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Advancing sensing solutions for data-driven seismic damage assessment of non-structural elements: current challenges and future directions

Daniele Sivori[1], Mauricio Guamán[1], Marco Todaro[1], Volkan Ozsarac[1], Davit Shahnazaryan[1], Gerard J. O'Reilly[1]

1- Centre for Training and Research on Reduction of Seismic Risk (ROSE Centre), Scuola Universitaria Superiore IUSS di Pavia, Italy

daniele.sivori@iusspavia.it

Abstract

Non-structural elements (NSEs) frequently account for the majority of earthquake-induced economic losses and operational downtime of buildings. While this issue is widely recognised by the engineering community, the adoption of modern sensing technologies to monitor NSEs during earthquakes and assess their damage state remains limited to a few isolated examples. The SONATA project tackles this open research challenge, proposing the integration of continuous and heterogeneous streams of experimental data into a holistic seismic assessment framework. The primary motivation is to enhance the speed and accuracy of damage evaluations for buildings, thereby improving the estimation of fragility and streamlining loss assessment. Within this context, the paper discusses the state-of-the-art sensing solutions that can be employed today to measure seismic demands and damage evolution of NSEs. A range of modern technologies is considered, ranging from traditional vibration-based sensors to emerging non-contact techniques, in particular computer vision, as well as autonomous systems such as drones for unmanned inspections. A critical aspect concerns the trade-offs between monitoring global engineering demand parameters (EDPs), such as floor accelerations, and local response quantities, such as component-specific deformations. While vibration sensors provide robust global information at a relatively low cost and are suitable for large-scale deployment, optical sensors offer the complementary granularity required to detect local defects (e.g., cracking, unseating) and assess component damage and loss of functionality. Framed within the SONATA project, the work addresses the challenges of implementing these systems in a real-world setting, as well as the computational architecture and analysis procedures to efficiently support these technologies. Strategies for managing continuous streams of data generated by monitoring systems and data fusion techniques are explored to merge heterogeneous datasets (e.g., experimental EDPs and unstructured image data from vision systems). Special emphasis is placed on automation, specifically on how machine-learning (ML) algorithms can reliably categorise damage states from images and inform experimental NSE fragility models through statistical updating. The first experimental campaign, focused on gypsum partition walls, is presented to illustrate the combined vibration- and vision-based monitoring strategy adopted within the project. The future extension of the framework to populations of buildings with similar NSE and structural characteristics paves the way for a generation of resilient, interconnected, and self-diagnosing structures informed by robust experimental data.

Keywords: Non-structural elements, Structural Health Monitoring, Computer vision, Data fusion, Fragility assessment.

1- INTRODUCTION

Non-structural elements (NSEs), including partition walls, suspended ceilings, cladding systems, mechanical and electrical equipment, and building contents, represent the dominant source of earthquake-induced economic losses and post-event downtime in modern buildings [1]. In many past earthquakes, losses attributable to NSE damage have exceeded those caused by structural damage, and NSEs begin to sustain significant damage at seismic demand levels well below those required to compromise the load-bearing system [2][3][4]. Beyond direct repair costs, failure of non-structural components has repeatedly disrupted the functionality of commercial and critical facilities, including hospitals, emergency response centres, and infrastructure nodes, at precisely the moment when continuous building functionality is most needed, in the emergency phase following an earthquake event.

Despite this recognised vulnerability, the seismic assessment of NSEs remains considerably less developed than its structural counterpart. Fragility functions for NSEs are derived predominantly from experimental shake-table campaigns [5], which often fail to reproduce accurately the in-situ installation and operation conditions of these components [6]. Even though post-earthquake damage surveys are common practice and empirical damage states are available, given the limited number of dynamic monitoring systems currently deployed in buildings, the corresponding floor demands are rarely measured. Field assessments are still largely conducted through visual inspection, a process that is time-consuming, subjective, and not suited for large-scale deployment [7].

These issues result in a persistent gap between the seismic demand and damage experienced by NSEs during an earthquake, and those reproduced by shaking table tests in a controlled laboratory environment. The consequence is reduced reliability of the experimental fragility functions [6]. The context highlights a broader limitation in current practice: the absence of consolidated frameworks capable of linking measurements of engineering demand parameters (EDPs) to the actual damage level of NSEs. Sensing technologies that could directly capture floor accelerations, storey drifts, and component-level deformations are available and technically mature, yet their systematic deployment for NSE monitoring remains sporadic. Similarly, computer vision and machine learning (ML) tools have recently become capable of automating seismic damage detection and classification from photographic or video data [8], but their application to NSEs, with their heterogeneous geometries, materials, and failure modes, presents unresolved problems of generalisation, training data availability, and operational scalability.

This paper analyses the challenges that must be addressed to bridge this gap, within the broader effort of the seismic engineering community to integrate structural monitoring and artificial intelligence for the automation of structural health assessment [9]. The contributions of the paper are threefold. First, it provides a critical analysis of state-of-the-art sensing solutions for measuring seismic demands on NSEs, identifying MEMS accelerometers as the most suitable option for scalable deployment. Second, it examines the role of vision-based machine learning models in automating post-earthquake damage detection and classification for NSEs, highlighting the requirements that training datasets must satisfy to achieve reliable performance. Third, building on these analyses, it proposes a methodological framework — developed within the SONATA research project — that integrates vibration measurements, image-based damage recognition, and Bayesian updating of experimental fragility curves to support risk-informed decision-making for NSEs, and presents preliminary insights from the first experimental campaign carried out to ground this framework, consisting of shake-table tests on gypsum partition walls with combined vibration- and vision-based instrumentation.

2- Sensing Solutions to Monitor the Seismic Response of Non-Structural Elements

The seismic response of NSEs can be correlated with a limited set of demand parameters, which depends on the type of element, its connection to the main structure, and the damage mechanism governing its response during seismic shaking. Acceleration-sensitive elements, including mechanical and electrical equipment, storage racks, furniture and building contents, are primarily governed by peak floor acceleration. Conversely, several architectural elements connected to the lower and upper floors such as partition walls, glazing systems, cladding panels, and vertical plumbing systems, respond predominantly to peak storey drift. Some categories, for example suspended ceiling systems, can be sensitive to both, and the evolution of their damage state cannot be accurately tracked by monitoring either parameter alone.

These EDPs can be classified as global, since they pertain to the whole storey and characterise the overall demand transmitted to NSEs by the supporting structure. These are the quantities commonly used in standard fragility functions derived from shake-table experiments or code-based procedures, since they can be easily estimated from ground-motion intensity measures such as peak ground acceleration or measured directly by building monitoring systems. In the latter case they can be extracted, in principle, from relatively sparse sensor deployments on the floors (e.g., one bi-axial sensor per floor, vertically aligned). Component-level EDPs, by contrast, describe the demand experienced locally, for example the relative displacement across a partition bay, the acceleration at a ceiling grid attachment point, or the rocking response of freestanding equipment. Local EDPs are often difficult to measure directly, yet they sometimes govern failure at component scale and can become relevant for damage-state identification.

Given this distinction, accelerometers remain the most widely deployed sensor type for global seismic monitoring. Acceleration records acquired on the floor can be used to reconstruct peak storey drifts through well-known double-integration procedures with appropriate baseline correction and filtering. Some limitations arise when floor-level coverage is sparse, as the spatial variability of demand across deformable floor diaphragms cannot be accurately reconstructed. Torsional components, which can amplify demands on perimeter NSEs relative to core-aligned sensors, cannot be systematically estimated when instrumentation is limited to one bi-axial sensor per floor. Indeed, to decouple the effects of rigid translations from torsion and local diaphragm deformability, at least one bi-axial and one mono-axial horizontal sensor placed some distance apart on the floor are required [10]. These considerations lead to a trade-off between monitoring cost and the ability to resolve spatial variability of seismic demand.

In this context, recent advances in micro electro-mechanical systems (MEMS) are making this sensing solution particularly attractive for both seismic monitoring and structural health monitoring (SHM) of buildings. These miniaturised devices are becoming increasingly affordable. They are easy to manage and deploy, thanks to their compact size, and easy to integrate into mobile acquisition units or permanent monitoring systems. In recent years, several urban-scale monitoring networks have been developed based on low-cost MEMS sensors deployed in sparse layouts, typically with only a few sensors per building [11]. This strategy makes it possible to contain installation costs and extend monitoring coverage to many structures [12]. However, low-cost MEMS sensors generally do not provide the low-noise performance required for vibration-based SHM under ambient excitation. Several low-noise MEMS sensors are currently available on the market (Figure 1a). They have been successfully tested and employed in dynamic monitoring applications of interest to earthquake engineering [13] and are becoming increasingly widespread in continuous health monitoring of structures based on ambient vibrations [14] (Figure 1b). Modern MEMS sensors, in fact, are extremely sensitive in the frequency range of interest for civil structures subjected to earthquakes, reaching noise levels as low as 0.02 μg/√Hz in the band 1–10 Hz (Figure 1c).

These advances are opening new frontiers in earthquake engineering, where hybrid monitoring solutions can support both seismic monitoring and continuous ambient vibrations-based SHM of civil structures. This includes relatively stiff systems exhibiting low-amplitude operational vibrations, such as mid and low-rise buildings. Such dual capability is particularly relevant for improving damage-state identification for both structural and non-structural components, as it allows combining global response indicators with changes in dynamic properties that can be associated with damage [15].

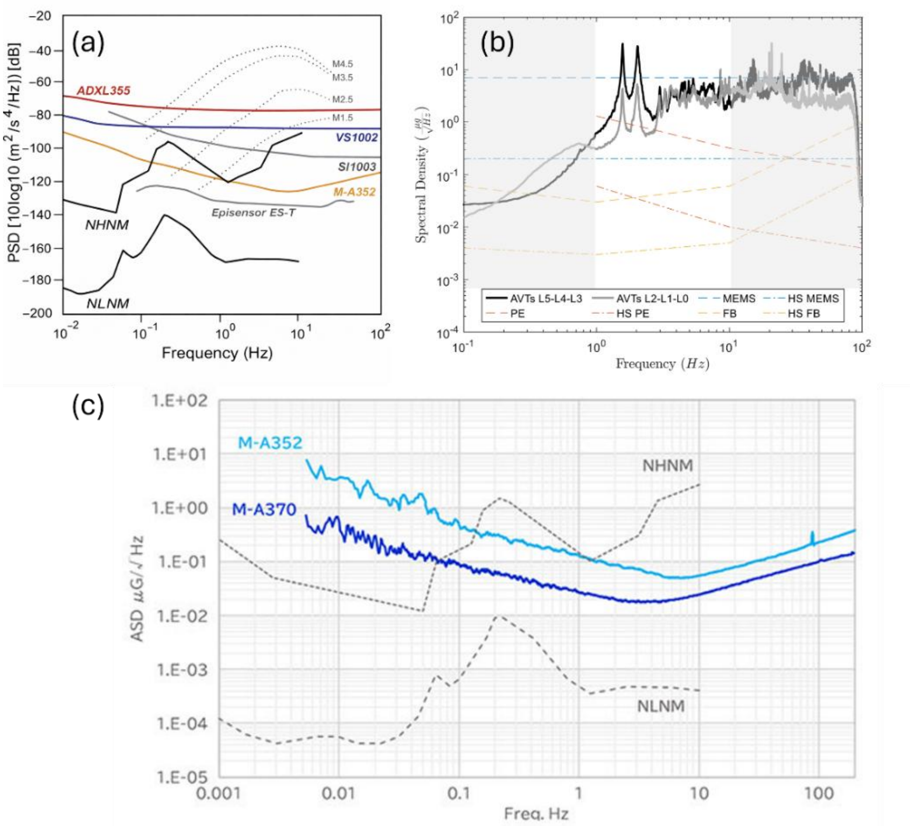


Figure 1- Noise levels for seismic MEMS accelerometers. (a) Comparison between different types of MEMS sensors, ground noise models and near earthquakes (adapted from [13]). (b) Employment of MEMS sensors with high sensitivity (HS) in the frequency band 1-10 Hz to monitor ambient vibrations for SHM of a masonry church

(adapted from [14]). (c) Commercial low-noise digital MEMS whose performance is below the USGS New High Noise Model (NHNM) (from https://corporate.epson/en/news/2025/250522.html).

3- AUTOMATING DAMAGE CLASSIFICATION THROUGH VISION-BASED TECHNOLOGIES AND MACHINE LEARNING TECHNIQUES

Quick post-earthquake evaluation is critical for determining the level of damage sustained by buildings after a seismic event, enabling structures to be promptly tagged as safe for immediate reoccupation or restricted until repair. Conventional assessments are influenced by several limiting factors, including accessibility to affected areas, the risk posed by entering damaged structures, the availability of qualified experts, and the subjectivity of technicians assessing damage. The utility of SHM systems for seismic performance evaluation based on measured EDPs is clear, but only in a few cases has it been extended to the assessment of NSEs [16]. While this approach significantly reduces assessment time, ambiguity remains in the interpretation of damage states, in particular for low levels of damage, which may correspond either to moderate but potentially life-threatening damage or to minor, repairable damage.

This uncertainty highlights the importance of obtaining more accurate damage discrimination, especially for NSEs, which can suffer significant damage even under low levels of ground shaking [4]. In this context, recent advances in vision-based ML models and, more generally, artificial intelligence (AI) technologies have gained increased attention in civil engineering.

For NSEs, it is relevant to investigate algorithms that allow object detection in complex scenes, for example building interiors, and to classify the damage state of each identified component. In the first case, convolutional neural networks (CNNs) are the primary models used for object detection and have been successfully applied across many fields, including earthquake engineering. A comprehensive review of deep learning-based damage detection and its integration with unmanned aerial systems to enable autonomous assessments with minimal or no human intervention is provided in [17]. This methodology could be relevant for post-earthquake evaluation, as it offers a viable solution for reducing inspection costs and overcoming difficulties in accessing hard-to-reach locations, where unmanned vehicles play a crucial role in data acquisition. Advances in deep learning have also increased interest in computer vision applications within civil engineering, with algorithms adapted to address a wide range of structural assessment problems. Recent studies have demonstrated the use of computer vision for multi-class damage detection [8], corrosion detection [18], and crack identification [19]. As a result, these approaches can complement or partially replace traditional inspection methods, improving efficiency in performance assessment procedures.

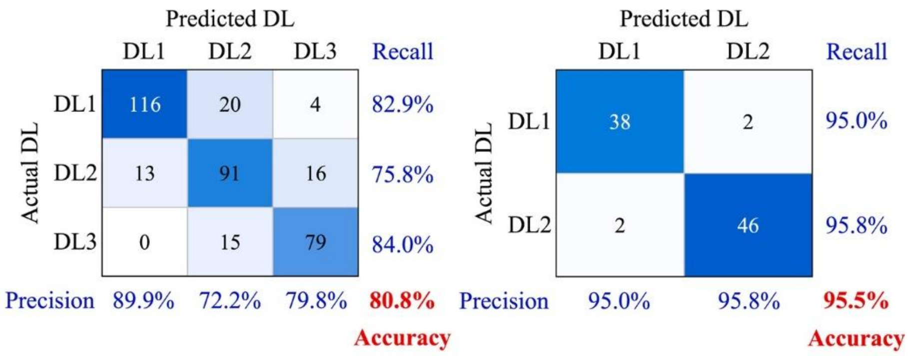
NSE detection and identification are important because most NSEs are located indoors, and many of them coexist within the same room. In addition, they are often displaced or disordered due to earthquake effects, and each of them presents different types of damage associated with different damage states [4]. Thus, it is necessary to isolate each component to enable separate analysis, since they have different damage mechanisms and visual patterns depending on the material and construction typology. As a result, this extraction process reduces noise compared to analysing all components simultaneously. To address this stage, i.e., object detection, CNN architectures appear to be the most suitable algorithms. Previous studies have compared different pre-trained computer vision models and shown that, among others, YOLO offers the best overall balance of speed and accuracy [20][21]. Other studies focused on concrete crack detection, corrosion detection, and spalling use this as the main model after applying transfer learning using task-specific datasets [18][19].

Concerning the second stage, i.e., damage classification, recent studies have confirmed that CNNs can also be adopted as an effective solution for post-earthquake damage surveys. A recent work [22] proposed a comprehensive deep learning framework for the classification of seismic damage in reinforced concrete buildings for both structural and non-structural components, demonstrating that refined damage classification criteria combined with transfer learning approaches can achieve high accuracy across multiple component types. In the case of NSEs, the study reported a damage classification accuracy of 80.8% for infill walls (minor, moderate and severe damage corresponding to damage levels DL1, DL2, DL3, see Figure 2a), and 95.5% for ceilings (for no damage DL1 or damage DL2, see Figure 2b), and emphasised the role of preprocessing and data augmentation in improving the quality of the training dataset. Furthermore, several analyses were conducted to evaluate model performance, revealing that a transfer learning approach based on AlexNet provided the best overall results. However, the authors also noted that a generalisation of the approach requires the development of a more comprehensive and representative dataset of observed damage, extending the coverage of different structural and non-structural components, structural types and levels of damage.

In addition, [8] analysed a range of CNN-based architectures for multi-class damage detection in reinforced concrete buildings, including quantum convolutional neural network (QCNN). Comparative analyses reported accuracy differences of up to 16% between the higher performance of QCNN and lightweight architectures such as MobileNetV2. Again, these studies indicate that model accuracy is not solely dependent on the network architecture, but it is strongly affected by the quality, balance and level of refinement of the training dataset. This suggests that carefully curated and representative datasets are essential for achieving robust performance, particularly for damage classification (see [23][24]).

In summary, the integration of CNN-based computer vision models may enable the development of automated pipelines capable of effectively addressing both object detection and damage classification tasks for NSEs, even in complex post-earthquake indoor environments. These models enable fast and reliable identification of individual components, while deep learning dedicated to classification can assign damage states consistent with engineering-based criteria, thereby reducing inspection time, cost, and subjectivity associated with traditional assessments.

However, the full potential of these approaches depends on the availability of large, well-balanced, and representative training datasets. The wide variability in typology, materials, and damage mechanisms characterising non-structural components requires ad-hoc image datasets with adequate coverage of different damage states and real-world conditions. The development and standardisation of dedicated datasets appear as a key step to ensure the reliability of AI-based applications for post-earthquake assessment of NSEs.



(a) Task 2: Infill walls (b) Task 3: Ceilings

Figure 2- Performance of CNN-based damage classification for NSEs (adapted from [22]). Confusion matrices for (a) infill walls and (b) ceilings.

4- SONATA PROJECT: DATA-DRIVEN RISK ASSESSMENT OF THE BUILT ENVIRONMENT

The previous sections discussed how seismic demands on NSEs can be estimated by measuring floor accelerations and extracting EDPs either directly or indirectly, from sensor layouts with regular vertical spacing and sparse floor coverage. In the vast panorama of possible sensing solutions, modern MEMS accelerometers appear to be the most suitable technology for seismic monitoring of buildings, thanks to their continuously improving performance and unmatched versatility.

In parallel, vision-based ML models can automate object detection and damage classification, even though they still lack dedicated training for NSEs. Moreover, no existing framework has yet been proposed to systematically fuse the heterogeneous data acquired from monitoring systems (vibration-based) with damage observations (vision-based).

In this context, the SONATA project addresses these gaps by proposing an integrated workflow that merges vibration-based seismic monitoring of buildings with image-based ML damage classification. The aim is to improve damage and loss assessment for NSEs in monitored buildings, grounding risk-assessment procedures in experimental data acquired during and after the earthquake.

Figure 3 shows the architecture of the project, which is organised in six Work Packages:

- WP1 – Experimental testing, dedicated to shake-table testing of NSEs to develop experimental fragility curves;
- WP2 – Sensors, which will select and deploy the most suitable sensing technology to monitor EDPs, aiming at automating their extraction in real monitored buildings;
- WP3 – Damage detection, employing data from WP1 tests to train image-based ML models to classify damage in NSEs;
- WP4 – Fragility models, in which experimental fragility curves (from WP1) will be statistically updated based on measured EDPs and identified damage states in the monitored building;

- WP5 – Prototype system, which will develop the algorithms, services, and pipelines to manage the real-time flow of experimental data from the monitoring system;
- WP6 – Case study, which will test and validate the instrumentation and procedures developed in the other WPs on a prototype case-study building tested on the shake table.

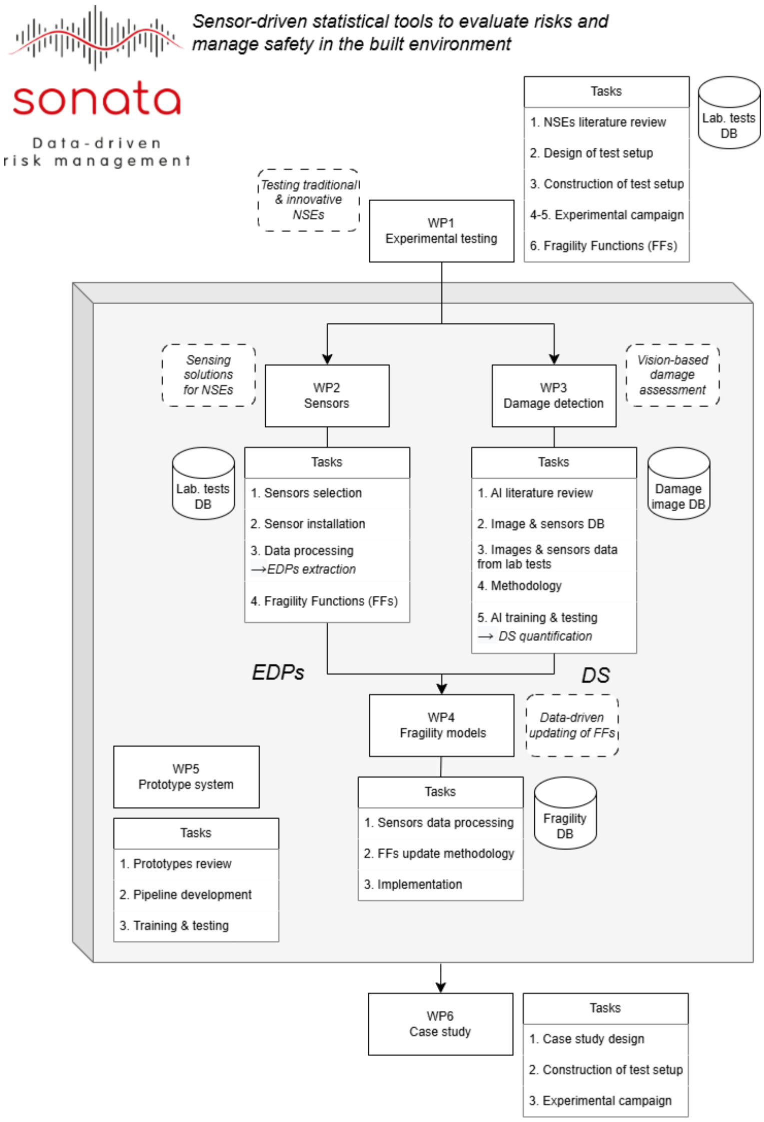


Figure 3- General workflow of the SONATA project.

The WP1 and WP6 experimental programmes are being carried out at the Eucentre 9D laboratory in two steps [25]: in the first phase, different types of NSEs (internal partitions, ceilings, facades, mechanical equipment, and building contents) are individually tested to develop experimental fragility curves and to produce a database of annotated damage observations — the first of these tests has been completed and is presented in Section 5; in the second phase, a full case-study room, representative of a typical installation in a commercial building, will be used to test the behaviour of multiple elements in a realistic setup, accounting for their mutual interactions.

WP2 will demonstrate the capabilities of low-noise MEMS accelerometers (Section 2) with two objectives: first, extracting floor EDPs and tracking the dynamic properties of NSEs with evolving levels of damage, supporting the assessment of damage states; second, monitoring the global condition of the structure according to consolidated SHM procedures, relying on pre- and post-event measurements of operational vibrations.

WP3 is focused on selecting suitable ML techniques to address the problem of object detection in complex environments (Section 3). Images of non-structural damage collected in WP1, enriched by annotated databases from the literature (see for example [24]), will be used to train component-specific ML models to classify damage states. This step is fundamental for the association between measured EDPs and damage levels, particularly if streams of images (videos) are available alongside data from dynamic monitoring.

WP4 tackles the problem of updating damage expectations based on new information acquired from monitoring systems and damage observations. This problem is attacked statistically by means of Bayesian updating and experimentally validated through shake-table tests. The prior distribution of damage states conditional on demand is updated as soon as new experimental EDP-damage state pairs are identified from the monitoring system (Figure 4). The posterior distribution, thus, accounts for the actual behaviour of NSEs during earthquake shaking, overcoming some of the limitations of experimental fragility curves previously discussed (see Section 1). The task will leverage recently published open-source fragility databases for NSEs (see [28]).

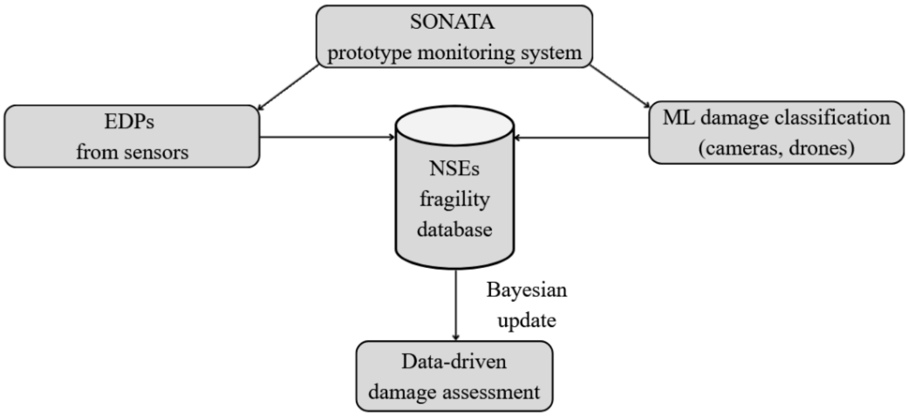


Figure 4- Bayesian updating of experimental fragility functions based on experimental demands acquired by sensors (EDPs) and ML-classified damage states.

WP5 is developing a real-time pipeline to manage streams of heterogeneous data acquired from monitoring systems. Continuous waveform streams follow a dual-protocol approach dedicated to archiving and to event-driven messaging and alerting, exploiting the miniSEED and MQTT protocols [29]. From the edge layer, data are ingested into a centralised cluster which provides processing capabilities to process vibration signals and extract EDPs and performs asynchronous inference using image-based ML models, thereby enabling the refinement of existing fragility models via Bayesian updating.

Finally, WP6 is devoted to testing the entire workflow on a real case-study prototype building tested experimentally, implementing the experimental fragility curves, trained damage-identification ML models, and fragility updating strategies developed in the other WPs.

5- PRELIMINARY INSIGHTS FROM THE FIRST EXPERIMENTAL CAMPAIGN

The first experimental campaign of WP1 was completed in June 2026 at the Eucentre 9D laboratory, providing the initial set of experimental data that grounds the methodological framework described above. The campaign focused on lightweight gypsum partition walls, a drift-sensitive non-structural typology that is both widespread in commercial and residential construction and representative of the damage mechanisms most relevant to loss of functionality and downtime. Full-height partition specimens in single- and double-layer configurations were installed on the lower shake table, connected to the upper one, and subjected to a sequence of dynamic tests employing ground motions of increasing intensity. The 9D laboratory setup is capable of reproducing the storey-level demands in terms of accelerations and relative displacements (drifts) that such elements experience during seismic shaking. Demands were estimated from numerical simulations of an 8-storey reinforced concrete building subjected to scaled versions of the 2009 L'Aquila earthquake.

The instrumentation layout combined the two sensing modalities at the core of the project (Figure 5a). A network of low-noise MEMS accelerometers (see Section 2) was deployed to capture the dynamic response at floor level and to extract the engineering demand parameters governing the partition behaviour, while a synchronised set of cameras (internal and external) recorded the progressive evolution of damage throughout the test sequence. This dual deployment allowed the damage process to be observed simultaneously and in real time from vibration and video measurements, generating the paired demand–damage observations required to train the image-based classification models (WP3) and to develop and update experimental fragility functions (WP4).

The tests produced a sequence of clearly identifiable damage states, ranging from cracking localised at the corner joints (Figure 5b) to more severe dislocation of the studs and panels at higher demand levels. The synchronised acceleration records and image streams are currently being processed. The experimental datasets generated by this and future tests will be made available on the Built Environment Data (BED) platform [26][27](https://experiments.builtenvdata.eu/).

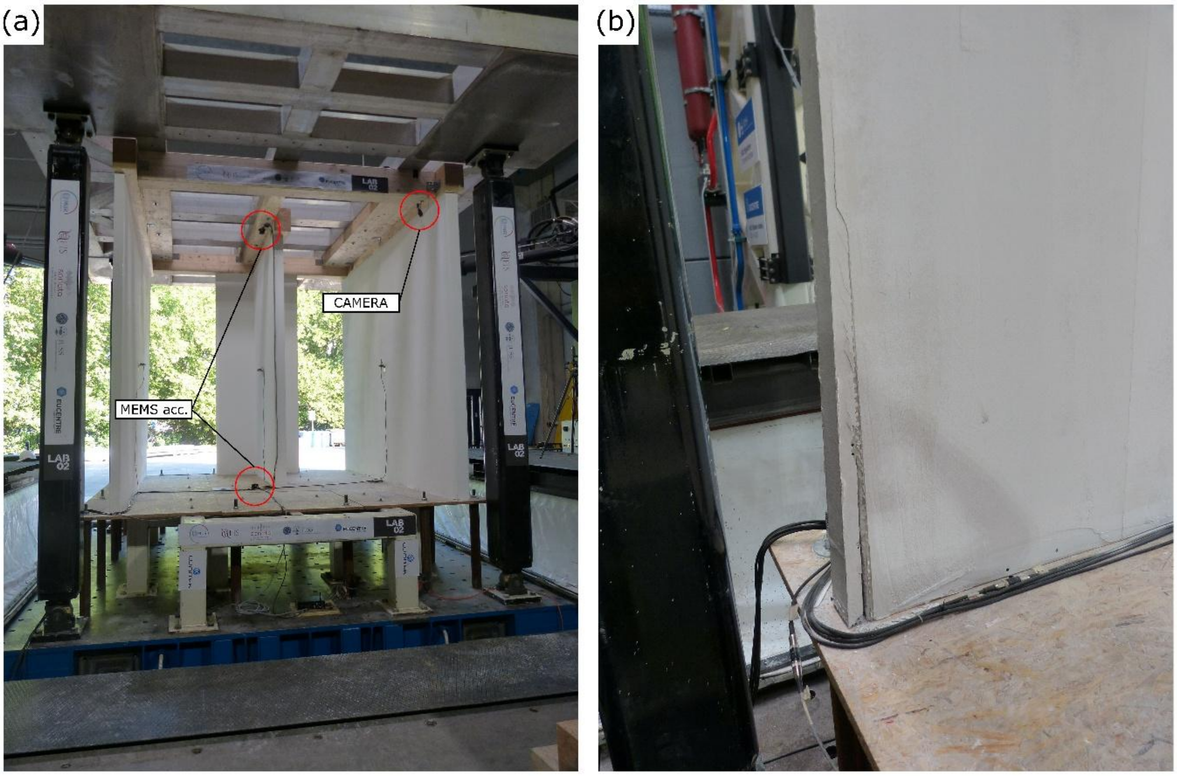


Figure 5- Shaking table tests on gypsum partition walls. (a) Location of sensors and cameras on the shaking tables. (b) Damage observed at the corners of the single-layer wall at a drift level of approximately 1.5%.

6- Conclusions and Future Directions

The paper proposes a structured framework to advance damage assessment for non-structural elements (NSEs) through modern sensing technologies, in which experimental data acquired from instrumented buildings play a central role in informing, calibrating, and validating the damage assessment process. The first experimental campaign, completed within WP1 on gypsum partition walls, demonstrates the feasibility of the proposed dual sensing approach and provides the experimental foundation upon which the subsequent components of the framework are being developed. The integration of dynamic monitoring with vision-based systems represents a concrete and increasingly feasible opportunity for next-generation monitored buildings, enabling damage assessment procedures to be continuously informed by measured data. Within this context, Bayesian updating provides a rigorous probabilistic framework to assimilate continuous streams of newly acquired heterogeneous data [30], allowing for the progressive refinement of experimental fragilities for NSEs. This capability is particularly relevant in seismic conditions that cannot be fully reproduced by laboratory experiments, such as complex boundary conditions, ageing, prior damage, and operational variability inherent to real buildings.

A key limitation lies in the scalability of such approaches to the urban level. Most existing building monitoring networks rely on low-cost sensors deployed in simplified layouts, which inherently constrain their ability to accurately estimate engineering demand parameters (EDPs), especially those associated with localised or strongly nonlinear responses. Moreover, the application of vision-based technologies for NSE damage detection is still at an early stage of development, with several challenges related to robustness, automation, and integration with traditional sensing systems yet to be fully addressed.

In this regard, a critical future research direction is the systematic extension of these technologies to large-scale monitoring frameworks, ensuring reliability across diverse building typologies and environmental conditions. Population-based structural health monitoring (PB-SHM) is emerging as a promising paradigm to achieve this goal [31]. By leveraging similarities among buildings belonging to the same seismic taxonomy classes, this approach mitigates the sparse distribution of monitoring systems at the urban scale, enabling more robust inference of damage states and enhancing the scalability of monitoring-based assessment methodologies. Extending this paradigm to non-structural components represents a novel and inherently challenging frontier, requiring the integration of heterogeneous data sources, the treatment of high variability in component behaviour, and the development of robust taxonomy-consistent seismic fragility models.

7- Acknowledgments

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