1109/MN60932.2024.10615780].

Availability:
This version is available at: https://hdl.handle.net/11585/1013710 since: 2025-04-01

Published:

DOI: http://doi.org/10.1109/MN60932.2024.10615780

Digital Smart Structure: Engineering a Sensor-to-Cloud Structural Health Monitoring Pilot

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***Abstract*—Real-time monitoring of civil infrastructures is of great importance to ensure their integrity and safety. Achieving these goals requires a strong synergy between multiple tools, disciplines, and approaches, which can be realized through a joint hardware-software co-design of the different components based on the Internet of Things (IoT) paradigm. Deploying IoT-based systems for bridge monitoring presents many challenges, including difficulties in deploying sensors in real-world testbeds, the lack of reliability of IoT devices, constant network disconnections, power outages, and challenges in rapid on-site maintenance. To address these challenges, we propose an IoT-SHM architecture that incorporates mechanisms to ensure robustness across system infrastructure, software components, data flow, and data quality. Our system was deployed on the Volto Santo bridge in Naples, where it successfully collected data for over six months, capturing more than 3000 acoustic emission events and more than 250 million accelerometer data points. Despite several interruptions due to environmental hazards, the system was able to automatically restart data collection. Additionally, we present the specifics of the testbed and a processing of the collected data based on operational modal analysis (OMA).**

***Index Terms*—Internet of Things, Structural Health Monitoring, Edge Computing, Real-world testbeds.**

I. INTRODUCTION

The aging of civil infrastructures, such as highway or railway bridges, along with their vulnerability to damage, has prompted authorities to adopt Structural Health Monitoring (SHM) systems [1], and fueled research on the sector. Through the continuous monitoring of various damage-sensitive features, SHM systems can assess the solidity of target structures and detect deviations from normal responses, prompting further safety measures. Effective SHM systems require seamless integration of sensing, communication, and decision-making subsystems to provide timely and reliable diagnostics [2].

Scientific research on SHM systems have focused on sensing technologies, aiming to achieve low-power and cost-effectiveness to facilitate dense deployments and support continuous real-time monitoring [3]. The IoT data collected, typically generated by sensors such as accelerometers and acoustic emissions (AE), can be analyzed using domain-specific or emerging Machine Learning (ML) techniques to detect anomalies and prompt alarms in the event of malfunctions. However, accurately characterizing the structural state needs long-term monitoring and reliable data collection, posing challenges in real-world deployments.

Typically SHM scenarios lack dedicated infrastructure for computational nodes and networking, rendering it vulnerable to various environmental hazards, including adverse weather conditions [2]. These challenges significantly impact the system's uptime, often requiring human intervention for maintenance tasks. However, this intervention comes with high costs and difficulties in accessing remote field locations. Managing real-world IoT solutions is more complex than traditional cloud systems due to factors as: (*i*) the absence of the stability provided by datacenters and the established cloud monitoring tools [4]; (*ii*) the distributed nature of IoT systems [5]; and (*iii*) the inherent unreliability of IoT devices [6].

This paper showcases a multidisciplinary collaboration involving electronics engineering, computer science, and civil engineering for the real-world design and implementation of an SHM system. Specifically, we describe the instrumentation and long-time monitoring of the Volto Santo highway bridge in Naples, as part of the DS2 INAIL BRIC 2021 project. We implemented a sensor-to-cloud IoT architecture for data collection from the monitored structure, incorporating robust mechanisms to ensure the reliability of data collection. Specifically, the contributions of this paper are as follows:

- We describe a generic IoT-SHM architecture and how the cyber-physical components have been properly deployed in the use-case of the Volto Santo bridge.
- We detail the data management system and the reliability mechanisms designed to ensure long-term operations, even in the presence of sensor or network failures. Following the taxonomy presented in [7], we distinguish mechanisms introduced at infrastructure, software, dataflow, and data quality layers.
- We present the experimental results related to the monitoring of the target bridge over a period of four months.

Specifically, we showcase results regarding the reliability of the proposed data management systems and insights into the structural state based on operational modal analysis (OMA).

In the remainder of this paper, Section II presents the architecture, while our use case is detailed in Section III. The data analysis results are discussed in Section IV. Finally, Section V concludes and proposes relevant future works.

II. IoT Architecture for SHM

In this Section, we introduce the overall hardware/software framework that have been used in our pilot. We deployed the `MAC4PRO` 4-layer IoT architecture [2] which was designed and validated in SHM environments. The architecture shows high adaptability to different conditions, since it supports heterogeneous devices, different communication technologies, applications with non-uniform interfaces, and multiple end-user roles. Figure 1 depicts the layered architecture adopted. Each layer defines a specific function, as detailed below:

1) *Sensing* layer, encompasses devices responsible for interacting with the physical world.
2) *Interoperability* layer, offering uniform and standard interfaces inter-layer interactions and on-boarding tasks, as automatic discovered of applications and devices.
3) *Data Management* layer, encompasses tools that are responsible for the data storing, filtering, processing, and transformation operations.
4) *Service* layer, is comprised of services for end-users and integration with third-party applications or systems.

The architectural design is decoupled from the deployment plan. Based on the requirements and the available resources, the software components can be variously configured and deployed along the edge-cloud continuum [5]. For instance, they can be assigned entirely to edge nodes near the monitored structure or distributed among the cloud and the edge nodes.

Regarding the *Interoperability* layer, our framework adopted the W3C Web of Things (WoT) standard [8], [9]. Indeed, the latter facilitates interoperability within IoT settings by abstracting the real components of the system as a Web Thing (WT), which has its capabilities, features and metadata formally described by a Thing Description (TD). The TD serves as a standardized representation of a WT, enabling consumers to discover and comprehend its capabilities. The TD contains a set of interaction patterns (i.e., affordances) that a service or device is capable of supporting. The WTs are implemented within a software runtime named *Servient*, which allows to host and expose a WT (i.e., to make it available over a network). Finally, a Thing Description Directory (TDD) serves as a central repository for managing a collection of TDs, offering a broader set of APIs for filtering and searching for the desired TDs, thereby enhancing the discoverability and accessibility of WTs within the system [10].

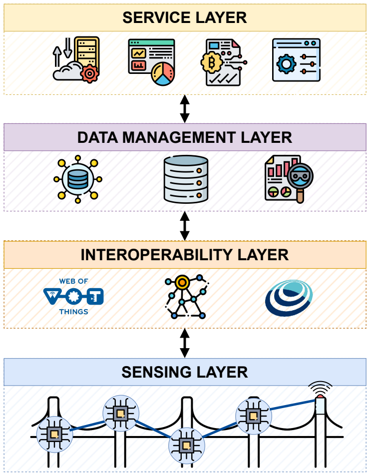

Fig. 1: High-level IoT Architecture, adapted from [2]

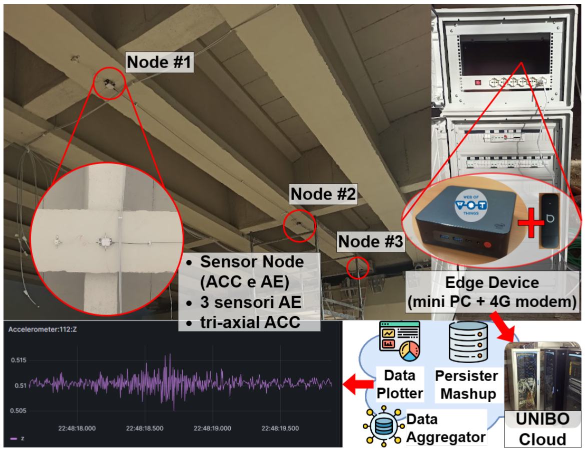

Fig. 2: Use case deployment of the IoT-SHM system

III. The Volto Santo Use Case

We deployed the `MAC4PRO` architecture to monitor the Volto Santo viaduct. Situated in Naples, the viaduct is a steel-reinforced concrete infrastructure serving as an important transportation hub for the city. Subsection III-A presents the hardware and structure components of the motoring system, while subsection III-B details the management mechanism adopted to enable a reliable long-time monitoring campaign.

A. SHM system

The deployed SHM system has the ability to continuously monitor the structure over time to detect and track long-term degradation. Figure 2 illustrates the deployment of the cyber-physical components within the monitored structure. The high-level depiction portrays sensors recording acceleration responses and AE from the structure. These data are then transmitted to an edge node, which functions as a network gateway and a first computation unit, performing pre-processing operations and offering abstraction features. Subsequently, the data is forwarded to the cloud, where it is stored. The cloud hosts computational-demanding software components responsible for tasks such as visualization and data analysis. Regarding the hardware components:

- **Sensor Hubs**: low-power peripheral devices that integrate the electronic components for performing data sampling tasks and data transmission. They are protected from environment hazards (e.g., dust and water particles) by a IP5 case. Each sensor hub is equipped with a triaxial accelerometer and three acoustic emission signals with sampling frequency of 2 MHz. Each sensor hub is capable of executing simple sensor-near computational tasks [3].
- **Edge Node**: the sensor hubs where connected to an embedded computational node which was installed in a cabinet near the monitored structure (as depicts Figure 2), which provided it an energy supply. The edge node is a mini-pc (Beelink U59 with an Intel Celeron N5105 and 8 GB RAM) connected to the network through a 4G LTE USB Dongle.
- **Cloud Server**: a small scale private data center comprised of two machines running a container orchestrator (i.e., Portainer[1]). Each application deployed on the cloud server is configured as a lightweight container (e.g., Docker[2]) with reserved access to two logical CPUs (Intel Xeon Gold 6238R CPU @ 2.20GHz) and 8 GB of RAM.

As stated in Section II, the architecture employed is agnostic regarding the location of the computational node on which it is deployed. Consequently, this flexibility has enabled us to make optimal choices tailored to the specific monitored pilot. Table I lists the software components utilized in the Volto Santo use case, along with their placement in the infrastructure and architectural layers.

The **Firmware** is responsible for interfacing with the hardware of the sensors and collecting data. Its current configuration enables the data acquisition process to be triggered in either a *passive* or *active* manner. The passive mechanism utilizes an auto wake-up threshold, where one channel constantly monitors the structure at a lower sampling rate. Upon reaching a predefined threshold, it initiates a data acquisition operation of 120 seconds, storing the collected data points in its internal buffer until retrieved by the edge device. The active mechanism involves sending a command via the SAN protocol [11], wherein the duration of the data acquisition session – whether short (30 seconds) or long (120 seconds) – is determined by the message sent. In both cases, data is transferred from the sensors to the edge node through a serial interface implementing the SAN protocol.

The **Feature Extraction** process involves extracting features from the time-series raw data points collected by the sensors, which serves to reduce data dimensionality and to reveal significant characteristics of the measurement data. The feature extraction algorithm for the acoustic emission sensors can operate independently for each sensor hub, whereas for accelerometers, it cannot. Relevant accelerometer features are characterized in the frequency domain, utilizing global damage indexes calculated during a post-processing phase after aggregating and synchronizing data from all sensors [12]. Consequently, feature extraction for accelerometers is performed in the cloud. In contrast, acoustic emission sensors excel at detecting sources of damage generated by energy releases. For this reason, features such as peak amplitude, signal energy, and acoustic emission event counts, can be computed locally. We deployed the feature extraction algorithm directly on the sensor hub, which significantly reduced data dimensionality (more than to by 99% of data reduction [13]), thereby reducing the amount of data transmitted to subsequent processing modules and lowering energy consumption by the sensor hub. Our previous studies demonstrated that transmitting raw data consumes more energy than executing the feature extraction algorithm itself [2]. Each sensor hub has its own capabilities (e.g., actions, properties, and events) and metadata (e.g., deployment location, units of measurement) mapped as a W3C TD [8] and deployed as in a Servient. The WTs of the sensor hubs are deployed in the edge node, acting as virtual sensors for the physical ones deployed. The WTs abstract the SAN interface and provide a standard interface that enables the triggering of data acquisition and adjustment of device characteristics.Further, WTs can be seamlessly integrated to other applications, examples are MODRON [14] and DESMO [15]. The collected data is stored in the **Persistor**, a specialized time-series database (InfluxDB[3]), which is tailored for efficient storage and querying of time-stamped data.

To efficiently index the sensors abstracted as WTs in our system, we utilized a implementation of a TDD. In specific, we adopted ZION [16], a scalable implementation of the W3C TDD standard. ZION stores the TDs of the sensor hubs used in the deployment along with their servient location – i.e., IP address or DNS. Through the TDD interface, users can pose semantic queries to discover TDs that match their requirements (e.g., retrieve all WTs that have a vibration sensor in the third column of the viaduct).

The **Data Plotter** component offers visualization capabilities for the data stored in a dashboard format, as depicted in the bottom left corner of Figure 2. The Data Plotter enables users to generate custom graphs, filter data based on time intervals or specific data features.

The deployed **Data Analysis** operates in two main modes: (*i*) Real-time: Anomaly detection analysis is applied to assess the condition of the viaduct in real-time, analyzing the data stream after the feature extraction processing step. Upon detection of significant anomalies, an alarm is sent to the administrator responsible for the structure, potentially triggering maintenance operations. (*ii*) Batch: The stored data is periodically analyzed to detect variations in the behavior of the viaduct over longer periods of time. This batch analysis allows for the identification of trends and patterns that may indicate potential structural issues or degradation.

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[1] https://www.portainer.io/

[2] https://www.docker.com/

[3] https://www.influxdata.com/

TABLE I: Deployment of the Software components on the Volto Santo pilot

Software Component	**Layer**	**Placement**
Firmware	Sensing	Sensor
Feature Extraction	Data Management	Sensor and Cloud
Web Thing Servient	Interoperability	Edge
Thing Directory Description	Interoperability	Cloud
Data Plotter	Service	Cloud
Data Aggregator	Data Management	Cloud

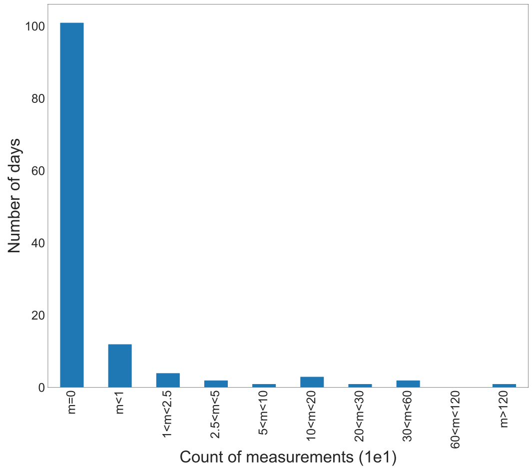

Fig. 3: Number of days per measurement (m) count interval for the acoustic emission sensor. The intervals should be multiplied by 10.

B. Management system

The system described in Subsection III-A was deployed for a long-term monitoring campaign in an environments with many disruptions on the data collection. Indeed, we experienced frequent network connectivity issues and power supply outages. In order to maximize the reliability of the our framework, we utilized the characterization of IoT management system proposed by Silva et. al [7] which defines that the management of IoT system should encompass four interconnected aspects. We present these layers and the mechanisms adopted in the Volto Santo setup to manage it:

- **Infrastructure**: the management of physical components of the system, such as the sensor hubs, the edge node and the edge-cloud network connection. In our specific use case, the primary infrastructure issue encountered was frequent power outages on the viaduct, affecting both the edge node and the sensor hubs. To mitigate this problem, we equipped the edge node with an mechanism that automatically turns on in case that power is detected.
- **Software Components**: the state of the software applications within the system. We deployed a management agent on the edge node: this agent periodically ensures that sensor data collection and the other applications are executing correctly. In the event that an application crashes, the agent automatically restarts it. This mechanism, combined with auto-wake functionality, enables the system to restore itself after power shortages.
- **Dataflow**: manages the flow of data between software components. In the Volto Santo setup, the most critical connection is between the sensor hubs and the edge node. The microcontrollers in the sensor hubs are susceptible to errors, since the communication channel employs a simpler protocol stack than IP/TCP, hence it lacks error correction and re-transmission capabilities. To address this, we implemented two strategies: (*i*) leveraging the SAN protocol by sending redundant commands spaced by a few milliseconds to ensure the sensor hubs receive the commands; and (*ii*) implementing error handling algorithms in the byte-stream conversion process (executed at the edge), mitigating issues from interferences.
- **Data Quality**: involves analyzing the collected data with respect to its accuracy and reliability (e.g., negative temperature values in an outdoor sensor during the summer). This process occurs offline and in batches, concurrently with the data analysis stage. During this phase, we conduct “sanity checks” on both accelerometer and acoustic emission data. If any issues are detected, further investigation is triggered to identify the source of the problem, which could stem from sensor calibration to a bug on the feature extraction component.

Each base layer needs to be operational for the subsequent one to be functional (e.g., without an working infrastructure it is not possible to have software components executing).

IV. DATA ANALYSIS

This section is divided into two distinct analyses. The first is a meta-analysis aimed at characterizing the collected dataset. In the second analysis, we apply some algorithms to extract modal parameters from accelerations and to visualize the AE features over the monitoring period.

A. Meta-analysis

The meta-analysis utilizes datasets from both types of sensors: the acoustic emission sensor (AE) and the accelerometer, with the recorded data spanning from November 2023 to March 2024. Fig. 3 illustrates the daily count of measurement intervals for the AE sensor, revealing significant data gaps in December and late November, during which the sensors were inactive due to a power outage. Consequently, December data was omitted from the analysis presented in Fig. 4. The boxplot in Fig. 4 depicts the monthly distribution of average AE amplitudes, typically clustering around 100 dB, suggestive of ambient noise from vehicular traffic on the viaduct, with outliers predominantly representing periods of lighter traffic.

Fig. 5 displays the counts of measurement per days for the accelerometer, which depicts the same interruption in data transmission. The data distribution per day under normal operational conditions typically ranges between 25,000 and 30,000 readings, as shown in Fig. 5. Fig. 6 presents a boxplot of the accelerometer’s magnitude ($|m| = \sqrt{x^2 + y^2 + z^2}$) variations across the x, y, and z axes over three months,

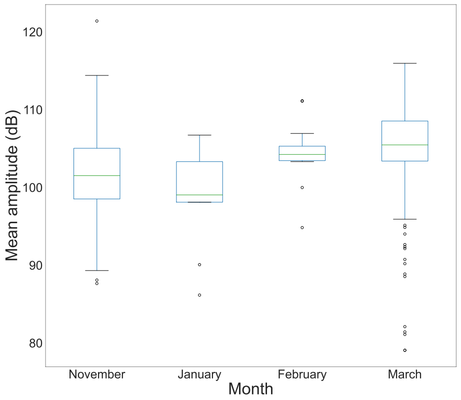

Fig. 4: Monthly distribution of mean amplitudes for the acoustic emission sensor

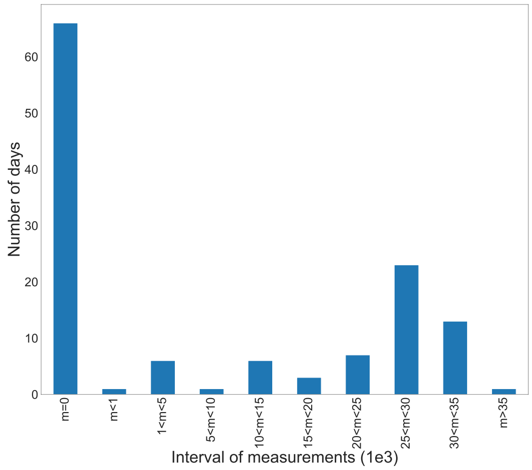

Fig. 5: Number of days per measurement (m) count interval for the accelerometer sensor. The intervals should be multiplied by 10^3

with relatively symmetric distributions centering around a median magnitude of 0.515g . The outliers are attributed to exceptional traffic loads, temperature fluctuations, and seismic activity, considering Naples' significant geological dynamics.

B. Data analysis

1) Operational modal analysis: In this Section, operational modal analysis (OMA) is employed to extract the modal frequencies of the bridge, which are subsequently used as the damage-sensitive features in the monitoring system [17].

Given the availability of one channel per direction, we employ the peak-picking (PP) technique [18], where auto-power spectral density (PSD) function of the acceleration time histories are computed, to extract the spectral peaks, interpreted as the modal frequencies.

At first, the raw accelerometer data are scaled by a factor of 2 to represent values in units of g, as specified by the sensor manufacturer, followed by detrending to remove offsets. Then,

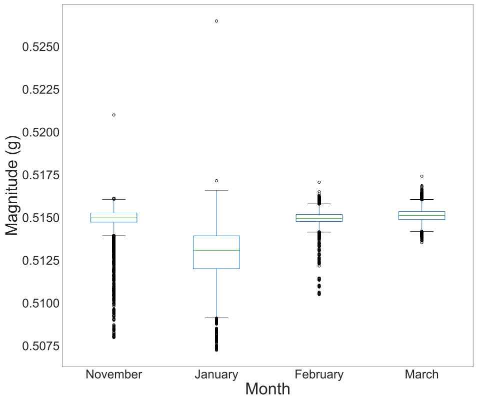

Fig. 6: Monthly distribution of the magnitude for the accelerometer sensor

signals of 500 seconds duration are utilized, from which the PSD functions of the signals are computed. With a registration sampling frequency of 208 Hz, resulting in 104,000 samples per signal, we employ the Welch method for PSD calculation. Specifically, we use Hann windows consisting of 2080 samples with a 50% overlap. With these settings, a frequency resolution of 0.0508 Hz is obtained for the PSD functions.

An example of the conducted analysis is depicted in Fig. 7, showcasing selected 500-second signals and their corresponding PSD spectra with detected peaks for the x direction (a, b), y direction (c, d), and z direction (e, f). The results reveal a fundamental frequency of approximately $f_1 = 7.70$ Hz appearing in both the y and z directions (7.72 Hz and 7.67 Hz, respectively), indicative of a torsional mode. Subsequently, a translational frequency of $f_2 = 9.34$ Hz predominates in the x direction. Then, $f_3 = 13.3$ Hz emerges in the y direction, followed by $f_4 = 22.95$ Hz and $f_5 = 28.49$ Hz in the z direction. All identified frequencies are close to the estimated values derived from an eigenvalue analysis conducted on a developed finite element model (FEM) of the bridge. For brevity, the FEM details are not provided here.

2) Acoustic emission: The alternative damage-sensitive features investigated in this study are the acoustic emission (AE) parameters, namely amplitude (A) in dB, number of AE events (counts), and the measured area of the rectified signal envelop (MARSE) in mJ, represented in Fig. 8a, b and c, respectively. It is possible to notice concentrations of events on November 16, 2023, during the period of November 20-23, 2023, on January 10, 2024, and during the periods of January 15-30, 2024, February 24-29, 2024, and March 1-14, 2024.

V. CONCLUSION

In this work, we have proposed an IoT hardware/software framework for Structural Health Monitoring (SHM) of civil infrastructures like bridges. Our system was deployed on the Volto Santo bridge in Naples, where it successfully collected data for over six months, capturing 3,181 acoustic emission events and 267 million accelerometer data points. The focus

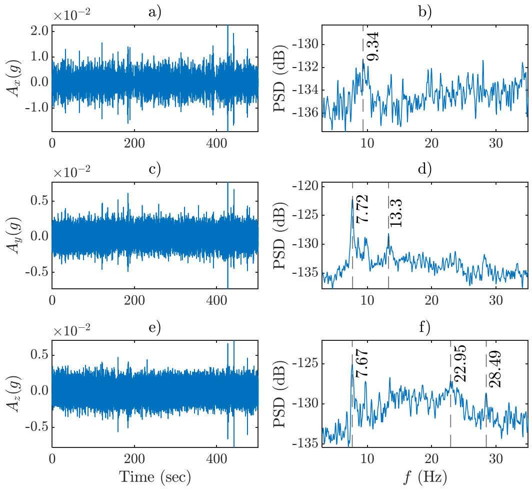

Fig. 7: Acceleration time histories of 500 seconds and their respective PSD spectra with detected modal frequencies in the x (a)-(b), y (c)-(d), and z (e)-(f) directions.

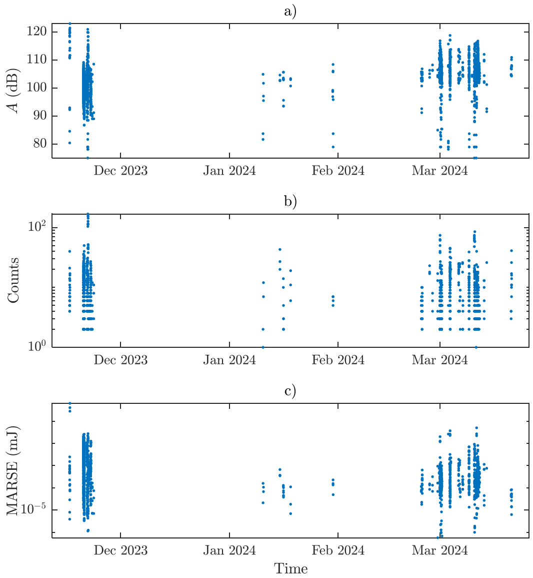

Fig. 8: a) Amplitude, b) counts, and c) MARSE. The y-axis of (b) and (c) are in log-scale.

of our study was on mechanisms ensuring robustness across system infrastructure, software components, data flow, and data quality. The experimental results show that the monitoring system has proven to be robust to power outages, network issues, and software/hardware problems. Future research activities include: application of anomaly detection and damage classification techniques based on ML approaches, integration of Over the Air (OTA) software update mechanisms across the continuum, testing of wireless communications between the sensors nodes and the edge devices for SHM data transfer.

ACKNOWLEDGMENT

The presented work has been partially supported by the project “DS2: Digital Smart Structures”, funded by INAIL (Italian Workers’ Compensation Authority), BRIC 2021.

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