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Review

Practical Implementation of Structural Health Monitoring in Multi-Story Buildings

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Abstract: This study investigated operational and structural health monitoring (SHM) as well as damage evaluations for building structures. The study involved damage detection and the assessment of buildings by placing sensors and by assuming weak areas, and considered situations of assessment and self-monitoring. From this perspective, advanced sensor technology and data acquisition techniques can systematically monitor a building in real time. Furthermore, the structure's response and behavior were observed and recorded to predict the damage to the building. In this paper, we discuss the real-time monitoring and response of buildings, which includes both static and dynamic analyses along with numerical simulation studies such as finite element analysis (FEA), and recommendations for the future research and development of SHM are made.

Keywords: structural health monitoring; buildings; sensors; accelerometers; damage detection; finite element analysis

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1. Introduction

SHM systems provide information about any significant change or damage occurring in a structure. The primary purpose of structural damage detection is to identify the reason, location, and type of damage, so as to measure the damage severity and predict the structure's remaining service life. Structural deficiencies causing collapses may result from internal factors, such as corrosion, fatigue, and ageing, and external factors, such as earthquakes, wind loads, and impact loads. The damage caused by the above factors may progress very slowly and become observable only when the structure's damage is considerable, and sometimes it is only repairable at a high cost. The detection of structural damage is essential in ensuring structural safety during a structure's lifetime. The structural damage detection objective is to evaluate the computable and qualitative deterioration of the structural system in service or under a severe load. It is necessary to monitor the location, occurrence, and extent of deterioration from both safety and performance viewpoints. As witnessed by the worldwide development of smart structures and materials, recent advancements in materials and sensing technologies have provided powerful new tools for improving building systems. While many of the structures have existed for decades in their basic form, the intelligence added through the various damage detection methods addresses the practical problems that challenge the effective implementation of active damage control in building structures. SHM has become a primary option for evaluating the overall behavior, preferably from the manufacturing process to the end of its service life. Figure 1 depicts the operating principle of SHM in multi-story buildings along with data acquisition and predictive analysis.

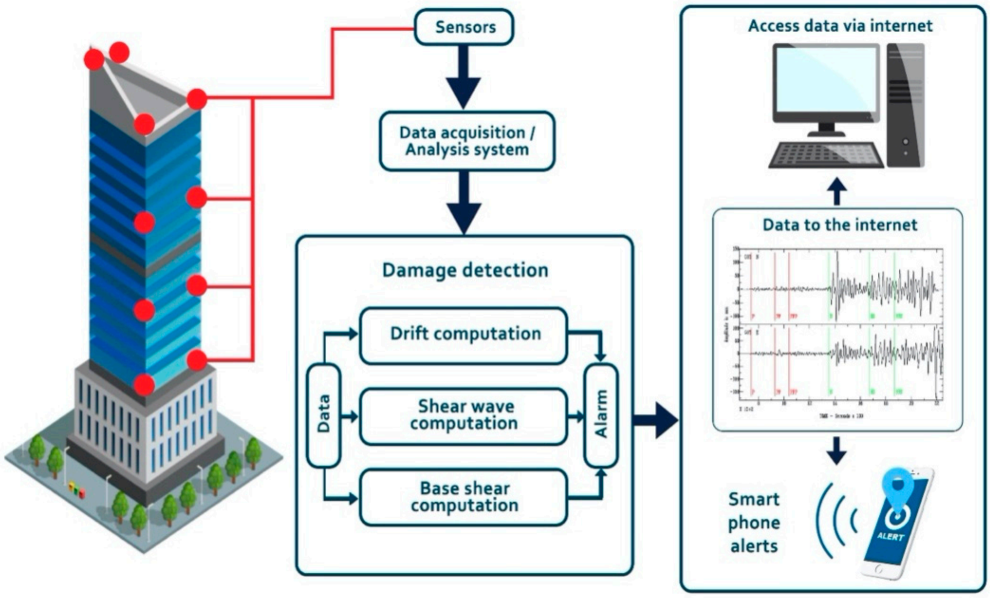

Figure 1. The operating principle of the SHM system in a multi-story building.

Damage detection is an essential consideration in SHM; therefore, a few techniques have been adopted to predict damage such as ambient vibrations. For example, the San Pedro Apostol church was monitored through the SHM technique for both short-term and long-term monitoring to find the variations in temperature and humidity [1]. SHM can be used not only for modern buildings but also for heritage buildings as well, so that historic structures, such as those of the Ottoman Empire, can be monitored using non-destructive techniques (NDTs) to predict damage and observe the current health status of buildings [2,3]. Seismic or any excess acceleration in buildings causes heavy damage to the structure such that the buildings undergo dynamic loading, so dynamic analysis should be carried out using SHM techniques; thus, the forever berated transfer function has been implemented to predict the action of seismic waves in buildings [4]. To diagnose the buildings' damage, by adopting a neural network (NN) approach, both damage and undamaged areas are assessed by applying artificial free vibration to forecast the range and level of damage due to dynamic loading conditions [5].

In SHM, buildings are subjected to static loading conditions for the most part. Furthermore, the main parameter for static loading is displacement, strain, temperature, and acceleration; hence, the deformation and inclination of 600 m tall canon tower were monitored using SHM in China and found slight changes in deformation in comparatively hot and cold seasons [6]. In general, buildings under static loading will use a 1D or 2D system to carry out monitoring, but by adopting a motion capture system (MCS) instead of a global positioning system (GPS), the structure can be monitored in 3D using advanced sensor technology [7].

The finite element method (FEM) and finite element analysis (FEA) are numerical simulation techniques used to analyze real-time experiments through analytical models using advanced software; hence, complicated analysis, e.g., of stiffness and damping, can be carried out using the FEM technique very easily and reliably, even for multi-story buildings. In one study, a 15% stiffness reduction was found after analyzing the nine columns, and a 1.67% stiffness reduction was found in the overall building structure [8]. The FEM was used for steel bracing to identify damage by adopting two methods; namely, the Bayesian estimation method and the weighted least squares methods in the initial stages for the eigen-sensitivity-based FE model [9].

2. Literature Review

2.1. Process of SHM

SHM is an automated system in civil engineering and helps to predict the damage of a structure in early stages with the help of advanced sensing technologies and automated data acquisition techniques, which allows for predictive analysis. This predictive analysis helps companies and researchers to determine the nature, standards, and bearing capacity of a structure against static and dynamic loads. Static loads occur because of displacement, acceleration, strain, stress, and temperature together with dynamic loads based on vibration, natural frequencies, model identification, time history analysis, and response spectrum, depending on the characteristics of the external and internal interactions and the type of structure [10,11]. Olivera Lopez et al. [12] carried out real-time monitoring in a 14-floor building stationed in a coastal area of Chile subjected to dynamic loading. The main objective of the study was to check the withstanding ability of the structure in a tsunami to predict the hydrodynamic forces and detect the damage, and it needs further development in terms of mode deformation. Yanet et al. [13] investigated the lifespan of sensors used for SHM and pointed out that the average life span would be 10 years, and they suggested that more sensors be fixed in a structure to distribute the load equally and enhance the durability and service life of sensors. This technique is known as the communication technology load.

Roghaei and Zabihollah [14] conducted an experimental process in a 3-story hospital steel structure using piezoelectric sensors to identify the stress and deformation by adopting a non-linear static analysis (pushover) approach using SAP2000 and FEMA35 software. Zhou et al. [15] managed to determine damage with an even more accurate vibration-based approach using the hysteresis loop approach (HLA) through an experimental process in a 12-story RC frame building; they determined the variation in stiffness using elastic, hybrid, and pinched approaches, and the results showed that the pinched approach was more effective because it could help to predict variation in fundamental frequencies less than 0.05 Hz. Figure 2 provides detailed information on the progress of SHM in buildings.

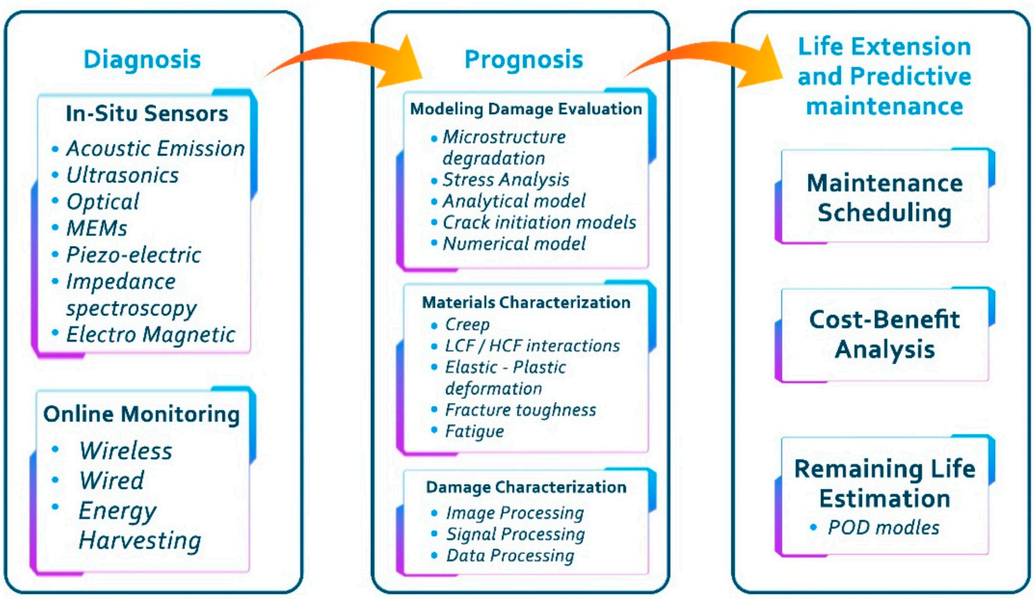

Figure 2. Progression and advancement of SHM in buildings.

Pierdicca et al. [16] carried out long-term monitoring for approximately one year in a reinforced concrete school building to analyze the dynamic behavior of buildings; they used an executing operational ambient vibration survey using an operational model analysis (OMA) approach and developed an FEM model for numerical simulation, and the results of the long-term monitoring approach were satisfactory in terms of economic benefits and accuracy. Demetriou et al. [17] presented numerical studies through the on-line monitoring of an existing three-floor building that had been affected due to reductions in stiffness because of the harmonic motion, and the results show that failures occurred at both the first and second floor, stiffness reduction occurred at 1.8 and 4 s, respectively, and no failures occurred at the third floor.

Dong et al. [18] carried out monitoring in two buildings, the Van Nuys hotel and an imperial country service building, by adopting an empirical mode decomposition (EMD) approach and vector aggressive moving average (VARMA) model in order to predict the sensitivity and effectiveness of a damage index based on noise. They reported that the damage index provides valuable information for analyzing damage and examining the relationship between the severity of the damage and the damage index to avoid future problems. Yang et al. [19] carried out real-time monitoring in a 20-story steel frame building in Alaska that was approximately 38.5 × 38.5 m, and the roof height was 80.5 m above ground level. This was carried out to analyze the dynamic behavior due to seasonal frost. Vibration data of the building were collected by adopting a permanent strong motion instrumentation system. Simulation was carried out for the foundation at the first phase, and the superstructure was monitored. Furthermore, numerical simulation was also carried out for the same building by assuming concrete as a material instead of steel to evaluate the performance of concrete in the same process. Thus, both concrete and steel simulation models were compared, and results showed that steel buildings outperform concrete building due to the effect of seasonal frost and the anticipated variation in fundamental frequencies of approximately 13%.

2.2. Sensors Used in SHM

Antunes et al. [20] carried out both static and dynamic analysis in SHM using optical fiber sensors (OFS) by monitoring an adobe masonry structure and found a reduction in stiffness when natural frequency decreased. A destructive cyclic test was carried out to predict natural frequency, which showed a 48% reduction [20]. Zhao et al. [21] demonstrated an advanced sensing system, namely, a multiple agent system (MAS), by combining three different types of sensors, piezoelectric sensors, fiber optic sensors, and a strain gauge, to monitor different parameters at the same time, especially for monitoring large structures, and found it to be more effective than conventional sensing systems.

Hison et al. [22] carried out real-time monitoring in a wall structure, namely, the Tufa wall, using magnetoelastic sensors to analyze the elastic deformation and fracture alarm, and this showed good reliability (1 mV/10 μm) and sensitivity and provided an output that was superior to that of conventional strain meters with low cost.

Mahjoubi et al. [23] studied a Shanghai tower with a 632 m height by applying a limited number of sensors to predict the damage and behavior of the structure. The ultimate motive of monitoring is to reduce the number of sensors and achieve optimum results, so new sensing technology is adopted, namely, a triaxial accelerometer using a hypotrochoid spiral optimization algorithm, such as flower pollination, lion pride optimization, a teaching–learning-based optimization colony, spiral optimization, particle swarm optimization, and Jaya. Three objective functions of automated modal monitoring by adopting seven algorithms are considered to identify modes. This approach is more effective in high-rise buildings. It cannot be applied to other structures without further research. Figure 3 shows some of the major sensors adopted for SHM.

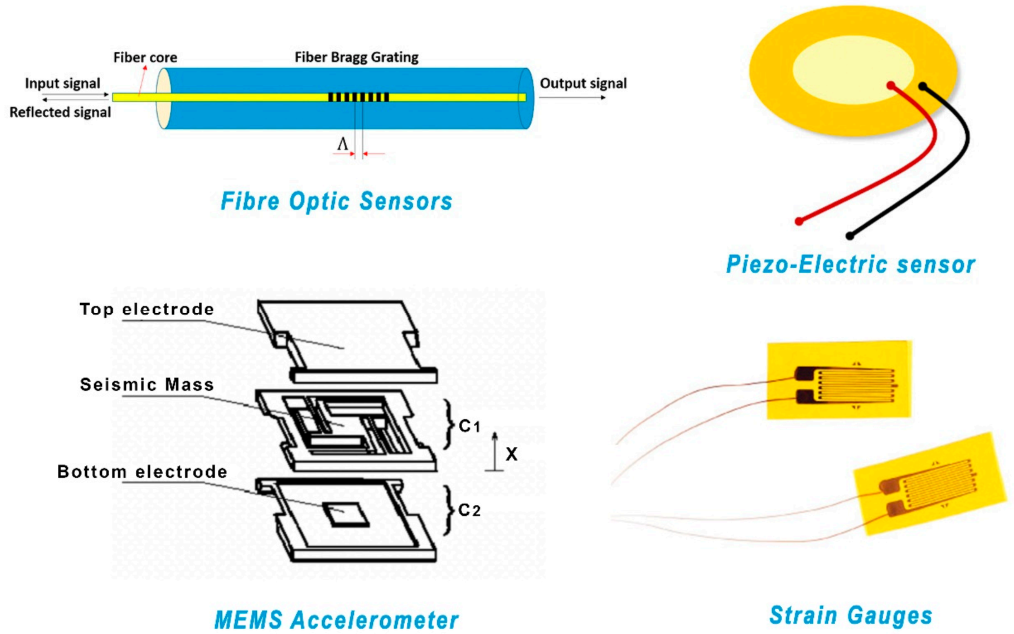

Figure 3. Various sensors used for SHM.

2.3. Overview of the Article

This study begins with an introduction to SHM in buildings in which the process of SHM and the sensors used for it are discussed, along with strategies of damage detection in previously reported works for real-time monitoring and laboratory experiments. The static and dynamic behavior of buildings implementing SHM is discussed with various methods and approaches. The FEM used to predict building behavior by developing computer models is also discussed. Finally, future research recommendations are reported along with conclusions. Figure 4 provides an overview of SHM applications in buildings.

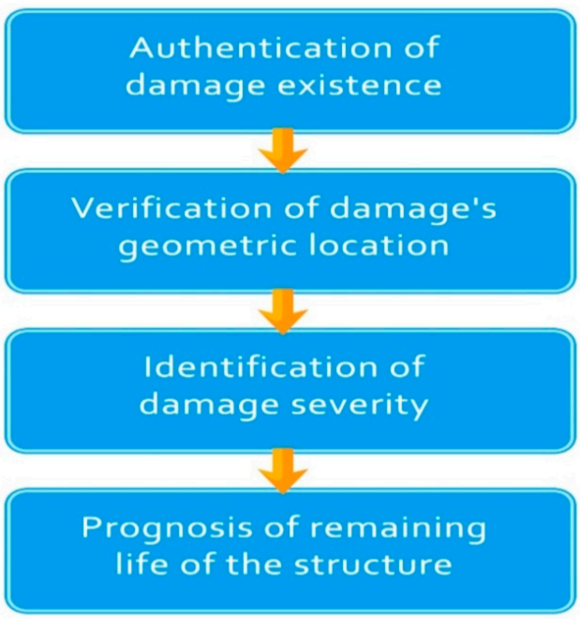

Figure 4. Outline of SHM applications in buildings.

3. Strategies of Damage Detection in Buildings Using SHM

Sajedi and Liang [24] conducted an experiment using 44 shake tables. They developed a framework model of a 3-story RC moment frame building, with 180 ground motions and a 5400 non-linear time history analysis, as specified for input using Openness software.

The simulation report showed that 96%, 87%, and 90% accuracies were predicted for damage existence, location, and severity, respectively. The laboratory experiment showed a 92% accuracy predicted for damage classes. Gao et al. [25] demonstrated a new a novel embeddable tubular smart aggregate (TSA) evolved from piezo materials and conducted an experiment recording the time of arrival and performing impedance analysis and sweep frequency analysis, and results were satisfactory for 2D concrete structures.

Chatzis et al. [26] carried out a laboratory experiment using shake tables by employing an accelerometer to analyze the severity and location of damage using subspace state-space system identification (SSID) with an advanced version T-SSID approach and an unscented Kalman filter (UKF). They adopted an n4sid algorithm and a Bayesian time-domain, respectively, and compared the T-SSID and UKF. The UKF approach was preferred due to fast approach towards damage prediction. Soltaninejad et al. [27] developed a simulation for two adjacent buildings to anticipate pounding as per a 36-case single-degree-of-freedom model by comparing a short time matrix pencil method (STMPM) and discrete wavelet transform (DWT). The results showed that STMPM helped to predict smaller damage and was not sensitive to the corresponding amplitude of damage response. It also helped to predict damage in both low- and high-resolution sensors. García-Macías and Ubertini [28] examined the Sciri tower located in Italy for approximately one month (February 13 to March 10, 2019) using 12 accelerometers and combined ambient noise deconvolution interferometry (ANDI) and OMA to analyze three levels of frequency, approximately 200, 1000, and 5000 Hz. This indicated that deformation occurs due to variations in temperature, and wave propagation mode was analyzed.

Sun et al. [29] demonstrated a skyscraper building model, namely, the Al Harma Tower in Kuwait, which is approximately 413 m in height with 86 floors, using E-tabs together with a building with two curved shear walls to the combined height of the buildings by applying three methods: system identification, interferometry-based wave propagation analysis, and wave-based damage detection. The building underwent large deformations due to heavy dead load and seismic response. Chellini et al. [30] experimented with a composite frame structure of three layouts with three accelerometer sensors to forecast damage in a beam-column joint by conducting a pseudo-dynamic (PSD) and cyclic test using eigen frequencies, a damping ratio, and mode approach. The increase in damping ratio and the high decrease in eigen frequency showed a variation in mode shapes for global sensors, whereas local sensors provided more accuracy and were easy to monitor. Morales-Valdez et al. [31] examined a prototype of a 5-story building with dimensions of $60 \times 50 \times 180$ cm by employing microelectromechanical system (MEMS)-based accelerometer sensor, whose model code is ADXL203E, to predict damage and by adopting a wave propagation algorithm. The damage was assumed as a stiffness reduction using two parameters, namely, the Kelvin damping coefficient and the nominal shear wave velocity, and it was reported that the wave method would outperform the modal analysis method.

Valinejadshoubi et al. [32] developed building information modeling (BIM) to manage data effectively using automated sensor-based data acquisition and a storage module approach to extract sensor data and damage identification. Pachón et al. [33] developed an FE model of a heritage building, i.e., the Monastery of San Jeronimo de Buenavista in Seville in Spain, to predict dynamic behavior such as ambient vibration and model identification to undergo an optimal sensor placement (OSP) technique. The dynamic behavior of buildings consists of four methodologies based on energy matrix rank optimization (SEMRO and KEMRO) and the effective independence of target mode shapes (EFIwm and EFI). The results indicated that EFI provided error to a smaller extent for the natural frequency, and KEMRO provided a large number of errors in modal identification.

Frigui et al. [34] demonstrated an FEM of an 18-story ophite tower with a 2.5 m height split up into 18 nodes subjected to artificial loading to assume damage severity. They adopted the Modal Assurance Criterion (MAC) method, the Mode Shape Curvature Method (MSCM), Curvature Damage Factor (CDF), the flexibility method, and an algorithm based on the eigen frequencies approach using the vibration-based damage detection method (VBDDM. The studies indicated 50% and 25% reductions for the first and second artificial damages by the MAC approach; however, a less than 0.8 mode shape is essential, and a more than 5% eigen frequency is necessary to predict damage. Suhaimi et al. [35] introduced new sensors, namely, passive sensors, to analyze three-dimensional (3D) frequency selective surfaces (FSSs), which are more reliable and enhance sensitivity compared with the 2D FSS structure. García-Macías and Ubertini [36] introduced new software, i.e., MOVA/MOSS, with various types of sensors to predict damage using an automated anomaly detection algorithm by considering the Consoli palace in Italy. Three categories of the model were considered—Principal Component Analysis (PCA), Autoregression with an eXogenous input model (ARX), and Multiple Linear Regression (MLR)—to analyze the local and global damage based on amplitude and resonance frequency.

Li et al. [37] carried out a field study and an FEM on a tall building; namely, the Ping an Finance Centre (PAFC), approximately 600 m in height and equipped with 553 different sensors, to identify vertical deformation in the various structural elements during the Nida typhoon by applying a modular design methodology. Zhang et al. [38] examined a 108-story (250 m) building, which is 56 stories below and 52 stories above ground level and is equipped with accelerometers and tilt sensors to monitor and predict damage for approximately 15 months based on OMA using a fast Bayesian FFT approach. The results showed a reduction in natural frequencies due to structural mass. Modena et al. [39] investigated heritage structures, namely, a Spanish fortress, a civic tower (L'Aquila), the Scrovengni chapel (Padova), and the stone tomb of Cansignorio, using an SHM approach to analyze the static and dynamic responses of the building. They used a robust statical model and numerical simulation. Mustafa et al. [40] recommended using new advanced wireless sensors (FSS) instead of conventional sensors to predict the damage of buildings with two designs, the circular ring (FSS) and the square loop (FSS). The square loop outperformed the circular loop due to an improved reflection coefficient and incident angle, and it covered a wide frequency range.

Aguilar et al. [41] carried out real-time monitoring for an adobe church in Peru for approximately two years (March 2017 to December 2018) by employing accelerometers to detect damage post-earthquake using a PCA approach and an autoregressive model (ARX). PCA showed more accurate results than ARX (non-linear) in terms of damage prediction. Brownjohn et al. [42] investigated 24 bridges, 3 buildings, 2 chimneys, and 1 tower to ensure communication between the laboratory and the site for transferring the vibration base monitoring (VBM) experimental setup. They found more variation when comparing laboratory and in situ operations and, therefore, suggested real-time monitoring. Coletta et al. [43] monitored a sanctuary of Vicoforte 74 m in height for approximately four months to predict dynamic behavior for all environmental degradation using various sensors. FE analysis was developed for the same building by adopting support vector machines (SVMs) and relevance vector machines (RVMs) for damage prediction.

García-Macías et al. [44] carried out real-time monitoring for approximately one month (February 13th to March 10th) using an accelerometer with the help of experimental data. An Abaqus FEM was developed to detect damage caused by earthquakes by adopting a Metamodel-based pattern recognition approach, and this helped to identify modal analysis using OMA. Lam et al. [45] monitored a boat-shaped building in Hong Kong; namely, Academic Building 3 (AC3), which is a 20-story building, and five adjacent stories in the subordinate building using the fast Bayesian FFT method, and results indicated changes in readings for the first two days in 12 of the 15 experiments set up due to the carpet in the building, so removing carpet is recommended for accurate vibration measurement. Lorenzoni et al. [46] practiced monitoring with the help of data available for approximately three years in a cultural heritage building, namely, a Spanish fortress with four bastions connected with a 60 m long wall and a civic tower with a 6.5 $\times$ 7 m base and a 43 m height, and developed an ARX model by employing MatLab software. The results suggested that using a robust statistical method and damage detection algorithms is an added advantage when monitoring buildings in any environmental variation.

Bhalla and Kaur [47], to find equivalence stiffness parameters (ESPs), implemented laboratory testing for reinforced concrete beams using piezo composite concrete vibration sensors (CVSs) to predict low strain fatigue and practice electro-mechanical impedance (EMI). They concluded that CVSs in the EMI mode work more effectively for the initial and final stages of monitoring but not for the intermediate stage. Kaya and Safak [48] developed new software, namely, REC_MIDS based on MatLab, to monitor inter story drift and modal identification parameters. It was applied to seven high-rise buildings in Dubai and to mosques, museums, suspension bridges, and tall buildings in Turkey.

Cheng et al. [49] carried out the real-time monitoring and ARCH model of 3-story and 8-story buildings using accelerometers, and the results of the experiment were compared with existing results collected from the laboratory. Two indicators, the cepstral metric indicator (CMI) and the second-order variance indicator (SOVI), were compared to identify damage. The SOVI showed a superior output. Rahmani et al. [50] implemented monitoring through experimental and analytical models using MatLab software by adopting time velocity analysis (TVA) for 12-story RC buildings; namely, the Sherman oaks office building, whose dimensions are approximately 18.3 × 49 m with a height of 48.5 m. They employed a uniaxial accelerometer. The experiments and analysis indicated that there was a difference in frequency and the average vertical wave velocity after comparing TVA with the analysis of inter-story drift, input power, and instantaneous frequency due to soft soil conditions.

Musafere et al. [51] developed a numerical model for a building with a 5-story shear beam structure and carried out experiments for a 17-story building and a Louis factor building using both sensors and accelerometers. They adopted a blind source separation algorithm under a time-varying autoregressive model and found that this approach is sufficient to predict the dynamic behavior. Yan et al. [52] presented a review on SHM transmissibility function (TF) in buildings with three different categories: modal analysis, modal updating, and damage detection. The results showed that a single input is enough to predict damage using TF.

4. Static Analysis in SHM of Buildings

Behnia et al. [53] executed the real-time monitoring of a concrete structure in November 1999 and June 2000 by employing piezoelectric sensors adopting an acoustic emission technique to anticipate damage in terms of frequency, amplitude, severity, cracks, and time domains subjected to static loading conditions, and findings suggested that this method is suitable for the in situ monitoring of a structure. Fortino et al. [54] conducted a laboratory experiment to check the efficiency of Wireless Sensor and Actuator Networks (WASN) to implement SHM for a building management framework. Hackmann et al. [55] demonstrated an FEM using MatLab for a truss and cantilever beam by adopting a damage localization assurance criterion (DLAC) algorithm to keep memory usage, latency, and energy consumption less than 1%, 65%, and 64%, respectively.

In Italy, Ierimonti et al. [56] implemented operational monitoring from September 2018 to March 2019 by dividing it into seven intervals for a 3-story RC school building with a height of 16.6 m by employing nine uni-axial accelerometers using the Bayesian modal updating method for the base-isolated building alone for a static analysis of, e.g., elastic deformation, humidity, and temperature. Carden and Brownjohn [57] carried out real-time monitoring in a 4-story steel building structure with two bays on each side and with dimensions of approximately 2.5 × 2.5 × 3.6 m to detect damage using an accelerometer. They applied a statistical classification algorithm based on an ARMA model and found the prediction of damage to be satisfactory. Wang et al. [58] conducted an experiment and numerical model of a 7-story RC hotel in California by employing an accelerometer to detect the story damage index (SDI) based on system realization using an information matrix (SRIM) technique to predict mode shape and modal frequency.

Kao et al. [5] monitored a 5-story steel building of 3 × 2 × 6.5 m. They developed a numerical model by applying an artificial neural network (ANN) to detect static responses, such as displacement, velocity, and acceleration. The results showed that this method helps to detect variations in structural properties and generate free vibrations accurately. Ramos et al. [59] carried out monitoring in a Saint Torcato church with towers of approximately $7.5 \times 6.5 \times 50$ m, a transept 37 m in length and 11.5 m in width, and a central nave that is $57.5 \times 17.5 \times 26.5$ m by employing accelerometer sensors to predict static analysis of, e.g., cracks and vertical deformation. Cracks were monitored by a crack meter, and an FE model was developed by employing TNO Diana software to predict crack and dynamic behavior. Mejri et al. [60] monitored an office building, namely, the Confort Bois construction company—with a total surface area of approximately 110 m^2 and a volume of 350 m^3—using HOBO sensors to measure energy consumption under static parameters such as the heat loss coefficient, utilization factor, and solar aperture.

Bhalla and Soh [61] monitored an RC portal frame of approximately two stories with a height of 2.9 m and a length of 3.3 m using a piezoelectric transducer to detect flexural cracks and shear cracks via an EMI technique, and results showed that this technique clearly monitors cracks. Pesci et al. [62] monitored two heritage buildings, namely, the Garisenda tower and the Asinelli building, 48 m and 97 m in height, respectively, using an accelerometer employing a terrestrial laser scanning (TLS) technique. An FE model was developed to predict deformation patterns due to gravity and seismic activities. The results showed that the Garisenda tower requires periodical monitoring to protect itself from environmental degradation, and the Asinelli building is not strong enough to withstand seismic activities, so it is necessary to decrease human-made vibrations.

Xu et al. [63] monitored a 3-story building using sensors to detect damage and isolation bearing properties and suggested the development of a model called bilinear hysteresis, which depends on regression analysis, and results showed that the properties of the superstructure and isolation bearing are less than 6% compared with the actual model and that this method is applicable only for 2D shear-type frame structures. Saisi et al. [64] carried out real-time monitoring of the bell tower of Italy's Santa Maria del carrobiolo church with a height of 33.7 m and approximately 5.93×5.70 m using five temperature sensors and 10 displacement transducers under static loading conditions, and results showed that there is no proper solution to determine abnormal cracking at one time. Only one crack was predicted due to temperature. Butt and Omenzetter [65] practiced monitoring a 3-story building in New Zealand approximately 44.7 m long, 12.19 m wide, and 13.40 m tall, called the GNS Avalon building, using 10 sensors. The FE model was developed by employing Abaqus software. Resonance frequency was less than 7.5%.

Zhang et al. [66] experimented with an aluminum beam with a 136.15 cm length and a cross section of 2.75×0.3 cm and developed a numerical model of a 10-story multi-span frame and for the same aluminum beam; therefore, three sensors were used for the beams, namely, piezoelectric actuators, and sensitivity analysis and the virtual distortion method (VDM) were adopted. The results indicated that stiffness-related parameters and identification error were less than 8.2% and 2.9%, respectively. Kane et al. [67] conducted SHM to enhance the impact adopting paradigm shift, which uses more number sensors with lower installation costs and easy-to-collect data; hence, it can be applied to all civil engineering structures, mainly buildings.

Hill-King et al. [68] presented a review of fiber optic strain sensors to practice SHM in many civil engineering structures, including buildings. This worked more effectively to predict damage and structural properties. The results showed that optical fibers are more effective but are more time-consuming for data acquisition compared with electrical strain gauges. Habel [69] experimented with concrete structural elements, such as column and pile foundations approximately 19 m tall, using two different fiber optic sensors, namely, long-gauge-length fiber optic sensors and short-gauge-length fiber optic sensors, which helped to identify chemical and physical properties and to determine reliability issues. Wang et al. [70] monitored two 12-story buildings (twin towers) in China for approximately 12 months; one building was built using natural-aggregate concrete (NAC) and the other was built using recycled coarse aggregates (RCAs) by employing acceleration sensors, angle sensors, and strain sensors to predict wind speed, ambient temperature, and structural response amplitude. The results showed that:

- Frequency increases when ambient temperature increases;
- There were 2.20% and 1.80% increases in the recycling aggregate concrete (RAC) structures;
- There were 2.03% and 0.76% increases in the frequency for NAC;
- There were 12.60% and 11.70% reductions in the damping ratio for RAC and NAC.

Bulajić et al. [71] developed a two-layer shear beam model to analyze a 12-story building above ground level in north Macedonia subjected to 11 earthquake events in the last 25 years, and significant stiffness variations of approximately 19% to 23% occurred during the Gnjilane earthquake in 2002, so damage occurred due to non-structural elements. Ayyildiz et al. [72] experimented with carbon fiber reinforced polymer concrete columns to detect damage and fractures of the column using piezoelectric sensors (PZTs) and provided satisfactory results. Jang et al. [73] proposed the design of wireless sensor technology to practice monitoring in buildings; three levels, i.e., new hardware, an open-source operating system for communication, and data acquisition, were developed to enhance monitoring.

Yang and Huang [74] demonstrated a new technique, namely, sequential non-linear least-square estimation (SNLSE), to replace old techniques such as least square estimation (LSE) and the estimated Kalman filter (EKF) to monitor a five-degree-of-freedom non-linear hysteretic building model and a 3-story steel frame FEM, this it helped to reduce the number of sensors needed to detect vibration and damage. Findings showed that the LSE is accurate and reliable.

5. Dynamic Analysis in SHM in Buildings

Ivanovic et al. [75] monitored a 7-story RC hotel building with dimensions of 62 × 150 ft in California using a range seismometer and a transducer to anticipate two ambient vibration surveys on 4 and 5 Feb 1994 as well as 19 and 20 Apr 1994 to detect vertical, transverse, and longitudinal deformations. Jin et al. [76] presented a comparison of PCA in two different approaches called adaptive principal component analysis (APCA) and conventional principal compound analysis (CPCA) to practice SHM, and results indicated that APCA provides superior results since it detects intrinsic behavior and time consumption. Chang et al. [77] experimented with a twin-tower-scaled model that was 1.17 m tall, 1.50 m wide, and 1.50 m deep using an accelerometer and a developed numerical model for the 7-story building to predict dynamic behavior such as natural frequencies and mode shape using OMA based on a neural network, and this helped to predict stiffness reduction in the building. The results showed that this method only applies to a single damaged column, not for multiple-damage conditions.

Pham et al. [78] proposed an optimization algorithm to solve inverse problems in the dynamic analysis of SHM. Dynamic characteristics such as natural frequency and mode shapes have been used to develop mathematical models that measure damage using modal parameters. In this research, a differential evolution algorithm was adopted to evaluate the structural modal parameters. The results showed that this method reduces computational effort and costs, so that uneconomical inverse problems can be avoided. Yuan et al. [79] discussed the mathematical inverse problem and performed automated damage detection for the dynamic modeling of beam structures by adopting machine learning algorithms, and this showed effective results, so there is great potential in real-time monitoring of SHM in future.

Kyriacou et al. [80] demonstrated a new toolbox called contaminant monitoring in a building (COMOB) based on MatLab software to monitor the Holmes house and divided it into 14 zones for sensor placement and to allow for input to the software. As per the results, this approach requires excess data for the software and is applicable for multiple-zone buildings. Nguyen et al. [81] demonstrated a new, cost-effective DAQ technique for the long-term monitoring of institution buildings in Australia and developed a numerical model by adopting vibration sensors, acoustic emission sensors, and accelerometers, and this provided satisfactory results. Yi et al. [82] presented a review to analyze sensor fault types, namely, precision degradation, drift, bias, gain, complete failure-1 (constant), complete failure-2 (constant with noise), and complete failure-3 (bottom noise). The detection of sensor faults was carried out via PCA, and it was found that these kinds of sensors fault will occur on tall buildings due to non-linearities. Todorovska and Trifunac [83] monitored a 6-story ICS building with dimensions of approximately 41.70 × 26.02 m, with a height of 25.48 m, using the triaxial accelerometer, and the monitoring data revealed that significant damage occurred in the first story column at the east end due to the inter-story drift, which exceeded 1.5%, and Gabor transform provided greater control over frequency resolution. Oh et al. [84] carried out monitoring in a high-rise building and conducted a wind tunnel test using Fiber Bragg Grating (FBG) sensors to predict dynamic behavior by adopting a radial basis function neural network (RBFN) based on a genetic algorithm. The results showed that the rigidity of the structure is weak in the wind direction, so it may cause maximum strain. Figure 5 shows the behavior of a multi-story building subjected to dynamic loading conditions.

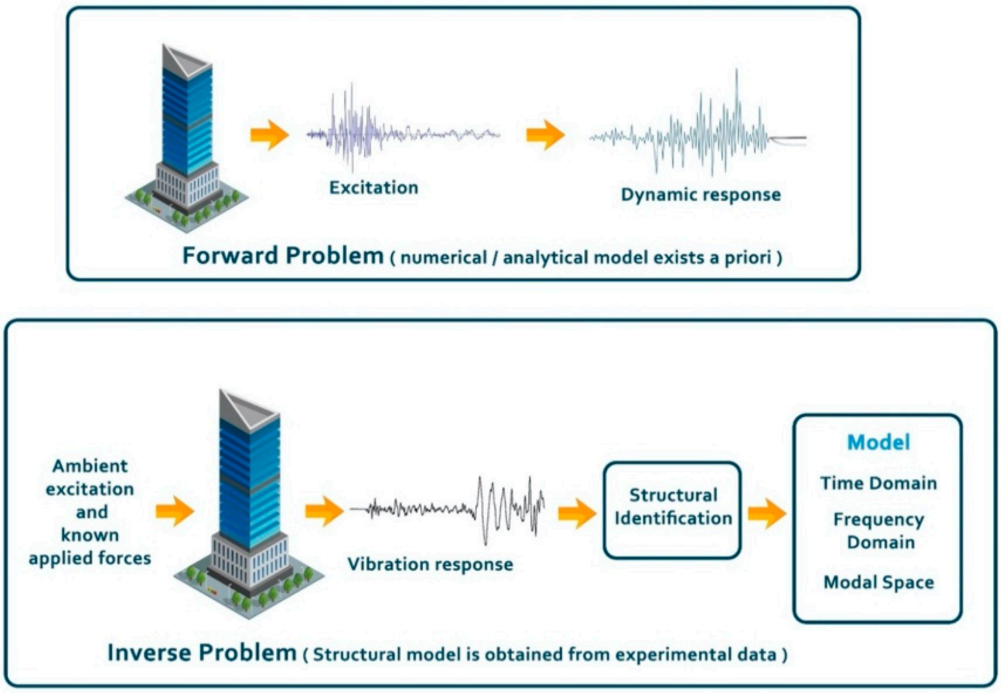

Figure 5. Dynamic response of a multi-story building using SHM.

Celebi et al. [85] experimented with a 30- to 40-story flexible building using steel bars and the real-time monitoring of a 44-story building by fixing GPS in the roof area, and results indicated that the GPS method provides more accurate results than the accelerometer in finding the relative displacement. Pisello et al. [86] monitored the inside of a university building using various sensors to predict the occupants' comfort zone and carried out a real-time survey. Theiler and Smarsly [87] developed a prototype of a 4-story shear frame structure in the laboratory and used assumptions of the BIM to collect monitoring data by adopting the Industry Foundation Classes (IFC) approach, and the results in terms of effective data transfer and data management were satisfactory.

Chen and Xu [88] conducted an experiment in a 5-story shear building using an accelerometer to analyze the semi-active friction dampers by adopting a local feedback control strategy with and without a Kalman filter, and results showed similar seismic responses both with and without a Kalman filter. Haque et al. [89] developed a new approach, namely, the hybrid topology scheduling algorithm, to anticipate a transmission control mechanism (TCP), and it provided superior output. Alonso et al. [90] presented a review on middleware based on a wireless sensor network (WSN) to protect sensors from a monitoring infrastructure called critical protection infrastructure (CPI), and the middleware was very user-friendly for maintenance and programming.

Pingue et al. [91] carried out real-time monitoring and experiments on a 2-story masonry structure that was 10 m long, 8.5 m wide, and 8.5 m tall using FBG for the experiment and geodetic monitoring for the field to predict change instabilities due to ground deformation and concluded that FBG-based investigation provides satisfactory results in the elastic phase, but the data were not easy to understand. Ma et al. [92] demonstrated a new technique called multi-dimensional SAR tomography to monitor and image the creep and shrinkage in concrete of newly constructed two buildings with an approximately, B1 = 500 m height and B2 = 250 m height, respectively. The investigation revealed that wall deflection, wall shortening, and thermal expansion were prevented.

Zapico and Gonzalez [93] developed a method for seismic damage identification for buildings with a steel moment-frame structure. To obtain the needed data, they used a simplified numerical model of a 4-story office building of approximately 16 × 18 m and 2-story heights of 3 and 4 m. This method consists of the following three steps: calibrating the initial stiffness of the structure, continuous monitoring of the live mass, and the subsequent calibration of the final stiffness after a severe earthquake. The frequency coefficient error should be less than 0.5% so that the damage prediction ratio is 95% precise. Park and Oh [94] developed a pseudo-frame model of a 123-story tall building under construction called the Lotte world tower, in Korea, to investigate the damping ratio and the modal shape by adopting visual modal identification. Strain gauges, an accelerometer, and an anemometer were used. The results indicated that field monitoring is necessary to predict exact data since this system is not sufficient to extract high-order modal data.

Fujino et al. [95] presented a review on buildings and bridges in Japan subjected to vigorous activities such as a seismic isolation system, damage detection, structural retrofit, and structural assessment. Findings suggested that sensors should be more robust and capable of excess usage, and wireless sensors were preferred for effective monitoring of a more massive structure. He et al. [96] experimented on a 5-story building model with a height of 1750 mm using three magneto rheological (MR) dampers for vibration control and health monitoring and found satisfactory results. Gao et al. [97] implemented on-site monitoring of a 335 m tall building with several floors using 128 vibrating wire strain gauges, temperature sensors, and accelerometers and developed an FEM for the building by employing Midas software; they concluded that there will be a decrease in elastic modulus greater than 20% due to the low quality of concrete and that deformation will hence increase approximately 20% more than predicted. Furthermore, relative humidity should be checked before constructing a tall building.

Saadat et al. [98] demonstrated two new methods to monitor civil structures, namely, intelligent parameter varying (IPV) and system identification techniques, to anticipate non-linear and non-modal based approaches, and IPV showed superior results compared with the conventional wavelet analysis method. Masciotta et al. [99] practiced monitoring in a Saint Torcato church in Portugal, approximately 58 m in length and 11 m in width, with an on-site campaign including visual inspection, geometric surveys, damage diagnosis, control and monitoring using a crack meter, a tiltmeter, and temperature sensors. An accelerometer and a combined sensor as per the results occurred due to the differential soil settlement damage at this building. Karapetrou et al. [100] monitored an 8-story AHEPA hospital located in Thessaloniki by separating it into two units, one being 29 × 16 m, and the other one being 21 × 27 × 16 m, with an inter story height of 3.4 m, by employing 18 sensors. A time building-specific fragility curve was generated and compared with the time-dependent curve to predict seismic vulnerability and the developed FE model. As per the results, the time building-specific fragility curve outperformed the conventional methods in terms of material properties, structural detailing, and mass distribution.

Lorenzoni et al. [101] monitored two heritage building for approximately three years, namely, a Conegliano cathedral and a Roman Amphitheatre (arena), using 16 single-axis piezoelectric accelerometers and displacement transducers integrated with humidity/temperature sensors, and significant damage identification results were found. Fan et al. [102] investigated a new TV tower in Guangzhou that was 604 m tall and 32 stories using various sensors such as accelerometers, strain gauges, and approximately 600 sensors of other types by adopting a residual convolution neural network (ResNet) approach based on vibration signals. Egidio et al. [103] dealt with a perturbation approach for dynamic analysis to predict the mode shapes and natural frequencies to monitor a 4-story shear frame. The damage of the columns was identified by considering random parameters as linear in the numerical analysis. A successful outcome was evident by the very slight errors in anticipating natural frequency [103]. Moreover, Egidio et al. [104] carried out similar uncertainty studies in simply supported beams to predict dynamic behavior adopting random stiffness parameters. Linear operation perturbation theory has been discussed using multiple mathematical solutions [105,106]. Sondipon et al. [107] presented a dynamic system of linear damping concerning the rate of change in eigenvectors and eigenvalues. An expression was derived to demonstrate a damped two degrees of freedom.

Park et al. [108] adopted two approaches based on vision-based displacement, such as the partitioning method and laser displacement sensors, to anticipate the horizontal displacement in a steel column structure for a high-rise building using two webcams and found a 0.5% difference when comparing the two approaches. Trifunac et al. [109] experimented with a 7-story RC building with dimensions of 62.7 $\times$ 150 ft, with a height of 65.7 ft, located in Los Angeles using various sensors, and the experiment showed repeated damage on the same spot several times, while an undamaged spot remained the same due to changes in the non-linear stiffness in the soil pile foundation.

6. Finite Element Analysis in SHM

Shih et al. [110] developed a dynamic computer simulation technique to assess damage in flexural members such as beams and plates in buildings by adopting two multi-criteria methods, namely, modal strain energy and the modal flexibility method. They experimented and demonstrated an FEM using SAP2000 for three beams, two continuous and one simply supported, by employing an accelerometer to predict building damage. Findings suggested that these two methods provide similar results for single damage, whereas multiple damage is more complicated, so further research is necessary on multiple-damage conditions. Cabboi et al. [111] carried out real-time monitoring and FEM analysis by employing strand software on a heritage building called the San Vittore bell tower with a 37 m height located in Italy using a piezoelectric accelerometer. PCA was applied to remove fluctuations due to environmental variations; as a result, a 10% reduction in stiffness was found.

Lautour and Omenzetter [112] demonstrated a non-linear FEM and seismic vulnerability curve along with the ANN approach to model the 2D-RC frame building; however, only one parameter was enough to anticipate ground motion using a seismic vulnerability curve. The results suggested that an ANN provides a superior output when predicting seismically induced damage because it provides output for both structural motion and ground motion compared with the seismic vulnerability curve. Isidori et al. [113] developed a prototype and an FEM of a 3-story building using MEMS sensors and a linear accelerometer to spot the distribution, occurrence, and rise of local damage and to estimate global damage. The FEM model was developed under two different conditions, including distributed plasticity, and was based on lumps to predict the local and global damage of the buildings. The experiment showed that the natural frequency was similar to that of the real structure, but the behavior of the damage seemed different.

Kaneko et al. [114] experimented with a substantial column and a weak beam moment frame in a 6-story structure using two sensors to identify the severity of damage by adopting a damage detection technique. Pushover analysis was carried out to predict shear-related displacement characteristics and its level of damage on each story. Moreover, two-dimensional non-linear FE analysis was carried out by employing ATENA software. As a result, correlations were found between the rotation angle of the column and the level of the damage in the heavy deformation stage. Monavari et al. [115] developed an FEM by employing MatLab software on 3-story and 20-story RC frames to spot deterioration in buildings. The analysis accurately showed minor deterioration pre-damage conditions. Enhancement of this method is mandatory when it comes to extreme levels of noise.

Leng et al. [116] experimented with the plane and composite wrap cylinder by using previously found FEA values based on the strain transfer efficiency of a fiber optic sensor protection system. FBG and extrinsic Fabry Perot Interferometric (EFPI) sensors are used for cylinders, but FOS sensors provide superior results compared with electrical resistance strain gauges, so it can be used for smart buildings.

7. Damage Diagnosis in Buildings

Rahmani and Todorovska [117] as well as Yuen and Kuok [118] suggested two algorithms, namely, time shift matching (TSM) and non-linear least square fit (LSQ) based on robust interferometry, to monitor a 9-story Millikan library approximately 21 × 23 m with a 43 m height located in California using multiple networks of sensors, and monitored a 22-story hall in East Asia with a height of 64 m using accelerometers by adopting a Bayesian spectral density approach for approximately one year to predict modal frequency; relative humidity and ambient temperature are necessary for the long-term monitoring of buildings.

Smarsly and Law [119] developed an onboard agent to embed into a wireless sensor to enhance the communication between buildings and the data receiving spot. As per the monitoring, the output derived a 96% reduction in power consumption and a 95%reduction in memory utilization. Picozzi [120] demonstrated an earthquake early warning system (EEWS) based on the analysis of P-waves by examining an area in Italy and adopting a tailor-made earthquake early warning (TEEW) process. This process consisted of four stages:

- Event characterization by employing an accelerometer;
- Pre-processing P-wave signals;
- The evaluation of predicted shaking;
- Deciding whether to declare alarm or not.

The results showed that the EEWS is suitable for a real-time process for time consumption. Villalba et al. [121] experimented with a concrete slab size, approximately 5.6 m in length, 1.60 m in width, and 0.285 m in thickness, to spot cracks using optical backscatter reflectometer (OBR) sensors. An OBR helps to monitor strains continuously, can be easily placed on the concrete surface, and helps to detect microcracks 1 mm or smaller. White [122] demonstrated a linear three-dimensional elasticity model for asymmetric building structures with data collected through experiments to anticipate the behavior of structures based on the inversion problem. Severino et al. [123] developed a prototype using COTS hardware to monitor a WSN in a physical infrastructure, and it was reliable and cost-effective.

Yang et al. [124] examined the shear building model with four degrees of freedom based on Hilbert Huang spectral analysis to analyze the damping and stiffness in pre- and post-damage. The analysis helped to identify damage and stiffness reductions in linear structures effectively. Lee et al. [125] suggested an integrated building fire safety (IBFS) system to improve the automated technology in high-rise residential buildings to avoid false alarms and other undesirable activities, and this provided satisfactory reports by ignoring the monitoring. Reaction durations of fire emergencies were reduced by approximately 63%.

Chase et al. [126] demonstrated the benchmark problem for ASCE with 4-degree-of-freedom and 12-degree-of-freedom structures by adopting an undamaged model matrix and a stiffness matrix that comes under the recursive least square (RLS) to monitor damage levels using structural parameters. RLS showed accurate outputs and variations. It requires less than 1.6 s for all cases and is suitable for real-time monitoring. Unzu et al. [127] implemented real-time monitoring for approximately one year on a telecommunication tower based on an alveolar polycarbonate structure by integrating 31 fiber optic sensors with a fiber optic accelerometer and six KNX sensors to predict reliability, mechanical properties, and thermal properties; results showed that it helped to bear thermal and mechanical stresses in a glass panel in a façade system.

Xu et al. [128] developed a two-scale model of a 12-story main building approximately 2400 mm in height, with a 184 mm floor height, and a 3-story podium structure approximately 600 mm in height, with a 168 mm floor height, using 16 charge amplifiers, 15 accelerometers, and a current eddy sensor and by adopting a frequency response function (FRF) to anticipate building damage. As per the results, the FRF curve is precise with respect to damage occurrences in connections and provides satisfactory results in terms of identifying the location and the severity of damage, even when the scope of the damages is greater than 5% and there is noise. Täljsten and Carolin [129] experimented with a 4.5-m-long beam in a laboratory using speckle pattern analysis to predict plate bonding to repair and strengthen RC building elements.

Zhang et al. [130] suggested two algorithms, namely, the probability density evolution equation (PDEE) based on the reliability evolution method and the statistical moment-based system identification method (SMB), for predicting reliability evaluations and system identifications in a building with data received from a 2-story stochastic shear building model with three damage events: a single damage on the second story and multiple damages on the first and third stories. The results showed that, when the threshold increases, reliability increases. Yu et al. [131] investigated the power monitoring system in buildings using the Internet of Things (IoT) to resolve the monitoring object location and the placement, and this helped to predict the voltage curve with the help of a display interface.

Su et al. [132] developed a 6-story shear building model and a 5-story, steel-frame non-sheer building model using accelerometers and adopted wavelet transform techniques to measure the damage in each story using sub-structural frequencies. The results showed that a decrease in natural frequencies of the severe damage found in 6-story buildings and variation in mass or stiffness damage in the first story of the 5-story steel frame. Burnett et al. [133] investigated an electrical distribution system found in high-rise buildings, which generates an extremely low-frequency magnetic field (ELF), and it creates several health problems when it interferes with sensing equipment, so using more bus ducts can reduce these problems.

Grinzato et al. [134] carried out real-time monitoring in a historic building located in Venice's arsenal using IR thermography to monitor moisture content, finishing status, and the hidden structure of walls, and mutual interaction differs due to various environmental factors and becomes challenging. This was found to be successful for thermal diffusivity, moisture mapping, and wall bonding. Tanet al. [135] experimented with steel bars to make full use of FBG sensors for monitoring purposes. FBG sensors were provided with a coating, such as a polydimethylsiloxane strain-sensitive coating or a pH-sensitive hydrogel adopting the Bragg wavelength method. The steel rod underwent three different tests by exposing it to air, acid, and alkaline, and a higher sensitivity was found in an acidic environment. These methods are only applicable for laboratory monitoring purposes, so further research on real-time monitoring is necessary.

Kruger [136] presented a review of wireless sensor systems in concrete buildings to demonstrate the design, concepts, and sensor requirements of short- and long-term monitoring. As per the results, data interpretation and data analysis are mandatory to analyze the nature of a building. Using intelligent data processing is more costly than conventional cable monitoring systems. Madan [137] introduced a new technique to anticipate earthquake-induced vibrations in buildings, using a counter propagation network (CPN), without considering target control forces. This technique was applied to an 8-story building for monitoring. Furthermore, the CPN was compared with the backpropagation neural (BPN) network, and the CPN provided a more satisfactory output in terms of time consumption, reliability in taking large data, and trainability.

Boutet et al. [138] developed a prototype of a school building in Argentina during June 2012 to predict thermal and hygro-thermal lighting behavior during the autumn season using HOBO sensors, and results showed an illuminance level up to 400l× on average. It saved in terms of electrical consumption, due to the use of natural light. De Wilde and Coley [139] presented a review on building responses due to climatic impact, so the history of collected data was considered for monitoring and other purposes, and occupants' thermal comfort were taken into account due to climatic changes. Jiang et al. [140] investigated a 7-story shear beam model using multiple sensors by adopting a fuzzy neural network (FNN) and data fusion techniques using fusion algorithms. As per the findings, damage identification can be made in the initial stage, and damage assessment can be conducted in the second stage. More experiments are necessary for real-time monitoring; as of now, it can be only be applied to numerical simulation. Kim et al. [141] investigated a plate girder approximately 24,500 mm in length and a beam in a building under construction, namely, the K Art Hall, using vibrating wire strain gauges (VWSGs), and results suggested that complicated wire connections can be neglected and are easy to maintain, and tensile stress was more than 6% due to variations in the stress in long-span girders.

Hajdukiewicz et al. [142] carried out real-time monitoring in two educational buildings, the Institute of Life Course and Society (ILCS) building and the Engineering Building (EB), as suggested by the National University of Ireland, using various gauges and sensors. Once the continuous monitoring in a building is safe, improved indoor environments and energy consumption follows, so energy efficiency measures are necessary to reduce the environmental impacts on buildings. Liet al. [143] presented an overview of fiber optic sensors used for SHM in buildings, including distributed fiber optic sensors, local fiber optic sensors, and quasi distributed sensors, and results showed that an FOS will play a crucial role in the future of SHM in buildings.

Bakis et al. [144] experimented with seven hybrid fiber-reinforced polymer rods to predict the pseudo ductility and the self-monitoring capability using piezo resistivity, and early catastrophic failure was observed. Hiromi et al. [145] studied the SHM application in a 5-story building adopting an SVM based on a machine learning technique under modal frequencies using two vibration sensors. The SVM helped to detect multiple damages in multi-story buildings. Naet al. [146] developed a 20-story shear beam model using sensors by implementing genetic algorithms using a flexibility matrix based on a damage evaluation method and developed numerical simulations using OpenSees software. This yielded excellent reports, even with inadequate data, and modal mass was exceeded by approximately 90% due to the genetic algorithm.

Zhang et al. [147] demonstrated a support vector regression (SVR) approach using 52 degrees of freedom and 30 degrees of freedom by applying an SVR training algorithm, and findings showed that SVR provided accurate and robust data for long-term monitoring on a large scale, even when contaminated by noise. Cataldo et al. [148] suggested a method known as time-domain reflectometry (TDR) using a passive, diffuse sensing element (SE) that looks like a wire to monitor the rising damping in the building structure. The SE was permanently embedded into a wall when the building was under construction or renovation to monitor the behavior of the wall, and it was concluded that this method not only monitors moisture content inside the wall [149], but also the overall health status of the building [148].

Ni et al. [150] carried out real-time monitoring in a structure using accelerometers and temperature sensors and by implementing SVM techniques to predict temperature effects. Kopsaftopoulos and Fassois [151] experimented on an aluminum truss with overall dimensions of approximately 1400 × 700 × 800 × 700 mm, using strain gauges and implanting a time series method to diagnose the building's damage. Nonparametric and parametric methods yielded effective outputs for the time series method to detect global or local damage and precisely predict actual damage [151,152]. Huang et al. [153] adopted an Autoregressive and an ANN model to predict variations in temperature to carry out a vibration-based damage identification process. FE models were used to demonstrate the reliability and effectiveness of this method. The American Association of Civil Engineers (ASCE) benchmark model and an FE model using SAP 2000 was adopted. The results indicated satisfactory outcomes by predicting temperature variation and noise disturbances according to the numerical results. Huang et al. [154] experimented with a two-span steel gird and three-span continuous beam. They used a model-based damage identification method by adopting a genetic algorithm approach to optimize the solution and assumed mode shapes and natural frequencies to predict the variations in temperature and noise. The FE model was developed with MatLab software, and findings were positive for 3, 5, 10, 20, and 30% of the mode shapes with a feasible range in a noise environment [154]. Huang et al. [155] adopted a hybrid algorithm, known as PSO-CS, a combination of particle swarm optimization (PSO) and cuckoo search (CS), to anticipate temperature and noise. The main objective was to find the elastic modulus variation due to the temperature effect using an FE model of the ASCE benchmark model, and MatLab software was employed for beam and frame structures. The outcome of the research using PSO-CS, monitoring almost all possible damages, showed an outstanding performance [155,156].

Huang et al. [157] used frameworks such as modal flexibility, enhanced moth-flame optimization, and modal frequency strain energy assurance criterion (MFSEAC) for the identification of damages in structures. Findings showed that the enhanced moth-flame optimization provided superior outcomes compared with particle swarm optimization, CS, and moth-flame optimization. Three numerical samples, such as 40-story shear frames with irregular noise, 31 bar truss structures with irregular temperature and noise, and three-span concrete that continued to beam with variations in temperature, were compared by the adopting modal assurance criterion (MAC), modal strain energy (MSE), modal flexibility, and the frequency change ratio (FCR). In addition, two laboratory samples were used to verify the outcome, and satisfactory results with substantial effects were found along with positive noise robustness [157]. Appendix A represents list of reviewed buildings with SHM implemented.

8. Comparative Study and Future Recommendations

A critical analysis of methodologies adopted to monitor buildings using various sensors was performed. Best-practice sensors were classified based on previously published literature. The findings suggest that accelerometers are used to monitor buildings much more widely than other sensors are. Accelerometers provide superior outcomes for static and dynamic analysis. Table 1 displays the role of various other sensors compared with accelerometers.

This article compares accelerometers with other sensors to monitor buildings. It is clear that accelerometers perform well in dynamic analyses and less effectively in static analyses. To solve this issue, we suggest a combination of sensors, such as strain gauges, FBGs, HOBOs, displacement transducers, temperature sensors, piezoelectric sensors, and IR thermography, with accelerometers. The SHM of buildings will increase in terms of various parameters such as cracks, indoor environments, displacement, strain, temperature, humidity, and elastic deformations.

In the present scenario, recommendations for future purposes are necessary to increase the overall efficiency of research to produce precise and quick data collection. Based on the detailed discussion of previously reported works, the following points must be considered to enhance research on the SHM of buildings [13,46,53]:

- Development is necessary to enhance the life span of sensors and their data transformations for long-term monitoring purposes; hence, advanced sensors should be designed with a high sensitivity and range.
- The prediction of damage should be implemented in various environmental activities, so that monitoring can be executed in buildings to an even greater extent.
- To improve consistency, DAQ and predictive analysis are needed to maintain communication between buildings and sensors for both short-term and long-term monitoring.
- A greater understanding of instrumentation, mathematical techniques, and signal processing is essential to understand the behavior of buildings in terms of monitoring and predicting damage.

- Further research is mandatory to practice SHM at low cost, especially for wireless communication.

A robust statistical method should be considered when measuring the static and dynamic response of buildings.

Table 1. Role of various sensors compared with accelerometers.

No.	Accelerometer in SHM	Other Sensors Used in SHM
1	Accelerometers perform more effectively in a smaller number of sensors.	In other sensors, a greater number of sensors is needed.
2	Accelerometers help to predict damage in beam-column joints more effectively, with an 85% accuracy.	In other sensors, the choice of assessing beam-column joint was occasional, and the level of accuracy was not as high.
3	The level of frequency and deformation can be predicted with 90% accuracy in accelerometers.	Optical fiber sensors alone can perform equally to accelerometers to predict the frequency level; however, other sensors show a lower accuracy.
4	Accelerometers, based on MEMS technologies, cooperate in assessing damage using wave propagation algorithms.	Other sensors do not have such advanced technology to assess damage.
5	Model identifications and ambient vibrations can be practiced in accelerometers for a dynamic analysis of all environmental changes	In other sensors, dynamic analysis can be predicted by assessing the vertical deformation and changes in the building's behavior.
6	Uniaxial accelerometers adopt TVA to carry out real-time monitoring using an analytical model and experimental data.	TVA is not used by other sensors for monitoring purposes.
7	Accelerometers poorly identify flexural cracks, shear cracks, amplitude, and time domains.	Piezoelectric sensors are better able to detect cracks, amplitude, and time domains, with a 75% accuracy.
8	Accelerometers outperform other sensors in dynamic analysis but show a limited response in static analysis, e.g., for temperature, humidity, or deformation	Temperature sensors, displacement transducers, and FBGs outperform accelerometers in anticipating temperature, humidity, or deformation
9	Accelerometers show a lack of efficiency in monitoring a wall's hidden structure, moisture content, hygrothermal behavior during the autumn season, energy consumption, and indoor environments.	Vibrating wire strain gauges, HOBOs, IR thermography, or KNX effectively monitor a wall's hidden structure, moisture content, hygrothermal during the autumn season, energy consumption, and indoor environments.
10	Accelerometers do not monitor stress, strain, temperature, cracks, or humidity well.	Other sensors such as strain gauges, temperature sensors, FBGs, piezo electric sensors, and displacement transducers provide satisfactory outcomes compared with accelerometers.

9. Conclusions

This review discusses the building structural health monitoring of all parameters using static, dynamic, and finite element methods to detect or predict building damage. The whole structural health monitoring consists of four characteristics: the presence, location, and severity of the damage and the remaining service life of the building after damage.

The article discusses the important approaches, processes, hardware, and sensors adopted for SHM in buildings. The following claims can be made:

- Currently available techniques can be used to implement SHM in buildings along with efforts made to enhance the technique both economically and practically for monitoring purposes.
- The Bayesian approach for SHM in buildings can predict damage and deterioration and to evaluate the variation in dynamic structural properties.
- Numerical models in SHM using Matlab, OpenSees, and other, similar software can help to determine structural responses adopting various algorithms.
- Damage severity can be predicted in the initial stiffness using piezoelectric sensor patches and electro-mechanical impedance techniques by acquiring a global dynamic technique, and medium to severe damage can be extracted through monitoring with utmost accuracy.
- The SHM approach is extremely suitable for real-time monitoring if the methods are carried out comfortably by precisely applying all techniques.
- Ambient vibration methods range from measured dynamic responses to real-time monitoring such as mode shapes, modal damping ratios, and natural frequencies.
- Various types of sensors are used for structural health monitoring such as fiber optic sensors, piezoelectric sensors, microelectromechanical system sensors, accelerometer, temperature sensors, and accelerometers.
- Predictive analysis and data acquisitions can be applied to buildings using sensors, so sensors inputs are safe and reliable in accordance with building conditions.
- SHM can be applied for different types of buildings, including multi-story buildings, commercial buildings, and heritage buildings, and various works have been discussed in detail.
- The static and dynamic behavior of buildings can be used to predict damage at an early stage by adopting SHM techniques along with finite element analysis reports.
- The in-detail analysis of software, hardware, and real-time data along with future perceptions are based on the operating principles for SHM in buildings.

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Appendix A

Table A1. List of the reviewed buildings with the implemented SHM.

No.	Source by Author	Subject of Study (Type of Building)	Number of Stories	Types of Sensors Used	Measured Parameters
1	Olivera Lópezet al. [12]	14 floor building	14		Hydrodynamic forces to detect the damage
2	Roghaeiand and Zabihollah [14]	Hospital steel structure	3	Piezoelectric sensors	To identify the stress and deformation
3	Zhouet al. [15]	RC frame building	12	_	Variation in stiffness using elastic, hybrid and pinched
4	Pierdicca et al. [16]	Concrete school building	–	–	Dynamic behavior of buildings

Table A1. *Cont.*

No.	Source by Author	Subject of Study (Type of Building)	Number of Stories	Types of Sensors Used	Measured Parameters
5	Demetriou [17]	3-story building	3	–	Reduction in stiffness because of harmonic motion
6	Dong et al. [18]	Van Nuys hotel and imperial country service building	–	–	Relationship between the severity of damage and damage index
7	Yanget al. [19]	Steel frame building	20	-	Dynamic behavior due to seasonal frost
8	Autunes et al. [20]	Adobe masonry structure	–	Optical fiber sensors	Natural frequency
9	Hisonet al. [22]	Tufa wall	–	Magnetoelastic sensors	Elastic deformation and fracture alarm
10	Mahjoubiet al. [23]	Shanghai tower	–	Triaxial accelerometer	To reduce the number of sensors
11	Sajedi and Liang [24]	RC moment frame building	3	–	Prediction of damage location, existence, and Severity
12	Soltaninejadet al. [27]	Two adjacent building	–	–	Anticipate pounding
13	García-Macías and Ubertini [28]	Sciri tower	–	Accelerometers	Levels of frequency and deformation
14	Sunet al. (2019) [29]	Skyscraper building (Al Harma Tower)	86	–	To find the building deformation due to heavy dead load and seismic response
15	Chelliniet al. [30]	Composite frame structure		Accelerometer sensors	Damage in beam-column joint
16	Morales-Valdezet al. [31]	5-story building	5	MEMS Technologies based accelerometers	Predict damage by adopting a wave propagation algorithm
17	Pachón et al. [33]	Heritage building (Monastery of San Jeronimo de Buenavista)	–	–	Dynamic behaviour like ambient vibration and model identification
18	Frigui et al. [34]	Ophite tower	18	–	Damage severity
19	García-Macías and Umbertini [36]	Consoli palace	–	various sensors types	Damage
20	Li et al. [37]	Tall building (Ping an Finance Centre)	–	different sensors	Vertical deformation in the various structural element
21	Zhanget al. [38]	108-story building	108	Accelerometers and tilt sensors	Monitor and damage prediction
22	Modenaet al. [39]	Heritage structures, Spanish fortress, and tower (L'Aquila), Scrovengni chapel (Padova), the stone tomb of Cansignorio	–	–	static and dynamic response of the building
23	Aguilaret al. [41]	Adobe church	–	Accelerometers	Damage post-earthquake

Table A1. *Cont.*

No.	Source by Author	Subject of Study (Type of Building)	Number of Stories	Types of Sensors Used	Measured Parameters
24	Coletta et al. [43]	Sanctuary of Vicoforte	_	various sensors	Dynamic behaviour for all environmental degradation
25	Lam et al. [45]	Boat-shaped building (Academic building 3(AC3)	20 main story and 5 adj. story	_	Monitoring for the changes in the behaviour of building
26	Lorenzoniet al. [46]	Cultural heritage building (Spanish fortress and tower)	_	_	Robust statistical method and damage detection algorithms
27	Kaya and Safak [48]	High rise building	_	_	Developed new software REC_MIDS
28	Cheng et al. [49]	3 and 8-story building	3 and 8	Accelerometers	Real-time monitoring to identify damage
29	Rahmani et al. [50]	Sherman oaks office building	12	uniaxial accelerometer	Monitoring through experimental and analytical models by adopting time velocity analysis
30	Musafere et al. [51]	A building with 17-story and Louis factor building	17	sensors and accelerometers	To predict the dynamic behavior
31	Behniaet al. [53]	concrete structure		Piezoelectric sensors	Anticipate damage like frequency, amplitude, severity, cracks, and time-domain
32	Ierimontiet al. [56]	RC school building	3	Uni-axial accelerometers	Static analysis such as elastic deformation, humidity, and temperature
33	Carden and Brownjohn [57]	Steel building structure	4	Accelerometer	Prediction of occurrence of damage
34	Wang et al. [58]	RC hotel building	7	Accelerometer	Detect story damage index (SDI)
35	Kao et al. [5]	Steel building	5	_	Detect static response such as displacement, velocity, and acceleration
36	Ramoset al. [59]	Saint Torcato church		Accelerometer	Predict static analysis like cracks and vertical deformation
37	Mejriet al. [60]	office building (Confort Bois construction company)		HOBO sensors	To measure energy consumption
38	Bhalla and Soh [61]	RC portal frame	2	Piezoelectric transducer	Detect flexural crack and shear crack
39	Pesciet al. [62]	Two heritage buildings (Garisenda tower and Asinelli)		Accelerometer	To predict deformation patterns due to gravity and seismic activities
40	Xuet al. [63]	3-story building	3	Sensor	Detect damage and isolation properties

Table A1. *Cont.*

No.	Source by Author	Subject of Study (Type of Building)	Number of Stories	Types of Sensors Used	Measured Parameters
41	Saisiet al. [64]	Bell tower of church Santa Maria del carrobiolo	–	Temperature sensors, displacement transducers	Real-time monitoring
42	Butt and Omenzetter [65]	GNS Avalon building	3	Sensors	FE model has developed by employing Abaqus Software
43	Bulajićet al. [71]	12-story building	12	–	Damage occurs due to non-structural elements
44	Ivanovićet al. [75]	RC hotel building	7	Range seismometer and transducer	Detect deformations like vertical, transverse, and longitudinal
45	Changet al. [77]	Twin tower	–	Accelerometer	To predict the dynamic behaviour such as natural frequencies and mode shape
46	Kyriacouet al. [80]	Holmes house	–	–	Demonstrated new toolbox called contaminant monitoring in a building (COMOB)
47	Nguyen and Chan [76]	Institution buildings	–	Vibration sensors, acoustic emission sensors, accelerometers	Demonstrated new cost-effective DAQ technique
48	Todorovska and Trifunac [83]	ICS building	6	Triaxial accelerometer	To monitor the damage occurrence
49	Oh et al. [84]	High-rise building	–	FBG sensors	Predict dynamic behaviour
50	Celebi [85]	44-story building	44		Monitoring by fixing GPS
51	Chen and Xu [88]	Shear Building model	5	Accelerometer	To analyses the semi-active friction dampers
52	Pingue et al. [91]	Masonry structure	2	FBG	To predict changes in instability due to ground deformation
53	Ma et al. [92]	Newly constructed two buildings	–	–	SAR tomography to monitor and imaging of creep and shrinkage occurs
54	Zapico and Gonzalez [93]	Office building	4	–	Seismic damage identification by adopting ANN
55	Park and Oh [94]	Tall building (Lotte world tower)	123	Strain gauges, accelerometer, anemometer	To investigate damping ratio and modal shape
56	He et al. [96]	Building Model	5	MR dampers	For vibration control and health monitoring

Table A1. *Cont.*

No.	Source by Author	Subject of Study (Type of Building)	Number of Stories	Types of Sensors Used	Measured Parameters
57	Gao et al. [97]	Tall building	–	Vibrating wire strain gauges, temp. sensors and accelerometers	onsite monitoring and developed FEM
58	Masciotta et al. [99]	Saint torcato church	–	Crack meter, tiltmeter, temperature sensors. accelerometer and combined sensor	onsite campaign like visual inspection, geometric survey, damage diagnosis, control and monitoring
59	Karapetrou et al. [100]	AHEPA hospital	8	sensor	Predict seismic vulnerability
60	Lorenzoni et al. [101]	Two heritage building (Conegliano cathedral and roman Amphitheatre (arena))	–	Single-axis piezoelectric accelerometer and displacement transducers integrated with humidity/temperature sensors	For damage identifications
61	Fan et al. [102]	Guangzhou new TV tower	32	accelerometer, strain gauge	(ResNet) approach based on vibration signal denoising
62	Trifunac et al. [109]	RC building	7	–	Monitoring for damage prediction
63	Cabboi et al. [111]	Heritage building (san Vittore bell tower)	–	piezoelectric accelerometer	carried out real-time monitoring and FEM
64	Isidori et al. [113]	3-story building	3	MEMS sensors and linear accelerometer	To spot the distribution, occurring and rise of local damage and estimate the global damage
65	Kaneko et al. [114]	6-story building	6	–	To identify the severity of damage adopting damage detection technique
66	Rahmani and Todorovska [117]	Millikan library	9	–	Suggested two algorithms TSM and LSQ
67	Yuen and Kuok [118]	22-story building	22	accelerometer	To predict modal frequency
68	Unzu et al. [127]	Telecommunication tower	–	fibre optic sensors with fibre optic accelerometer and KNX sensors	Predict reliability, mechanical properties, and thermal properties
69	Xu et al. [128]	1 Main Building and podium structure	12 and 3	charge amplifier, accelerometers, and current eddy sensors	Anticipate damage of the building by FRF

Table A1. *Cont.*

No.	Source by Author	Subject of Study (Type of Building)	Number of Stories	Types of Sensors Used	Measured Parameters
70	Su et al. [132]	Shear building model and non shear building model	6 and 5	Accelerometer	To measure damage in each storey using substructural frequencies
71	Grinzato et al. [134]	Historic building (Venice's arsenal)	_	IR thermography	To monitor moisture content, finishing status, and walls hidden structure
72	Madan [137]	8-story building	8	_	Anticipate earthquake-induced vibration in building
73	Boutet et al. [138]	School building	_	HOBO sensors,	To predict lighting thermal and hygrothermal behavior during the autumn season
74	Jiang et al. [140]	Shear beam model	7	_	Damage identification
75	Kim et al. [141]	Kart Hall	_	Vibrating wire strain gauges	Monitoring of under-construction building for detection of damage
76	Hajdukiewicz et al. [142]	2 educational buildings (ICLS and EB)	_	Various gauges and sensors	Indoor environment and energy consumption in the building
77	Hagiwara et al. [145]	5-story building	5	Vibration sensors	Suggested SVM for damage prediction
78	Na et al. [146]	shear beam model	20	_	Implementing genetic algorithms using a flexibility matrix based on a damage evaluation method
79	Kopsaftopoulos et al. [151]	Truss building	_	Strain gauges	To diagnose the building's damage

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