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Leveraging Steel Structures to Measure Real-Time Environmental Hazardous Seismic Activity: A Comprehensive Review

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Abstract

Steel structures are a potential network of distributed sensors to do real-time seismic surveillance and detect environmental hazards. This review discusses the state-of-the-art in existing ways to leverage steel buildings, bridges, and infrastructure as integrated seismic monitoring systems. The present study examines sensor technologies, real-time extensions, communication frameworks, and analytical structures and mechanisms that allow steel structures to serve as both structural resources and environmental apparatus. The combination of accelerometers, strain sensors, fiber-optic systems, and wireless networks turns steel structures into active seismic observatories that will record, characterize, and report real-time dangerous seismic activities. This method has major benefits compared to conventional seismic networks, such as an increased spatial resolution, structure-specific damage, and real-time post-event safety assessment. Some of the major problems are longevity of sensors, bandwidth, variability of the environment, and the necessity to have standardized benchmarking protocols. This review suggests a roadmap through which researchers, engineers, and policymakers can contribute to the development of the field at practical stages of a large-scale implementation. Future research includes multi-sensor fusion, edge computing, the incorporation of digital twins, and field validation research.

Keywords: *Structural Health Monitoring, Steel Structures, Real-Time Seismic Monitoring, System Identification, Wireless Sensor Networks, Earthquake Early Warning (EEW)*

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I. INTRODUCTION

The seismic susceptibility of the contemporary urban hubs, which are usually crowded and constructed along the active areas, is a serious threat to society. The effect of an earthquake is not evenly distributed; localized site effects, interactive processes between soils and structures at complicating sites, can form pockets of excessive damage that would be missed by the traditional, sparse seismological networks. This is a severe data desert for first responders and structural engineers, as they cannot conduct immediate post-event safety evaluations and recovery actions due to the lack of high-resolution data. It has never been more necessary to have dense, real-time, and structure-specific seismic data.

Along with this seismological difficulty, Structural Health Monitoring (SHM) has become more mature. SHM has been motivated by the necessity to provide the infrastructure that helps in critical transportation infrastructure protection [1], as well as its viability by having extensive sensing technologies deployed to inspect real-time structural integrity [2]. The conventional SHM system, as shown in Figure 1, is characterized by sensors such as accelerometers or piezoceramics applied directly onto the frame of a structural object, data collection, and the subsequent analysis to detect damage.

It is transforming into a more radical paradigm shift, which can rethink these instrumented structures as not passive objects that submit to seismic forces, but intelligent, active sensors of these forces. This method will enable the development of a network of distributed seismic sensors through the use of the buildings themselves as the sensors.

Steel structures are an ideal platform on which this new application can be applied, among other types of constructions. The common occurrence in the present-day high-rise and critical infrastructure [3], coupled with their well-established ductile characteristics, resulted in their dynamic response being an

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effective sieving effect to the incoming ground motion. Information recorded by an instrumented steel frame can be analyzed to measure both its long-term safety in a sequence of seismic events [4], but most importantly, it can be deconvolved to give an accurate real-time measure of the hazardous seismic activity occurring at that particular location.

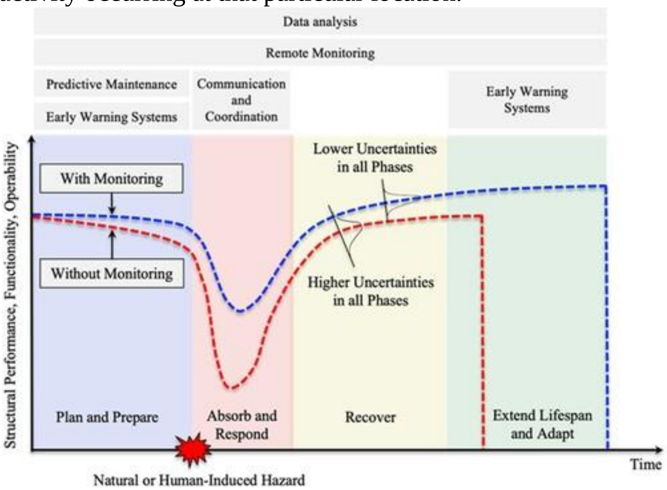

Fig. 1. Conventional Structural Health Monitoring (SHM) Schematic Diagram for Environmental hazardous seismic activity on steel structure [5]

This review paper is a synthesis of the state-of-the-art in the application of instrumented steel structures to monitor real-time hazardous seismic activity in the environment. It traces how the field has developed and evolved, starting with the sheer conceptual framework underlying the structure as sensor, to the particular technologies that render it possible. In the present paper, the study mainly includes the sensing and data capture equipment, such as fiber optics and advanced wireless sensor networks (WSN) [6]. Along with it, the computational intelligence and data analysis models needed to support real-time interpretation and draw conclusions, and the major challenges and future directions that should be covered to enable deployment on a wide scale and in practice.

Even though there are a few reviews on structural health monitoring (SHM) and seismic sensing systems, most are focused on component-level sensor summaries or general information on data acquisition and analysis models. Such reviews tend to neglect the incorporation of newer technologies into a real-life urban setting, in particular to older buildings. This is a clear development in the field since it places steel structures as active distributed seismic observatories that can simultaneously record the characteristics of ground-motion and threshold structural safety in real time. The primary research gap to be filled in this paper is the unification of multi-modal sensing technologies (i.e., accelerometers, distributed fiber-optic sensing (DFOS), piezoceramic impedance (PZT-EMI), and GNSS) along with real-time data processing using edge computing and 5G/6G connectivity, and the challenges associated with their implementation in resource-limited urban environments. This paper presents a cooperative ecosystem of real-time seismic and structural health monitoring in old urban buildings to solve the following limitations (complexity of installation, network reliability, energy consumption, and maintenance cost). The novelty of the present work is that it is a three-dimensional integration: (i) supporting multi-modal sensing to achieve a complete monitoring picture, (ii) supporting real-time computational intelligence based on recursive system perception and AI-based damage analytics, and (iii) supporting edge-cloud communication structures to achieve ultra-low latency responses. Moreover, the review presents a taxonomy of sensing technologies in terms of measurand, bandwidth, and technology maturity, and a quantitative comparison of instrumented steel structures and traditional strong-motion networks. A roadmap towards addressing interoperability, cost, cybersecurity, and large-scale field validation is also described in this paper. With this proposed city-scale ecosystem, the study will set aside current surveys and define smart steel frames as smart seismic sensors in the robust urban systems.

To achieve transparency and reproducibility, the methodology used to identify and select the literature reviewed in this paper was structured in the present study. The academic databases such as Scopus and Web of Science were searched to retrieve publications, which were published between 2000 and 2025. It used the literature with a range of Boolean keywords such as Structural Health Monitoring (SHM), steel structures, seismic monitoring, IoT, and so on. Review papers, theoretical-only studies with no evidence of implementation, were discarded. Selection was done to provide relevancy and quality to the selection process with regard to the around 130 articles initially identified and reduced to the 70 most relevant papers reviewed in this review.

II. Background, Conceptual Framing, and State-of-the-Art

A. Conceptual Basis: The Structure as a Sensor

The structure as sensor concept is implemented by equipping steel structures with sensors such as accelerometers, strain gauges, fiber-optic sensors (DFOS), and piezoceramics (PZT-EMI) to monitor real-time seismic and structural responses. These sensors measure accelerations, drifts, and strain, which are processed using system identification (SysID) algorithms to estimate seismic forces and structural behavior.

The basic assumptions of the method are to consider the building as a non-inertial receiver of the ground motion, rather than as a dynamic filter sensor. Here, the input signal is the ground motion, and the physical properties of the building, including mass, stiffness, and damping, form a multi-story mechanical filter [3]. The dynamic response of the building is the output signal, and this is what is recorded with sensors as accelerations of the floor, inter-story drift, or localized strain in members of the structure [7,8].

The main problem in science is to find a solution to the inverse problem. In traditional structural engineering follows a forward problem follows, which includes a known input (design-basis earthquake), is used, and the corresponding model is applied in order to predict the output (the expected response). In this review, we consider the converse, the known output (data on the sensor), and we need to find out the initial input (the motion of the ground).

This is where System Identification (SysID) becomes applicable to the entire concept. SysID is a suite of analytical techniques used to create and calibrate a high-fidelity, data-driven digital twin or mathematical model of the structure based on its measured sensor data. This model provides the critical link needed to solve the inverse problem. However, this is exceptionally challenging because, unlike a simple electronic filter, a building is a highly complex, nonlinear system. Its properties change with time, occupancy, and environmental conditions [9], and most importantly, with damage.

A seismic event is a high-amplitude, destructive test. During strong shaking, a steel structure will behave nonlinearly, and its stiffness properties will change as it sustains damage. Therefore, to accurately measure the ground motion, the SysID cannot be static. The model of the structure must be updated in real-time to reflect its changing condition during the earthquake. An early demonstration of a real-time SysID algorithm on a nonlinear four-story steel frame shows that it was feasible to monitor changes in stiffness and permanent deformation during a simulated event [10].

Recent developments have concentrated on recursive algorithms, including the Recursive Subspace Identification technique, which is specifically tailored to complete this real-time model update with seismic excitation [11]. Introducing real-time SysID, which is successfully applied, having two advantages: 1) the new model of the building structure indicates the current state of the health and damage more quickly and quantitatively, and 2) the newly obtained, time-dependent model can deconvolve the sensor response to obtain an accurate real-time measurement of the hazardous ground motion at the building base.

The model assumes nonlinearity during strong seismic events, with real-time updates to the building's stiffness and damping to account for damage. Additionally, soil-structure interaction (SSI) is incorporated through spring-dashpot models that simulate foundation behavior, using foundation accelerometers or GNSS data receivers to distinguish soil effects from structural motion and improve ground motion estimates. Advanced models incorporating SSI effects adjust the output of the system identification process to provide a more accurate measure of the ground motion and improve the reliability of real-time seismic assessments.

B. State-of-the-Art Review

The present state-of-the-art review is described as a combination of sophisticated sensing, fast computation as well as smart data analysis. Some of the most important developments in state-of-the-art review are:

Advanced Sensing: Discrete accelerator devices are being replaced with Distributed Fiber Optic Sensing (DFOS) [12]. Such technologies as dynamic Optical Frequency Domain Reflectometry (OFDR) can enable nowadays millimetre-scale distributed strain measurement at interrogation frequencies (e.g., 100 Hz), sufficiently rapid to measure real-time seismic events [13]. This is supplemented by active-sensing methods based on piezoceramic transducers (PZT) to observe structural integrity based on Electromechanical Impedance (EMI) [14,15].

Intelligent and Real-Time Analysis: AI systems are now the most developed ones. An AI-based framework of automated real-time system identification and event notifications is applied in the SHM system on the Al-Hamra Tower, which identifies and notifies in real-time [16]. This is accompanied by hybrid analysis methodologies, including the so-called M and P method, which involves the incorporation of live monitoring data and the previously determined pushover analysis to determine the seismic damage in real-time [17,18].

Advanced Data & Communication Architectures: Since the volume of data contributes significantly to bottlenecks, state-of-the-art review targets 5G-based structures and edge computing. This strategy, commonly a component of an Internet of Things (IoT) architecture [19], handles raw data in the field (at the edge), transmitting only important output, which is crucial to low-latency notifications during an ongoing seismic event [20].

Dense, Low-Cost Networks: This is a technique that augments state-of-the-art systems by installing very simple sensors, such as Raspberry Shake devices, in very large numbers inside each building [21]. This results in a sensor network of urban scale, and current research is being done to calibrate these sensors so that the data quality can be guaranteed [22].

The combination of all these various technologies leads to a powerful, multi-layered system, as illustrated in Figure 2, which integrates proven technologies of sensing, processing, and analytics to create a single, real-time ecosystem of seismic SHM. Steel structures, which are instrumented with multi-modal advanced sensors, are fed with data into an advanced processing pipeline. With the low-latency features of 5G/6G networks, edge computing can manage time-sensitive applications such as System Identification, data quality assurance, and drift estimation [20]. This high-speed connectivity, in its turn, enables the cloud-scale analytics to perform more in-depth, non-real-time operations such as damage detection, mapping the shake in the city, and updating the digital twin. Lastly, this decision layer provides real-time outputs in the form of safety tags, Earthquake Early Warning (EEW) alerts, and resilience scores to the stakeholders, establishing the basis of an autonomous, city-wide response to an earthquake [23].

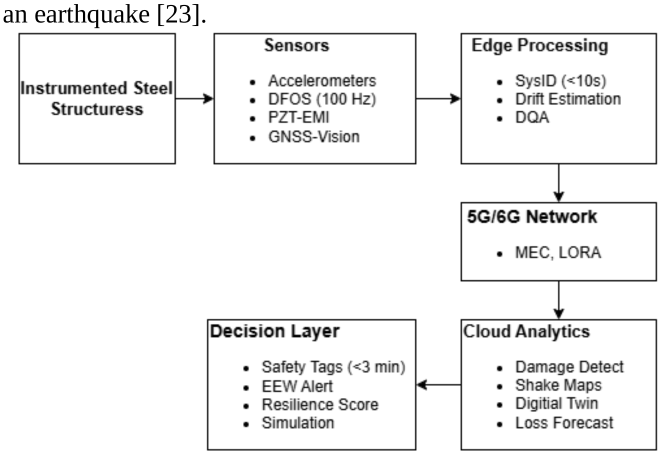

Fig. 2. Integrated Seismic SHM Ecosystem for Instrumented Steel Structures [24,25]

The existing structural health monitoring (SHM) and seismic sensing technologies have strengths and weaknesses. Distributed Fiber Optic Sensing DFOS is high-spatial resolution and long-range strain and temperature measurement but expensive and vulnerable to environmental changes, and it is difficult to deploy in older city buildings. Systems based on accelerometers are cheaper and simpler to implement, but offer lower resolution and do not offer the detailed structural information available with DFOS. The emergence of 5G/6G and edge computing offers low-latency communication and real-time processing at the sensor level, improving response times. However, their deployment in urban settings faces high infrastructure costs, energy demands, and reliability issues, especially in dense cities. Hybrid systems combining accelerometers, DFOS, and edge computing promise to address these challenges by providing more accurate and timely monitoring, but are limited by high deployment costs and complex integration.

C. Performance Comparison of Instrumented Steel Structures

Multi-modal sensors on instrumented steel structures are very beneficial in spatial resolution, real-time processing and detection of damage. Instrumented steel structures achieve a 100x improved spatial resolution, with sensors distributed at the different critical locations within the structure, and give localized, high-resolution data on the structural behavior and seismic activity. The instrumented steel structures have 5 times less latency, due to edge computing on a sensor level, which enables the detection of damage and the safety tagging of buildings immediately after seismic events. Steel buildings with instruments have a ±10 percent higher hypothesis of ground movements and hazards. Instrumented steel structures enable structural health monitoring in seismic events as well as precise localization of damage, in contrast to conventional strong-motion networks that are unable to localize damage. Instrumented steel buildings offer a high level of redundancy since there are various sensors throughout the building or throughout the city. Although instrumented steel structures could be more expensive to install initially, the cost of maintenance and deployment is less than conventional strong-motion networks in the long run.

III. Real-Time Processing, Sensing, and Data Acquisition Technologies

The viability of using a structure as a sensor completely relies on the quality, nature, and location of the instrumentation. The literature shows that gradually, sparse, conventional sensors have been transformed into dense, interconnected, and intelligent networks. Table I gives an overview of the main sensing technologies that are covered in this review, with a comparison of their main applications and distinguishing features. This part describes these technologies, both traditional and state-of-the-art, and also analyses the essential data acquisition and communication architectures that are needed to process their data in real-time.

A. Conventional Instrumentation: Accelerometers and GPS

Accelerometers and Global Positioning System (GPS) are the mainstays of SHM. The accelerometers, especially MEMS (Micro-Electro-Mechanical Systems) and piezoelectric ones, are essential in measuring the dynamic response of a structure [26]. These are installed at different levels of the floor to measure accelerations, which are in turn used to estimate modal properties, e.g., natural frequencies, damping ratios, and mode shapes [3].

TABLE I. Comparison of Various Sensing Technologies and Data Acquisition

Modality	Primary Measurand	Deployment Scale	Frequency/ Bandwidth	Technology Maturity	Latency	Noise Level	Key limitations /mitigation
Accelerometer (MEMS / force-balance)	Acceleration, Drift	Local (floor, beams, joints)	100–500 Hz	Mature (Commercial)	Low (<10 ms)	Low (0.1–0.5% of full scale)	Baseline drift integration error, use constraints/ fusion; clipping near pulses.
Fiber Bragg Grating (FBG) / DFOS	Strain, Temperature	Local/Global (beams, braces, foundation)	100–1000 Hz	Emerging (Commercial)	Medium (20–50 ms)	Medium (0.5–2% of full scale)	Thermal sensitivity, installation quality critical
Distributed Fiber Optic Sensing (DFOS)	Strain, Temperature	Global (long structures, entire beams)	100 Hz to 1 kHz	Emerging (Experimental/ Commercial)	Medium (50–200 ms)	High (1–3% of full scale)	Temp channels/ compensation; Installation quality critical
Global Navigation Satellite System (GNSS)	Absolute Displacement	Global (tall structures, bridge towers)	1–10 Hz	Mature (Commercial)	High (1–10 s for data post-processing)	Low (0.5–1%)	Multipath Effects, Availability of Signals, Low-frequency Response
Piezo / EMI (PZT)	Local stiffness/ impedance change	Bolts, welds, plates (local monitoring)	kHz range	Emerging (Experimental)	Medium (50–150 ms)	High (up to 5% of full scale)	Not a global shaking sensor; power/routing
Tiltmeter/ Inclinometer	Tilt/Rotation	Columns, tower legs, bearings	50–200 Hz	Mature (Commercial)	Low (<10 ms)	Low (0.1–0.5% of full scale)	Temperature bias; calibration
Hybrid node (Accel+GNSS+FBG)	Acceleration, Displacement	Systemic (multi-building)	Mixed	Emerging (Commercial)	Low (<10 ms for accelerometer, High for GNSS)	Low (accelerometer)	Complexity, cost
Wireless Sensor Networks (WSN)	Multiple (e.g., Acceleration, Strain, Tilt)	Systemic (multi-node for large structures)	10 Hz to 200 Hz (depending on sensor)	Mature (Commercial)	Medium (50–100 ms)	Medium (1–2% of full scale)	Network dependency, Power Consumption

One of the main inputs of the System Identification (SysID and damage detection algorithms. The effectiveness of an accelerometer network is highly dependent on its layout; significant research has focused on optimal sensor placement to ensure that the most critical structural modes are captured with the minimum number of sensors, often using modal strain energy as a key criterion [27].

While accelerometers measure vibration, Global Positioning System (GPS), or more broadly, GNSS (Global Navigation Satellite System) receivers, are used to measure absolute displacement. In very tall, flexible steel structures, displacement at the roof can be significant, but it is a low-frequency response that is difficult to capture accurately by double-integrating noisy acceleration data. High-precision (RTK) GPS provides a direct measurement of this displacement, serving as a crucial baseline to correct and validate the data from accelerometers [3]. As an alternative to GPS, novel optical sensors, such as biaxial discrete diode position sensors, are also being developed for rapid, non-contact measurement of post-event structural displacement and damage assessment [28].

B. *Wireless Sensor Networks (WSNs)*

Wired systems are expensive and difficult to install, especially in existing structures. WSNs have emerged as a scalable and cost-effective alternative, with extensive reviews available on their application in SHM [6]. Lynch (2010) reviewed the potential of WSNs for both pre-event mitigation and post-event response [29]. The main advantage of this architecture is that it is able to decentralize the computational load. As an example, Lynch et al. (2006) have shown a WSN on a three-story steel building that utilized embedded computing on the sensor nodes to conduct localized data analysis [30,31]. The concept of this smart sensor is currently implemented in practice, which is demonstrated with Lu et al. (2024) in an Internet-based, real-time observatory of a steel railway bridge [31]. Nevertheless, WSNs do not go without difficulties. One of the key concerns is power management, in which case long-life batteries, energy harvesting (e.g., solar or ambient vibration), or a duty-cycling strategy are required. It is also important that time synchronization of all nodes is a requirement of proper modal analysis, and proper high-vibration, high-fidelity data transmission in the chaotic and high-vibration environment of an earthquake is a major research interest [32].

Figure 3 illustrates the inverse process used in this study to estimate ground motion and detect structural damage. The sensor data from the steel frame is captured in real time, followed by preprocessing (noise removal and signal processing). This data is then input into the inverse model, which estimates ground motion and localizes any damage in the structure.

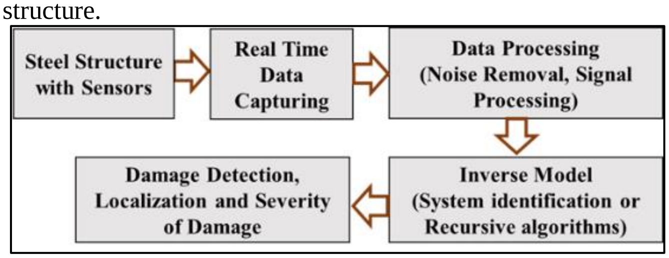

Fig. 3. Schematic of the inverse process used for seismic damage detection in a steel frame structure

C. *Advanced Sensing: Fiber Optic, Piezoceramic, and Novel Materials*

Fiber Optic Sensors (FOS): FOS is a breakthrough in sensory capability. They are not vulnerable to electromagnetic interference, are extremely durable, and may be multiplexed, unlike discrete electrical gauges. Initial uses showed that they could be applied in extreme conditions, and also used for corrosion detection [33].

Distributed Fiber Optic Sensing (DFOS): According to a review by Loayssa et al. (2020), DFOS enables the transformation of a fiber-optic cable into a sensor in its entirety: it can detect strain or temperature at thousands of locations with a spatial resolution of a few centimeters [12]. Luo et al. (2025) showed a distributed temperature and strain sensing (DTSS) system in a real-time well-being check, a concept which can be directly applied to the foundations and structural components of steel structures [34].

Optical Frequency Domain Reflectometry (OFDR): High-speed interrogation is required in the case of dynamic events such as earthquakes. Lee et al. (2025) introduced a dynamic OFDR platform that was able to measure strain at a millimeter-scale distributed strain sensing with a 100 Hz interrogation rate, which is fast enough to measure seismic response in real-time [13].

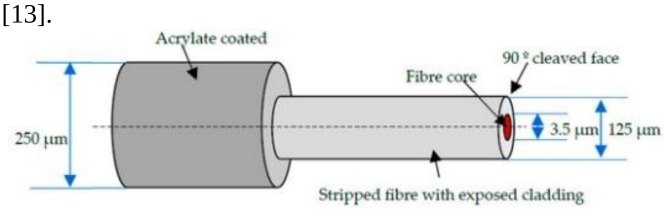

Fig. 4. A schematic illustration of an optical fibre used as an alternative to piezoelectric sensors for structural health monitoring [35]

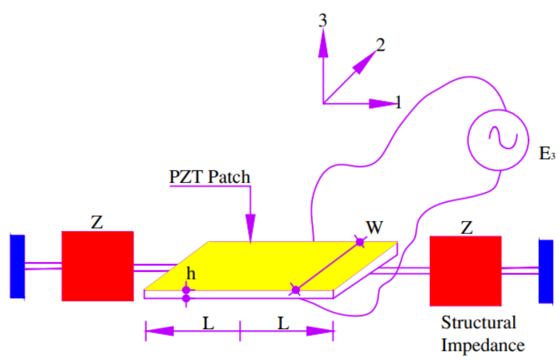

Fig. 5. A Schematic Illustration of a one-dimensional model of interaction between PZT patch of Structural Impedance [36,37]

Piezoceramic (PZT) Active Sensing: Piezoceramic (PZT) transducers are actuators that produce high-frequency wave resonances and detect the subsequent response by employing the Electromechanical Impedance (EMI) principle [38,39]. This active-sensing method is very sensitive to any start-up of damage, such as micro-cracks. Preliminary studies by Zhang et al. confirmed this impedance-based technique, piezoceramic-transducer-enabled active sensing [14]. It is a significant research direction of SOTA, and most recent works combine it with machine learning to identify particular failure modes, including bolt looseness in steel connections [36].

Self-Sensing Materials: It has also been investigated into new materials capable of sensing themselves, and one example is carbon fiber-reinforced cement which can be applied as a coating to measure strain [40].

D. Low-Cost and Crowdsourced Sensors

At the opposite end of the high cost, high fidelity system spectrum, there has been an emergence of low-cost sensors, which have made possible a crowdsourced seismic monitoring system. This theory capitalizes on the density aspect against the precision of each sensor. The concept of the Internet of Things (IoT), which is supported by low-cost MEMS accelerometers (such as smartphones) and single-board computers, has expanded the relevance of vibration monitoring [19,26].

An example is Raspberry Shake, an inexpensive, hobbyist-grade seismograph which have been distributed to citizens all around the world to form a global seismic network [21]. The application was demonstrated in the work by Ozcebe et al. (2022), who showed how they could be used to rapidly identify the structural characteristics of such buildings in Bucharest and could record the basic vibration behavior of buildings during an earthquake [21]. Although a low-cost sensor will contain more noise, thousands of units deployed in a city will offer a high resolution of ground motion and structural response unprecedented anywhere on Earth. The use of this citizen seismology method could determine the level of response of various buildings in various locations to the same earthquake; this would be priceless information for updating urban hazard maps. One of the main problems still exists in the calibration of these low-cost devices to guarantee good quality of data and in establishing the data-driven approaches that are strong enough to address the intrinsic noise and variability of crowdsourced data [22].

E. Data Acquisition and Communication Architectures

A single building with DFOS and accelerometers can generate terabytes of data. Transmitting this volume in real-time during a chaotic event (when cellular networks may be overloaded) is a significant challenge. Research is now focusing on 5G-based architectures and edge computing within an Internet of Things (IoT) framework [41,42]. As depicted in Figure 4, this advanced architecture shows how building sensor networks connect via local gateways to a 5G radio access network. Data is then routed through a 5G common core to a Multi-access Edge Computing (MEC) server, operating within a low-latency domain. This edge computing involves processing data locally on the sensor node or an on-site server, sending only the results (e.g., Damage Detected on Floor 5) rather than the raw vibration data. Gattulli et al. (2022) proposed a 5G-based architecture specifically designed to support data-driven digital twins for seismic monitoring, addressing the need for high-bandwidth, low-latency communication [20]. Furthermore, aggregated data can then be sent to cloud servers via the Internet for long-term storage and more complex, non-time-critical analyses.

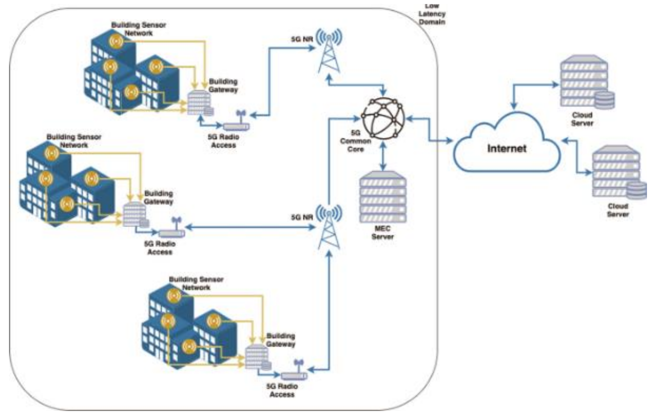

Fig. 6. IT architecture supporting the structural health monitoring and earthquake early warning application [20]

IV. Data Analysis and Computational Intelligence

Raw data from thousands of sensors is not, in itself, useful; it requires sophisticated processing pipelines to filter noise, extract features, and infer structural states amid the complexity of seismic dynamics, where delays can exacerbate risks [43]. This information should be computed in real time to provide us with actionable data, including signal processing to perform denoising (e.g., wavelet transforms) [44], statistical outlier detection, and more advanced computational models to combine multi-modal data into probabilistic damage estimates [45]. The process of converting raw time series into actionable intelligence is carried out over a tiered pipeline, between sub-second edge inference and minute-scale cloud computation. The software and algorithms to convert raw data into actionable data, and the increasing role of AI, especially machine learning paradigms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in automated anomaly detection and predictive modeling with operational conditions are discussed here [46,47].

Table II records a systematic summary of significant real-time data analysis activities in seismic structural health monitoring (SHM) of steel structures. It cross-lists the tasks with common sensor inputs, computation procedures, performance outputs, latency goals, deployment approaches, and validation methods. This framework highlights the tiered processing pipeline from sub-second edge decisions to minute-scale cloud analytics and underscores the critical role of hybrid edge-cloud orchestration in achieving low-latency, actionable intelligence during and immediately after seismic events [19,20].

A. Real-Time Damage Detection

The primary goal of SHM in seismic applications is rapid, reliable damage identification, transforming raw sensor streams into quantifiable structural state changes within seconds of peak ground motion. This requires detecting shifts in dynamic properties, e.g., natural frequency (ω_n), damping ratio (ξ), mode shape curvature, or localized strain anomalies that signal yielding, buckling, or fracture in steel members. As outlined in Table II (Row 4), damage change detection targets latency under 60 seconds using a combination of statistical process control, model-based residuals, and deep learning autoencoders, with deployment shifting from edge-based anomaly flagging to cloud-based fleet-wide scoring [48].

Early methods relied on modal parameter tracking. Kurata et al. (2005) introduced a story-wise impulse response function (IRF) approach, where inter-story acceleration differences are convolved with a unit impulse to estimate local stiffness degradation in steel moment frames [49]. This was extended by Li et al. (2015), who used dynamic strain time histories from fibre Bragg grating (FBG) sensors to quantify crack initiation and propagation near beam-column connections via wavelet packet energy ratios, achieving sub-second localization in laboratory tests [50]. The physics-based methods are both interpretable and limited by non-stationary excitation and confounding the environment includes the drift in frequencies due to temperature.

To solve this problem, hybrid physics data structures have been developed. Makarios et al. (2024) suggested the M and P (Monitoring + Pushover) technique, which projects the real-time frequency drops onto pre-computed nonlinear pushover curves, which are not linear. This technique estimates the damage state (e.g., IO, LS, CP per FEMA P-58) with less than 5% error in blind predictions [18,51]. This solution, which has been demonstrated to work on X- and V-braced steel structures, replaces system identification with performance-based engineering, allowing instant post-event safety tagging [17].

Anomaly detection based on data has become more popular recently. Generalized Likelihood Ratio Test (GLRT) and Cumulative Sum Control Charts (CUSUM) keep track of recursive residuals in online subspace identification to signal the loss of stiffness with a false alarm probability of less than 2% in ambient noise [11]. Autoencoders trained on healthy response manifolds recover the input feature (e.g., AR coefficients, strain spectra) and raise alarms when reconstruction error surpasses adaptive thresholds with 95%+ detection rates on shake-table tests of damaged steel trusses [52]. Graph Neural Networks (GNNs) further enhance spatial localization by modeling the structure as a graph, where nodes are sensor locations and edges represent member connectivity, enabling damage triangulation from sparse instrumentation [53].

A critical challenge is distinguishing seismic damage from operational and environmental variability (OEV). Cointegration-based methods remove long-term trends (e.g., thermal expansion) by pairing non-stationary variables like frequency and temperature into stationary residuals, improving damage sensitivity by 40% in field data from high-rise steel buildings [54]. Table II emphasizes continuous data quality assurance (DQA), including clipping detection, synchronization audits, and gap imputation as a prerequisite for reliable damage inference. In operational systems, damage detection outputs feed directly into rapid triage engines, where peak inter-story drift, connection demand indices, and occupancy data are fused via Bayesian networks or rule-based fragility look-ups to assign Green/Yellow/Red safety tags within 3 minutes of shaking cessation [16,55].

B. Seismic Hazard Applications

Beyond structural assessment, instrumented steel buildings form a dense, urban-scale seismic array, enabling high-resolution characterization of the hazard itself. When synchronized across a city, their responses can be inverted to reconstruct spatially variable ground motion fields, site amplification patterns, and wave propagation effects critical for earthquake early warning (EEW), real-time shake mapping, and rapid loss estimation.

a) Earthquake Early Warning (EEW)

Steel structures act as on-site P-wave detectors. Foundation-level accelerometers identify the initial, compressional P-wave (traveling at ~6–8 km/s) 3–10 seconds before the damaging S-wave (~3–4 km/s), providing a brief but actionable warning window. The online system identification can estimate site predominant frequency within 5 seconds of P-wave arrival, enabling magnitude and epicentral distance scaling relationships [56]. The MyShake network and Raspberry Shake deployments have demonstrated crowdsourced EEW using building-embedded MEMS sensors, issuing alerts with >80% reliability for M>5 events in California and New Zealand [21,57].

TABLE II. COMPARATIVE FRAMEWORK OF REAL-TIME DATA ANALYSIS TASKS IN SEISMIC SHM OF STEEL STRUCTURES

Task	Inputs (typical)	Method examples	Output / KPI	Latency target	Validation & QA
Online system identification (SysID)	Floor accel; optional tilt	Recursive SSI/OKID; Bayesian tracking; subspace ID	f, ζ, mode shapes; change-point flags	< 5–10 s	Baseline envelopes; repeatability across events
Story-drift estimation	Floor accel (multi-level); accel+GNSS	Constrained double integration; Kalman/RTS fusion	Δ(t) per story; peak drift	< 10 s	Sensor cross-check; integration residuals
Connection/brace demand proxy	FBG strain + accel	Strain-to-force mapping; reduced-order observers	Member/connection demand index	< 10 s	Temperature normalization; field calibration
Damage/change detection	Multivariate features (f, ζ, strain stats)	CUSUM; GLRT; PCA/Q; autoencoders	Anomaly score; alarm state	< 30–60 s	False-alarm rate; back-testing
Rapid triage / tagging	Peak drift; demand indices; occupancy	Rules + fragility lookups	Green/Yellow/Red tags	< 5 min	Confusion matrix vs inspection
Near-real-time loss/downtime	Drift, demand, building meta	Bayesian nets; ML regressors	Loss class; downtime band	< 15 min	Hold-out events; calibration to claims
Digital-twin updating	Sensor streams; model priors	Model calibration; UKF/EnKF; ROMs	State estimate; residuals	~seconds–minutes	Residual norms; prediction error
Data quality assurance	All channels + meta	Noise/clipping checks; sync audits; gap fill	Health flags; channel scores	Continuous	QA dashboards; audits

b) Real-Time Shake Maps and Intensity Measures

By deconvolving building response using real-time digital twins, floor accelerations are transformed into foundation ground motion parameters: Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and Spectral Intensity (SI). Cheng et al. (2023) reviewed real-time intensity measure (IM) estimation methods, including filtered Arias Intensity, cumulative absolute velocity (CAV), and JMA instrumental intensity, all computable within 30 seconds of record end [58]. When aggregated across a network of buildings, these yield high-resolution shake maps with <100 m spatial granularity, a 100-fold improvement over traditional strong-motion stations [26].

The end-to-end validation of the integrated system using real buildings ensures that the instrumented steel structures can function as effective seismic sensors in the field, providing accurate real-time ground motion data, damage localization, and post-event safety assessments. By comparing with conventional seismic networks and conducting real-world testing, this approach will pave the way for the large-scale deployment of smart buildings in seismic-prone areas.

The phenomenon of soil-structure interaction (SSI) is implicitly represented. The tall steel buildings are seen as a low-pass filter, which removes the high-frequency content and enhances the site-specific resonances. Noise-cancelling contests. Building-derived IMs have been demonstrated to improve epistemic uncertainty in loss models by 25-40% over interpolated station data.

C. Role of AI and Computational Intelligence

The size and complexity of sensor data have become essential to real-time analysis, and AI and machine learning (ML) have become important. Figure 3 shows that a standard AI-based SHM framework is a multi-stage process. Raw sensor data is pre-processed to isolate and combine important features. These characteristics are then provided to an AI model, which is trained and tested to make high-level decisions like the diagnosis of damages, where to damage is, and prognosis. The AI/ML methods are applied to filter the noise caused by environmental factors and detect sophisticated damage patterns that may not be observed by conventional models, and the system identification process can be automated [11]. According to Parol et al. (2023), the SHM system on the Al-Hamra Tower is characterized as an advanced AI-powered system, which demonstrates the need to have AI to control the data of a well-instrumented skyscraper and give real-time alerts [16]. This combination of ML and sensor data is a strong trend, and researchers have been applying it in the automatic interpretation of EMI data to detect damage in steel joints [36]. Equivalent statistical and ML-based methods are also being implemented to measure the seismic sensitivity of complicated constructions, like plan-irregular RC buildings, to different ground movements [59]. Comparative research, including one by Reuland et. al. (2023), would be essential in the analysis of various data-driven characteristics quantifying the sensitivity and reliability of each of the data-driven characteristics to real-time seismic damage detection [48]. This study aids the design of the long-term safety in order to monitor building health following a sequence of seismic events [4].

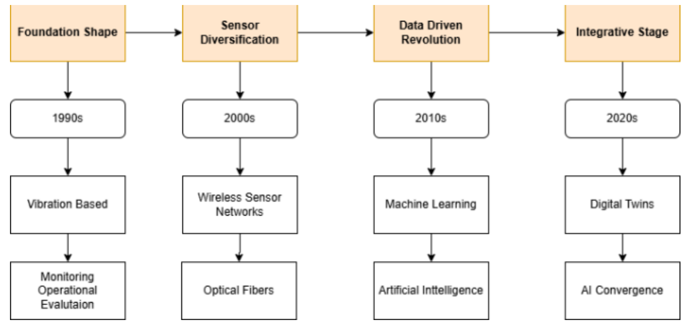

Fig. 7 Workflow of an AI-based Structural Health Monitoring system [60]

V. Key Challenges and Future Directions

Although steel structures are fast-growing as seismic observatories, there are multidisciplinary challenges that need to be overcome in order to have a large-scale, robust, and credible application. These issues include hardware, software, data control, and integration into society, and the future trends move towards more autonomous, adaptive, and city-scale intelligent systems.

A. Key Challenges in Seismic Monitoring and SHM Integration:

a) Cost and Long-Term Durability: Despite the democratization of SHM by low-cost MEMS and Raspberry Shake devices [21], high-fidelity systems (e.g., DFOS, PZT networks) are prohibitively costly to retrofit existing buildings. Self-diagnosing self-healing material or modular replaceable sensor pods are required, especially in the 20 to 50 year lifecycles with sensor drift, corrosion, and fatigue, particularly in the harsh seismic areas [61]. The requirement of ongoing Data Quality Assurance (DQA), but automated recalibration under realistic loading conditions, is still unresolved.

b) Data Volume, Bandwidth, and Communication Reliability: A 100 Hz high-rise using DFOS yields an event-driven data of over 10 GB/hour [12,13]. Network congestion, power outages, and jamming during disasters are some of the factors affecting telemetry using 5G - MEC architecture. Post-blackout resilience requires protocols and opportunistic mesh networking (e.g., LoRa, satellite backhaul) [62].

c) Environmental and Operational Variability (OEV): Frequency changes to 5-10 percent due to temperature, humidity, traffic and occupancy obscure damage-induced changes of less than 2% [9]. Although cointegrated and machine learning normalized, recursive SysID model drift is cumulative in false positives in the long term. Physics-informed neural networks (PINNs) modelling laws of thermal expansion are promising but need large volumes of labelled field data [63].

d) Lack of Standardization and Interoperability: There are no standard protocols for sensor metadata, data scheme, or damage index, which makes it difficult to cross-build analytics and harmonize public and private data. The BIM-SHM integration is not consistent, and the damage tagging is different according to the jurisdiction. The NHERI DesignSafe and CESMD efforts are a move in the right direction, but urban digital twins will require open APIs and semantic ontologies [64]. One of the barriers to large-scale seismic monitoring systems between multiple vendors and buildings is the absence of common standards and interoperable systems. Existing SHM systems have proprietary data formats and irregular protocols, limiting the sharing of data and analytics. The possible coordination of Building Information Modeling (BIM) with SHM, with open APIs and IFC extensions, might guarantee the stability of sensor data and the tags of damage [65]. Unified data sharing algorithms (e.g. Sensor Things API, OPC UA) will be essential to interoperability with a wide variety of hardware and city digital twins, multi-vendor cooperation, and real-time analytics at the city scale.

e) Cybersecurity, Privacy, and Ethical Data Use: SHM systems are vital infrastructure entry points. The acceleration data spoofing may result in false evacuations; occupancy trends are revealed in a data breach. Privacy is preserved due to the privacy of federated learning, where models are trained locally, and only gradient exchanges are provided, but edge analytics is computed using homomorphic encryption, which is computationally costly currently [66]. Ethical frameworks are not well developed in automated building tagging.

With the growing use of IoT-based sensor networks, cybersecurity in SHM and seismic early warning systems is becoming more important. Cyber threats such as data spoofing have the capability of generating false alarms or evacuations, and a denial-of-service (DoS) attack can cause crucial data to be disrupted in the event of seismic activity. End-to-end encryption and authenticated protocols (e.g., TLS, MQTT-SN) would ensure data integrity, and redundant edge nodes and mesh networks should mitigate these risks in the event of DoS conditions. Also, privacy-resistant methods such as federated learning and homomorphic encryption can ensure the privacy of occupants by allowing the model to be trained without access to raw data. Cyber resilience tests, such as penetration tests, should be regularly conducted to ensure a strong level of security against changing threats.

f) Validation and Benchmarking Gaps: Most algorithms are validated on shake tables or synthetic data, not real post-yield steel damage in the field. The overfitting can be found in blind prediction contests (e.g., NHERI SimCenter), where the localization of damages is inaccurate (more than 50% error) during unmodeled SSI. Table II validation columns (e.g., confusion matrices, residual norms) are rarely reported in operational deployments.

B. Validation Protocol

Reliable deployment of AI-driven seismic monitoring systems requires standardized validation protocols to objectively assess model robustness and transferability. The validation of the traditional laboratory tests, which tend to be restricted to shake table tests, offers good evidence of concept but does not emulate the variability in the boundary conditions, soil structure interaction, and nonlinear response properties that real buildings face. Thus, validation is required to go beyond controlled tests to include field-scale benchmarking and blind prediction activities.

Blind prediction structures involve algorithm developers receiving incomplete data collected by instrumented structures or shake-table campaigns, and the ground truth responses are not made available until after model submission. Through this process, a fair assessment of each model's predictive power can be done in real-life, unobservable circumstances. Multi multi-institutional validation scheme that is transparent and incorporates blind prediction and cross-building results will expedite the transfer of intelligent SHM systems between research prototypes and field-validated instruments that can be used in the actual application of seismic resilience.

C. Addressing Integration and Deployment Challenges

Distributed Fiber Optic Sensing (DFOS) system offers the benefit of a high resolution of space, but is expensive, particularly in the case of retrofitting old buildings. Installation of fiber-optic cables in these buildings is tedious and interruptive. One way out is to target modular fiber-optic sensor systems, which can be more easily deployed and attached to structural elements of importance, such as beams and columns. Costs can also be minimized using cheap cable and subsidized retrofitting through construction companies.

The implementation of 5G/6G networks in cities and old buildings is associated with the problem of network reliability and coverage. Space-limited buildings present a challenge in installing new infrastructure, such as base stations. As a solution, the 5G/6G can be supplemented with long-range protocols such as LoRa or NB-IoT to transmit data reliably. Mesh networks and edge computing can reduce the reliance on continuous network connectivity and guarantee real-time data processing even in the event of network path failure.

5G/6G and edge computing consume energy, and it is not always ideal in city environments that are resource-limited. Its energy consumption might be excessively high to ensure long-term sustainability. One of the ways is to apply energy-efficient edge devices together with solar panels or other systems that harvest energy to power sensor nodes. Energy optimization through battery management systems that can be applied when there is low demand can prolong the system's life and minimize the need to rely on external sources of power.

The sensor data in urban settings are prone to noise contamination caused by temperature variations, electromagnetic distortion and vibrations of the surrounding machines which may affect the quality of measurement. To reduce this, more complex noise filters such as Kalman filtering algorithms and wavelet transforms are capable of separating seismic signals and noise. The data reliability can also be enhanced by regularly calibrating sensors and having redundant sensors.

With multi-modal sensors (e.g., accelerometers, DFOS, GNSS) and real-time processing of the data, computing resources can be overloaded. The volume of data is huge, and speed is needed in the processing and synchronization. It can be assisted by edge computing, which is able to process data on the edge, thereby decreasing the amount of data transmitted to central servers. Sensor fusion algorithms have the potential to integrate the information of various types of sensors to give a complete, precise analysis of the structural reactions.

IoT, edge computing, and cloud systems applied in SHM and seismic monitoring have put cybersecurity risks, including data spoofing, denial of service attacks, and unauthorized access. To overcome these, end-to-end encryption and safe transmission protocols are to be employed to guarantee data integrity. There will be multi-factor authentication and role-based access control, which will restrict access, and frequent security patching and intrusion detection systems (IDS) will safeguard against possible threats.

D. Future Directions:

1. Multi-Sensor Fusion and Uncertainty Quantification Future systems will fuse accelerometers, DFOS, PZT-EMI, GNSS, and vision-based drones using Bayesian sensor fusion and ensemble Kalman filters to yield probabilistic damage maps with confidence bounds [67]. Quantum sensors (e.g., nitrogen-vacancy diamond magnetometers) may enable sub-micron strain resolution in harsh environments [68].
2. Edge–Cloud Continuum and Autonomous SHM 6G networks with terahertz backhaul and in-network computing will push digital twin updates to <1-second latency. Autonomous agents will self-configure sensor networks, adapt sampling rates based on P-wave triggers, and self-heal via redundant nodes [69].
3. Federated and Continual Learning for Urban-Scale Resilience Federated learning across city buildings will train global damage models without raw data sharing, enabling transfer learning from Japan to California. Continual learning will update models online as structures age or are retrofitted, preventing catastrophic forgetting [70].
4. Living Digital Twins and City-Scale Simulation Real-time SHM streams will feed physics-based digital twins (FEM + ROMs) embedded in urban simulation platforms (e.g., Unity, Cesium). What-if aftershock scenarios will run in <10 minutes, guiding dynamic evacuation routing and resource allocation [71].
5. AI-Driven Predictive Maintenance and Resilience Scoring Graph neural networks will forecast residual life under repeated shaking using damage accumulation laws (e.g., Miner's rule). Resilience indices (e.g., REDi, USRC) will be continuously updated via meta-models, enabling performance-based insurance and adaptive building codes [72, 73].
6. Citizen Science and Community-Driven Validation Crowdsourced networks (Raspberry Shake, MyShake) will evolve into community-validated benchmarks, where citizens label post-event damage via mobile apps, creating ground-truth datasets for ML training [21].

VI. CONCLUSION

Instrumented steel structures are evolving into active seismic observatories, combining multi-sensor networks (DFOS, PZT, WSNs, GNSS) with AI-driven analytics and edge–cloud–5G/6G frameworks. This integration makes post-event safety tagging fast and high-resolution seismic mapping possible, minimizing the uncertainty of losses by up to 40%. For researchers, future work should focus on creating open benchmark datasets, cross-building validation, and physics-informed AI models that capture nonlinear behavior and soil–structure interaction. For practitioners, emphasis should be on pilot deployments using low-cost hybrid sensor systems and secure IoT networks that can be scaled across existing buildings with minimal retrofit effort. For funding agencies, priorities include supporting standardization consortia, interoperability frameworks, and national testbeds that link academia, government, and industry.

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