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CASE STUDY

Internet of things (IoT)-based structural health monitoring of laboratory-scale civil engineering structures

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Abstract

Rapid advances in the Internet of Things (IoT) domain have made it a crucial technology for the real-time structural health monitoring (SHM) of civil engineering infrastructures. The availability of quick and accurate vibration data is essential for SHM, and such data can be obtained through IoT devices mounted on the structures. This study proposes a real-time damage prediction and localization approach using a low-cost "do-it-yourself" wireless sensor node with IoT capabilities for SHM. The proposed sensor node comprised a microcontroller (NODE MCU ESP8266) and a 6-axis accelerometer (MPU6050). The IoT devices track the real-time frequency of the laboratory-scale structure indirectly via measurement of acceleration-time history, and their results are compared with conventional industry-standard accelerometers. Promising results, with a <6% average difference from the conventional accelerometer (difference ranging from 1.3 to 14.3%), provided an innovative SHM for vibration-based real-time SHM using the IoT paradigm. The performance of the proposed methodology was validated numerically and experimentally on two laboratory-scale structures, and the potential of IoT technology for enhancing the efficiency of SHM was demonstrated. The proposed method thus can enable the early detection of damages in infrastructures such as buildings and bridges and thus can reduce the likelihood of accidents via continuous SHM.

Keywords Real-time monitoring · Internet of things · Structural health monitoring · Nondestructive testing · Intelligent sensors · Smart buildings

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Introduction

Civil engineering infrastructures are usually monitored using wired sensors, and in some cases, wireless sensors, but they tend to be cumbersome to install at the site, and extensive preparation is required prior to data acquisition. Data acquisition has associated costs, as personnel often must go to the site to retrieve data manually from the data loggers or for maintenance and repair. In this regard, an alternative technology to transfer and acquire SHM data is the Internet of Things (IoT). IoT-based technologies have been pointed out as emerging areas for driving industrial revolution 4.0 and future technological growth. IoT can be helpful for addressing challenges in traditional SHM. However, it is a less explored domain in SHM where compact alternative solutions are sought for inspection professionals. SHM using IoT combines wireless data transfer from sensor nodes through WiFi mainly to detect and monitor structures in real-time. IoT implementation in SHM can surpass existing limitations by enabling sensor nodes to transmit and process data to cloud devices, enabling real-time

SHM. By integrating IoT devices such as sensors, cameras, and other monitoring devices mounted on civil engineering infrastructures, data on various structural health parameters, such as strain, displacement, vibration, relative humidity, and temperature, can be collected and analyzed. Applying such IoT-based solutions enables monitoring in cases where traditional SHM cannot reach. IoT can help improve structural safety by detecting damage early and enabling timely maintenance or repair [1]. IoT-Based real-time data capture and monitoring systems can supervise operation of civil engineering infrastructure, data, and performance [2].

Mishra et al. [3] discussed IoT's use for monitoring the structural health of civil engineering infrastructure, including real-time data collection from various sensors. They proposed using these technologies to automate the SHM process and extend structures' service live. Recent studies have explored some applications of IoT-based sensors for concrete/lime-mortar compressive strength monitoring [4, 5], real-time monitoring of construction projects [6], energy management system for metro rail projects [7], IoT for solar energy measurements [8], IoT for automated personal protective equipment tool for construction safety [9, 10], IoT for masonry cultural heritage [11, 12], tunnel construction monitoring [13], and checking the vibration quality of fresh concrete combining IoT and deep learning [14].

Numerous studies have used IoT devices for SHM of concrete structures [15, 16] using the maturity index method and micro-climate monitoring [17] where mainly temperature, relative humidity, and CO_2 sensors are deployed. Few studies have explored the potential applications of IoT in real-time SHM of infrastructures in the damage detection field using vibration signals for SHM [18]. Many existing studies have focused on the development of IoT devices and accelerometer nodes for monitoring dynamic behavior; however, further research is needed to accurately detect and localize damage in structures. Additionally, there is a lack of research on integrating different types of sensors in a single system to improve the accuracy of damage detection for SHM purposes. Additionally, many case studies in the field of damage detection/inverse problems for dynamic SHM, where the location and severity of damage are located are based on simulated data from finite element analysis [19, 20] of damaged cases, some take into account experimental validation data from literature benchmark studies [21] and do not take into account experimental field data.

An important aspect of IoT is the network type used for data transmission and it varies depending on the need. An increasing number of studies are using IoT for SHM; these use various networks to communicate data and ensure user dependability. For example, some of the communication networks used in IoT and SHM include wireless sensor networks (WSNs), low-power wide-area networks (LPWANs), cellular networks, long-range (LoRa) technology [22], and satellite networks for global coverage in remote areas. Specifically, WSNs are often used in SHM applications to monitor the health conditions of structures such as bridges, buildings, and dams [23–25]. LPWANs are well suited for IoT applications where devices need to communicate over long distances, such as in smart cities and industrial settings. Cellular networks are often used in IoT applications, where cell phones paired with unmanned aerial vehicles (UAVs) process video data with deep learning algorithms [26]. Case study applications of such communication technologies in engineering include LoRa technology for monitoring of early age concrete compressive strength [27], LPWANs for slope and river monitoring system [28], GPS systems (satellite networks) for displacement study in bridges [29], and UAVs for fire detection using video-feed [30]. The current study uses WSN for transmitting acceleration-time data for SHM the case study structures.

One of the most significant and efficient ways to assess the current health condition of a structure is through the analysis of vibration data, which can describe the dynamic response of a structure. These data can then be analyzed using machine learning (ML) and other advanced algorithms to identify patterns and anomalies that may indicate damage or deterioration. Several IoT applications and applications supported by IoT-compatible accelerometers use vibration data for damage detection in civil engineering structures.

Several applications of SHM systems based on vibration data from accelerometers have been reported for SHM of bridges and buildings. Muttillo et al. [31] used an IoT-based SHM system for damage detection in a cantilever aluminum bar structure. They deployed a triaxial accelerometer ADXL355 and used damage indicators that reported a tenfold increase in value with a 2.5 mm engraving in aluminum bars, compared with healthy beam data. Duc et al. [32] estimated the first mode shape and natural frequencies by using a calibrated ADXL345 acceleration sensor in the Arduino platform. Reddy et al. [33] compared the results of an analytical model with natural frequencies obtained experimentally via the frequency response function (FRF) of a cantilever beam. They concluded that low-cost Arduino-based sensors can extract modal parameters with $<8\%$ error compared with an expensive FFT analyzer. Hassan et al. [34] calculated modes for the undamaged and damaged structures of a five-story practical building using the IoT SHM system and determined that a shift of$>5\%$ indicated damage. Chilamkuri and Kone [35] performed a field experiment under the Varadi Road bridge using an ADXL accelerometer and analyzed the vibrations of the bridge deck. They considered a critical threshold value of >16 Hz, which indicates a weaker span. Peng et al. [36] developed an IoT sensing system for bridge SHM to capture the acceleration response, temperature, and GPS coordinates of moving vehicles. The test results indicated that the IoT-based SHM system captured the first-order natural frequency of a full-scale footbridge, and Fourier spectra of the acceleration responses of the developed IoT sensor matched adequately using wired sensors. Koene et al. [37] reported the functionality of an IoT-based Memsio accelerometer for capturing the translational motion and vibration of the rotating machinery. Similar to our case study, Danish et al. [38] instead of a metal beam used a reinforced concrete (RC) beam to carry out the real-time SHM process using vibration data and then acceleration response via fast Fourier transform. Table 1 lists the different accelerometer sensors employed by different researchers along with their location in the civil engineering infrastructures.

This study deployed IoT for real-time monitoring of the modal parameters, such as natural frequencies and mode shapes, of two laboratory-scale case study structures. Real-time frequency analysis was used to continuously monitor the health of the laboratory-scale case study structures. For SHM purposes, the raw data of the acceleration of a structural member, a low-cost IoT-based sensor was used herein, resulting in a cost-effective solution. The novelty of this study is twofold, (i) damage prediction and localization for two case study structures in civil engineering using IoT devices, and (ii) validation of the low-cost IoT-based sensor node by comparing the results with a benchmark sensor node.

Methodology and framework

When the natural frequency is determined experimentally, it deviates from the analytical value, similar to when there may be some deviation in the structural element from the ideal condition; this causes the stiffness to vary along the beam. When a structure has damage, its stiffness decreases, which can lead to a higher period or lower frequency. Model updating is an important process in structural dynamics, which involves updating the structural properties such as stiffness and mass based on the measured modal parameters such as natural frequencies and mode shapes [39, 40]. In this study, ant lion optimizer (ALO) optimizing algorithm is selected for model updating because it can efficiently search through a large and complex solution space compared with other algorithms. ALO combines local and global search strategies, which can prevent it from getting stuck in local optima and improve solution quality. ALO is a multi-objective optimization algorithm inspired by the hunting behavior of ant lions; it can efficiently balance exploration and exploitation while searching for optimal solutions. ALO is a flexible algorithm that can be easily customized for optimization problems and constraints [41, 42]. It can effectively solve complex optimization problems with nonlinear and multi-objective objectives, making it suitable for model updating.

For model updating for a rectangular cross-sectioned beam when analytical and experimental frequencies are known, the ALO algorithm can be applied as follows:

(i) Initialize the population of antlions with random positions: x_i^0, where i represents the ant lion index, and 0 denotes the initial iteration.

(ii) Update the position of each ant lion using,

$$x_i^t = x_i^{(t-1)} + s_i^t \times d_i^t \tag{1}$$

where x_i^t is the position of the ant lion at iteration t; s_i^t is the step size that controls the movement of the ant lion; and d_i^t is the direction vector indicating the movement direction.

(iii) The step size is updated using a linearly decreasing function (Eq. 2)

$$s_i^t = s_i^0 \times (1 - t)/MaxIter \tag{2}$$

where $MaxIter$ represents the maximum number of iterations.

Table 1 Accelerometer sensors based on IoT/Arduino-based platforms used in literature for vibration-based SHM and their specifications

References	Sensor type	Sampling frequency	Location
Muttillo et al. [31]	ADXL355	250 Hz	The first accelerometer is on end of the cantilever bar, and the second is 16.6 cm from the blocking point
Duc et al. [32]	ADXL345	NA	Free end of the cantilever beam
Reddy et al. [33]	ADXL355	NA	Free end of the cantilever beam
Hassan et al. [34]	MPU6050	100 Hz	Center of every floor
Chilamkuri and Kone [35]	ADXL335	10 Hz to 360 Hz	Under the bridge span at one of the piers
Peng et al. [36]	ADXL355	120-200 Hz	Vehicle body during the drive-by test on footbridge of building
Koene et al. [37]	ADXL355 (MEMS accelerometer called Memsio)	4000 Hz	One end of the roller machine and placed on the opposite side of the other
Danish et al. [38]	waspmote	40 Hz sampling selected	Sensors at one-third of the length from both sides

(iv) The direction vector is calculated as a weighted average of three components,

$$d_i^t = w_1 \times d_i^{(t-1)} + w_2 \times c \times (x_{best} - x_i^t) + w_3 \times r_i \quad (3)$$

where $d_i^{(t-1)}$ is the direction vector for ant lion in the previous iteration; w_1, w_2, w_3 are the weights controlling the contribution of each component; c is a constant scaling factor; x_{best} is the position of the best ant lion in the current iteration; and r_i is a random vector generated from a uniform distribution.

(v) Evaluate each ant lion's fitness based on the optimization problem's objective function, which in this case could be a measure of the discrepancy between the analytical and experimental frequencies.

(vi) Update the best ant lion per fitness value as well as the population by applying crossover and mutation operations to the antlions, allowing for exploration and exploitation of the search space.

(vii) Repeat steps (ii)–(vi) until a termination condition is met (e.g., the maximum number of iterations or desired fitness threshold).

Thus, ALO employs the behavioral patterns of ant lions, adaptive step size, and direction vector updates to effectively navigate the search process toward improved solutions. Through iterative population updates, the algorithm systematically exploits the search space, aiming to identify optimal or near-optimal solutions for the problem of model updating in an aluminum rectangular cross-sectioned beam. By leveraging the inherent characteristics of ant lions and employing strategic updates, ALO offers a promising approach to efficiently tackle the challenge of optimizing the model in this specific context.

One of the methods for quantifying the change in curvature of the mode shape involves using the curvatures of the mode shape at two adjacent locations [43]. Considering a mode shape at a specific frequency containing n points, the following equation can be used to calculate the curvature of the mode shape at point i:

$$C(i)^n = \frac{y(i+1) - 2 \times y(i) + y(i-1)}{d^2} \quad (4)$$

where $y(i)$ is the displacement at point i, and d is the distance between adjacent points. The n^{th} root of the resulting expression gives the curvature value at point i, and it is denoted as $C(i)^n$. The value of n represents the order of the curvature. It is possible to then calculate $\Delta C(i)$ between adjacent points i and $i + 1$ using Eq. (5) [44]:

$$\Delta C(i) = C(i+1)^n - C(i)^n \quad (5)$$

Further, by analyzing the sign and magnitude of the change in curvature, the location of the damage was determined. Damage in a structure can be determined by observing changes in its natural frequency resulting from the addition or removal of mass. Adding damage alters the stiffness, mass, or both and the structure's natural frequency. Measuring this frequency change enables the detection of damage, with the magnitude of the shift indicating the severity of the damage. The mode shape's curvature provides valuable information about the location of the damage. Figure 1 presents a flowchart of a comprehensive IoT environment with the full methodology suggested for damage identification. In cases where the damage is localized and minor, the local deformation of the mode shape in the damaged structure differs from that of the undamaged structure. Analyzing these differences allows for pinpointing the location of the damage within the structure [45].

IoT-based SHM system

Utilizing various materials in IoT systems enables devices and components to establish connections, communicate data, and interact seamlessly. This study specifically focused on the initial component of the system, an MPU6050 accelerometer sensor that plays a vital role in numerous electronic applications, including drones, robots, and gaming devices. It is commonly integrated into IoT systems because of its compact size, low-power consumption, and compatibility with various microcontrollers and platforms.

In this laboratory-scale two case studies, the MPU6050 sensor was employed to collect acceleration-time domain data from structures, such as the rectangular cross-sectioned aluminum cantilever and fixed-fixed beam mentioned in next section on "Experimental investigation". As pointed out by Mishra et al. [3] in their review paper, five IoT layers should work in tandem for the SHM system. The Layer 1 (sensors and actuators) in this case study comprises (MPU5050 sensor for recording acceleration data) for the laboratory-scale structure. Layer 2 (internet gateways and network communication) is supported by Node MCU ESP 8266 microchip with WiFi connecting capabilities. Layer 3 (data analytics and cloud computing) allows the acceleration data transmitted to extract the natural frequencies of the cantilever and fixed beam. Layers 4 and 5 (SHM data interpretation and session/message) are carried out to detect and locate the location of the damage in the two case study structures.

Experimental investigation

An 80 cm x 50 mm × 5 mm cross section of an aluminum beam with an elastic modulus of 69 GPa was considered for the experiment at structures laboratory of IIT Bhubaneswar,

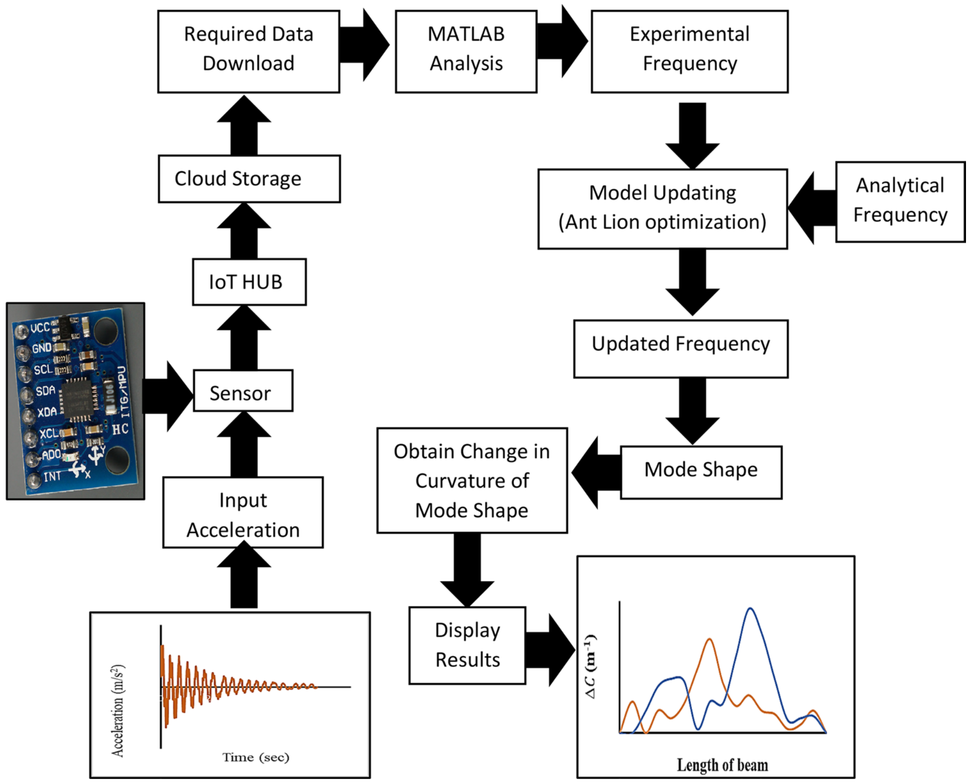


Fig. 1 Comprehensive IoT environment: A proposed methodology for experimentation on two laboratory-scale civil engineering structures

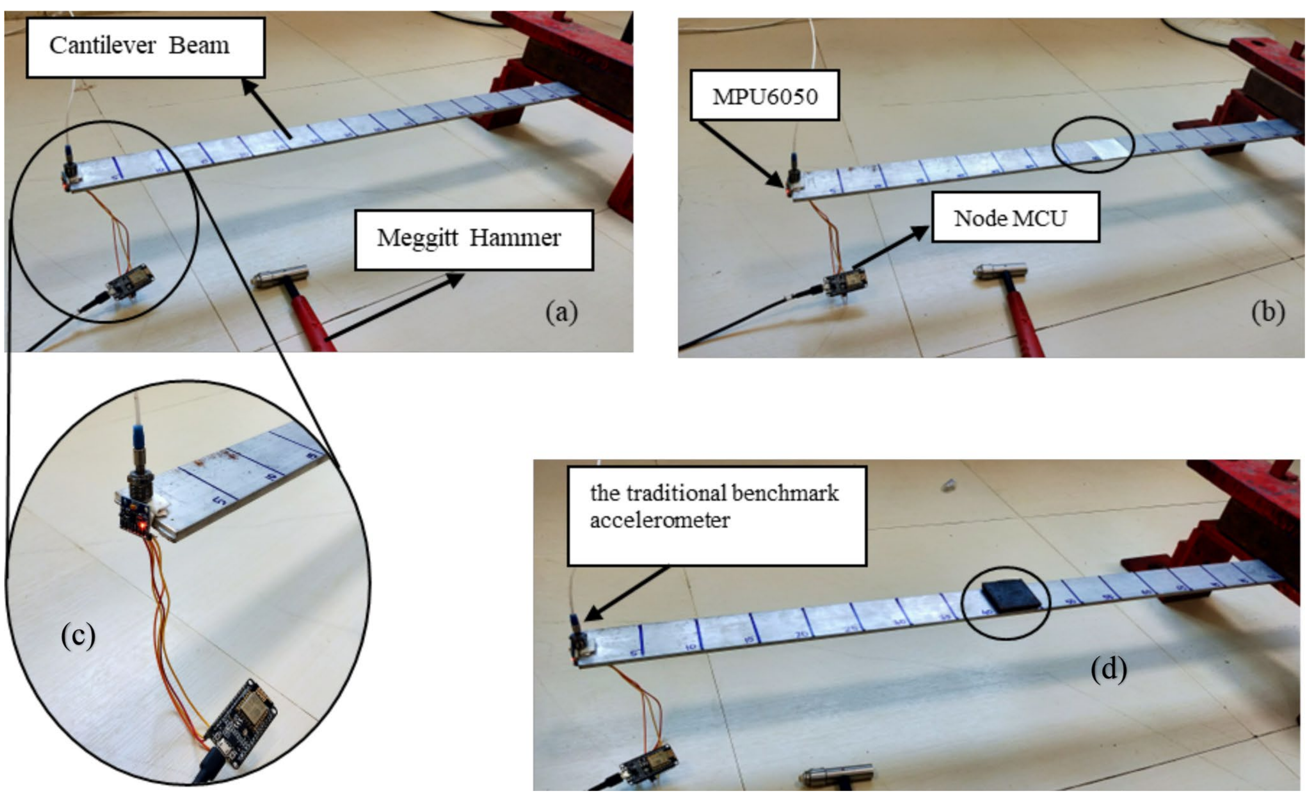


Fig. 2 Experimental setup of a cantilever beam using MPU6050 and the conventional accelerometer: (**a**) healthy beam; (**b**) beam with subtracted mass shown in circle; (**c**) placement of the conventional accelerometers, MPU6050 sensors, and node MCU; (**d**) beam with mass added shown in circle

as shown in Fig. 2. The impact hammer (MEGGITT 2302-01) was used to provide a sudden impact on the beam, which caused it to vibrate at its natural frequency. An MPU6050 and conventional accelerometers were attached to the beam to collect acceleration data. The sampling frequency of the MPU6050 sensor was 180 Hz, and the conventional accelerometer was 2048 Hz. These data were transferred to Azure IoT Hub for storage. A virtual machine was set up in the cloud for post-processing the data set using MATLAB, and the natural frequency of the material was determined. Frequencies obtained from the MPU6050 sensor were validated with those obtained by analytical modeling and the conventional accelerometer analyzer. The conventional accelerometer analyzer offers a range of features, such as frequency analysis, time domain analysis, order tracking, and modal analysis, which can be customized to meet specific needs. Analytical modeling of a cantilever beam in MATLAB involves using mathematical equations to describe the behavior of the beam under different loads and boundary conditions. The analytical approach involves using principles of mechanics, such as stress and strain, to derive equations that relate the loads applied to the beam to its deflection and deformation. MATLAB can solve these equations to obtain a quantitative understanding of the beam's behavior. The frequencies obtained by experimental results were updated using the ALO algorithm.

Cantilever beam

Accelerometers were installed first at the free end, and the impact was given at the free end of the cantilever beam, as shown in Fig. 2a. Later, the sensor was placed at 400 mm from the fixed support, and the impact load was applied again at the free end. To minimize errors, the conventional and MPU6050 accelerometer sensors were placed near each other, as shown in Fig. 2c. After performing the frequency calculation for the healthy state, damage was created in the beam 400 mm away from the support. Different damage conditions were designed, one with removing mass (Fig. 2b) and one with the added mass of 50 g square metal (Fig. 2d). In the latter case, a mass fragment with 50 mm × 50 mm × 2 mm proportions was chipped off to create a second damage case.

Fixed beam

The experimental configuration of the same aluminum beam, but now with both ends fixed, was adopted as a second case. Again, applying heavy weights at each end to maintain the boundary conditions of the fixed beam provided the extremities with rigid support. Figure 3a depicts the modal test structure with an accelerometer attached. The test structure comprised 16 zones and 15 hammering nodes. The length of each element was maintained at 5 cm, and the accelerometer was attached to the node 7. Repetitive modal testing was performed on the structure to collect experimental frequencies and mode shapes, as described in section 4, at all 15 nodes and record acceleration response at node 7. After conducting frequency calculations for the healthy state, an approach similar to that of the cantilever beam was applied; two distinct forms of structural change were produced, one by adding mass and the other by subtracting mass from the total mass. Mass was added at 500 mm from one end of the beam, and it was then chipped off at 350 mm from one end, as shown in Fig. 3b. This mass fragment measured 50 mm × 50 mm × 2 mm.

Results

Cantilever beam

Figure 4a presents the raw data obtained from conventional accelerometers, representing acceleration over time, and Fig. 4b illustrates similar acceleration data collected from the MPU6050 sensor. Post-processing techniques were applied to both raw data sets to analyze the data further. Figure 5 shows the resulting graphs displaying the frequencies extracted from the conventional accelerometer and the MPU6050 sensor. MPU6050, when paired with the NODE MCU, had a sampling frequency of 180 Hz, resulting in a recorded frequency range of 90 Hz (Nyquist frequency). MATLAB was employed to generate analytical frequencies to validate the accuracy, which exhibited less divergence from the obtained frequencies. Table 2 compares the updated frequencies from the analytical model, analytical frequencies, and conventional and MPU6050 accelerometer measurements. This analysis provided valuable insights into

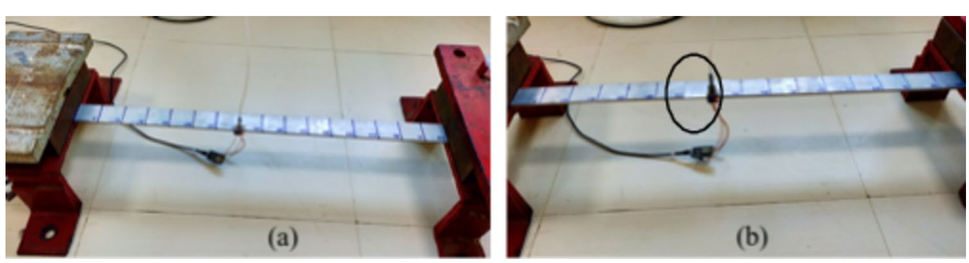


Fig. 3 Experimental setup of the fixed beam using MPU6050 and the conventional accelerometer: (**a**) healthy beam; (**b**) beam with a subtracted mass shown inside circle

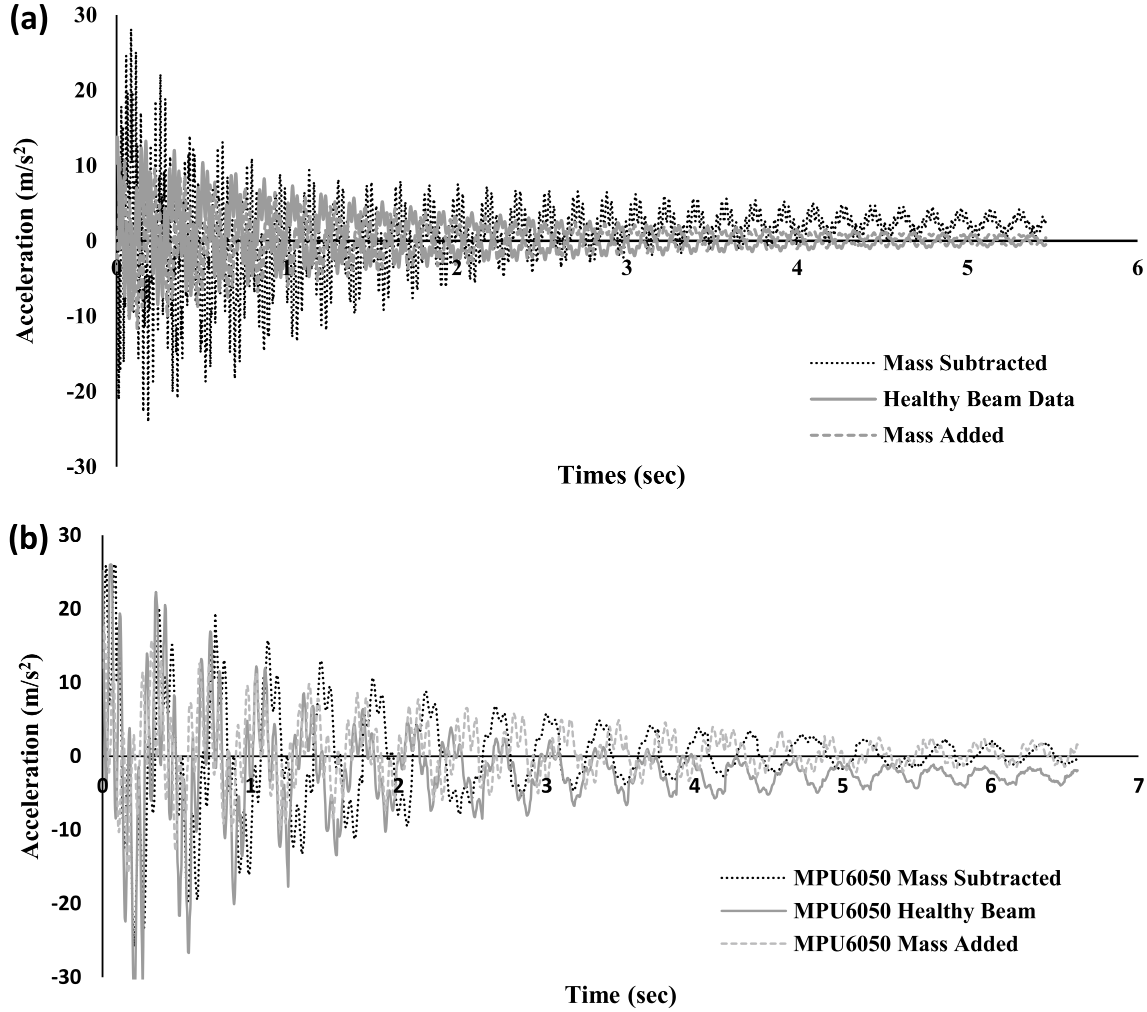


Fig. 4 Time domain data of (**a**) conventional accelerometers; and (**b**) MPU6050 for cantilever beam

the consistency and reliability of the recorded frequencies across different measurement techniques. Slight deviations from the model's updated frequencies were observed when using conventional accelerometers for measuring the healthy (undamaged) beam.

Specifically, the measured frequencies were $f_1 = 5.68$ Hz and $f_2 = 36.02$ Hz, indicating an error of 5.08% and 3.43%, respectively. Instead, employing the MPU6050 yields resulted in lower variations from the analytical frequencies. For the healthy beam, MPU6050 recorded the frequencies of $f_1 = 5.24$ Hz and $f_2 = 35.54$ Hz, resulting in the errors of 11.85% and 4.70%, respectively. These findings suggest that MPU6050 exhibited comparable accuracy compared with conventional accelerometers in capturing the natural frequencies of the beam. Mass addition to the cantilever beam significantly impacted the frequencies measured by conventional accelerometers and the MPU6050 sensor. When mass was added, frequencies detected by the conventional accelerometers decreased to 4.89 Hz and 33.72 Hz, deviating by 13.92% and 6.4%, respectively, from the readings of the healthy beam.

The MPU6050 sensor registered frequencies of 4.19 Hz and 31.87 Hz, with percentage shift of 20.04% and 10.31%, respectively, compared with the frequencies of the original beam. This frequency reduction was attributed to the influence of mass addition on the structural stiffness of the beam. In contrast, when the mass was chipped off from the beam, the conventional accelerometer and the MPU6050 sensor reported higher measured frequencies. This was expected because the removal of mass decreased the structural stiffness of the beam. The conventional accelerometers recorded frequencies of 6.41 Hz and 38.47 Hz, exhibiting percentage shifts of 12.72% and 6.79%, respectively, compared with the frequencies of the healthy beam.

Similarly, the MPU6050 sensor captured frequencies of 6.05 Hz and 37.67 Hz, with percentages difference of 15.48% and 5.99%, respectively, compared with healthy beam frequencies. Figure 6 shows the first two

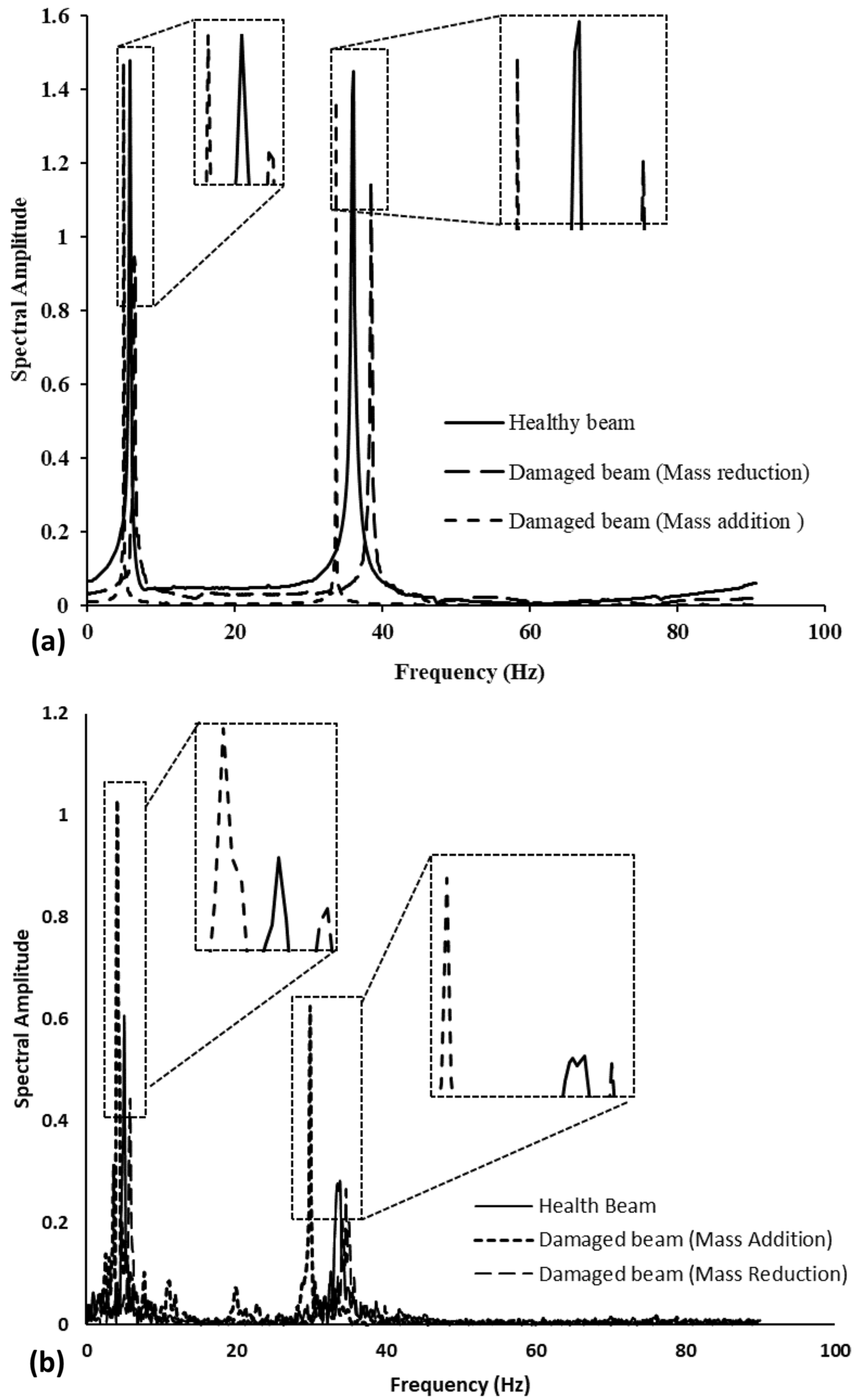


Fig. 5 Fourier spectral amplitude plot of the acceleration responses captured by (**a**) conventional accelerometers; (**b**) MPU6050 for cantilever beam

mode shapes of the cantilever beam subjected to different conditions, illustrating the influence of the addition or removal of mass on its behavior. Figure 6 depicts a notable alteration in the mode shape of the cantilever beam. The beam with removed mass showcased a significantly larger amplitude than the healthy beam, while the beam with added mass exhibited a lower amplitude. This intriguing change in mode shape helped precisely locate the damage. Figure 7 graphically represents the curvature phenomenon. By analyzing the difference in curvature within the mode shape, the location of the damage could be easily discerned. The highest peak in the

Table 2 Comparison of first two frequencies (f_1 and f_2) for cantilever beam (Hz)

			Healthy beam		Mass addition		Mass subtraction	
	Updated frequency (Hz)	Analytical frequency (Hz)	Conventional accelerometers (Hz)	MPU 6050 (Hz)	Conventional accelerometers (Hz)	MPU6050 (Hz)	Conventional accelerometers (Hz)	MPU 6050 (Hz)
f_1	5.95	6.34	5.68	5.24	4.89	4.19	6.41	6.05
f_2	37.28	39.88	36.02	35.54	33.72	31.87	38.47	37.67

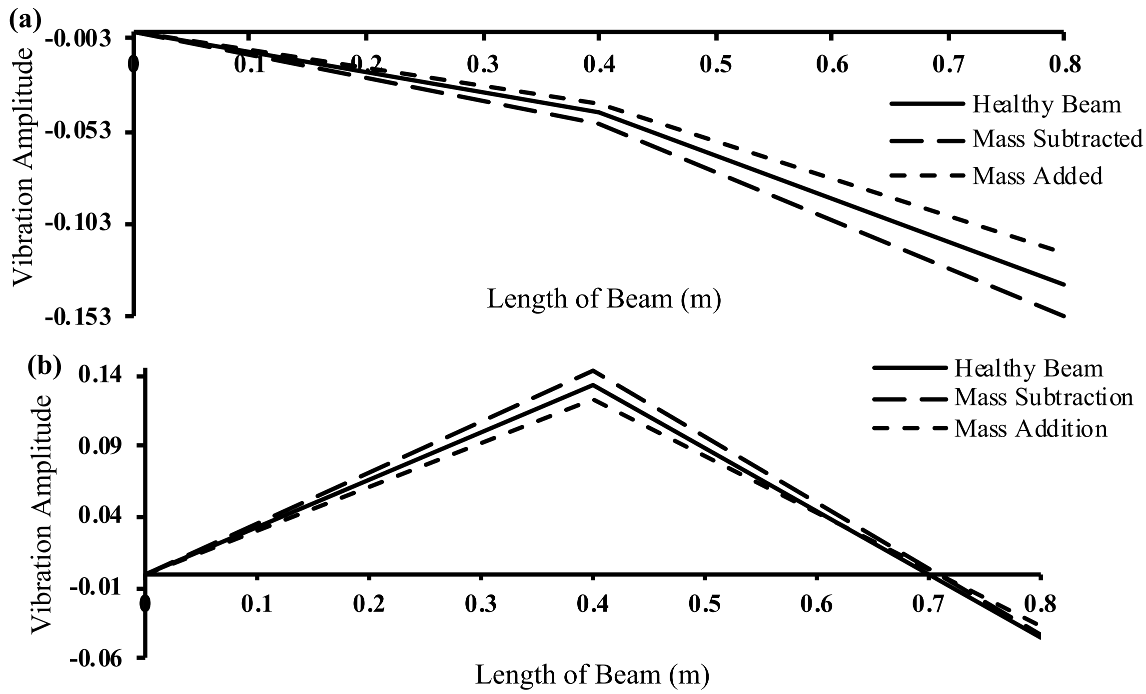
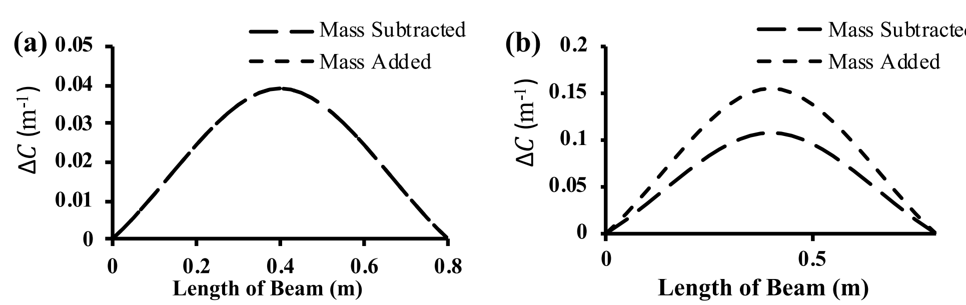


Fig. 6 Cantilever beam (**a**) 1^{st} mode shape; (**b**) 2^{nd} mode shape

Fig. 7 Curvature change (cantilever beam) obtained from (**a**) conventional accelerometers; (**b**) MPU6050 sensor



graph unmistakably indicated the precise location of the damage, which occurred consistently at 0.4 m for both modes, indicating that the damage had occurred precisely at 0.4 m from the support. These results provide valuable insights into the structural integrity of the cantilever beam.

Fixed beam

Accelerometer sensors were deployed at various nodes to collect acceleration-time domain data. Figure 8a presents the raw acceleration-time data obtained from the conventional accelerometer with the OROS data acquisition program at

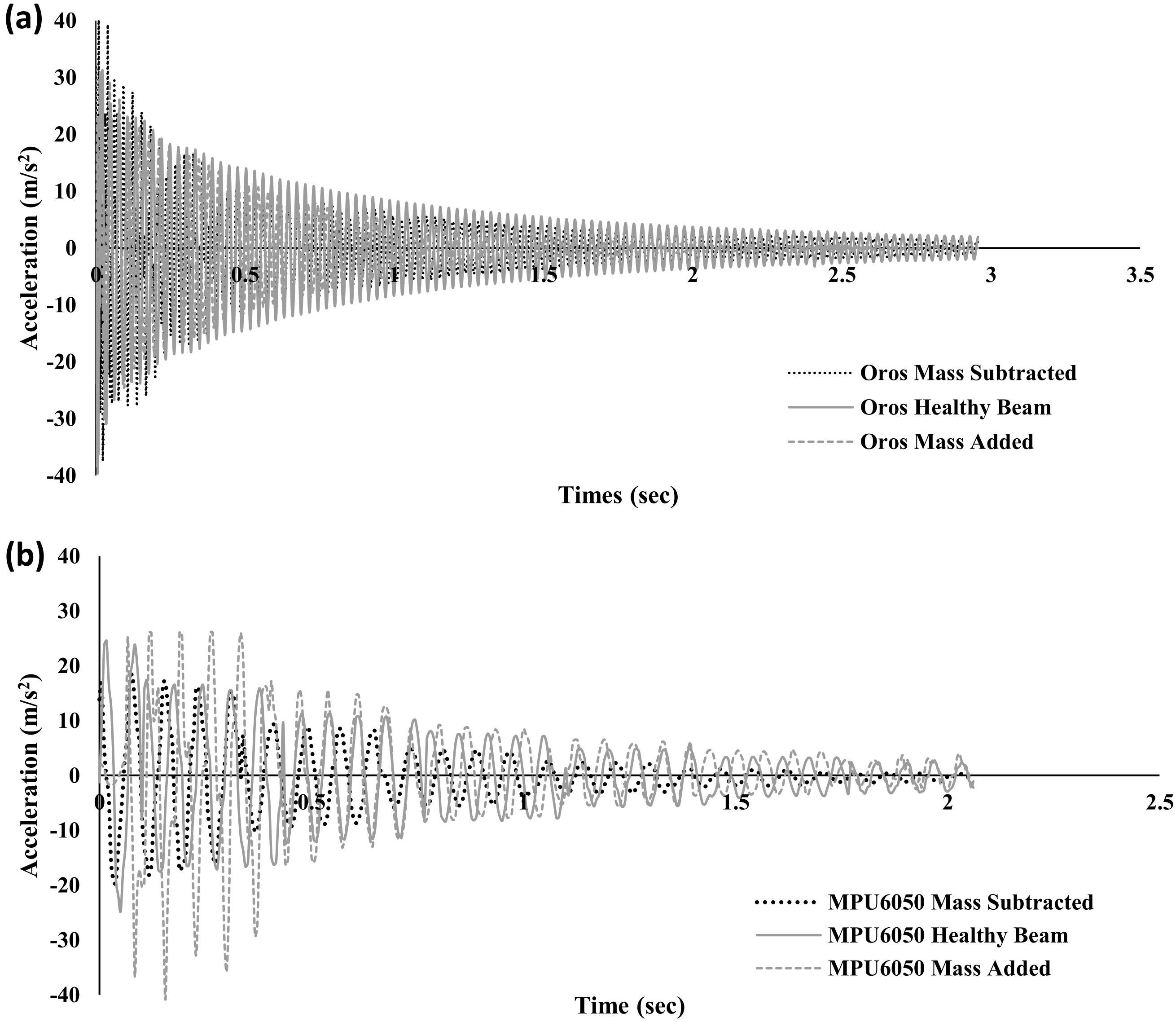


Fig. 8 Acceleration-time domain data of (**a**) conventional accelerometers (by OROS data acquisition system); and (**b**) MPU6050 for fixed beam

node 7. In contrast, Fig. 8b displays the acceleration data collected at node 7 using the MPU6050 sensor. Following data collection, both raw data sets were subjected to post-processing techniques.

Table 3 presents the frequency results obtained from post-processing the sensor readings. Using the conventional accelerometer analyzer, when mass was added and removed, shifts of 13.78% and 4.07% and 6.13% and 3.44% in f_1 and f_2, respectively, were observed. Due to the frequency exceeding 90 Hz, only a single frequency was detectable by MPU6050. For MPU6050, when mass was added and removed, shifts of 14.53% and 4.07%, respectively, were

Table 3 Comparison of frequencies for fixed beam

	Healthy beam		Mass addition		Mass subtraction	
	Conventional accelerometers (Hz)	MPU 6050 (Hz)	Conventional accelerometers (Hz)	MPU6050 (Hz)	Conventional accelerometers (Hz)	MPU 6050 (Hz)
f_1	35.17	33.65	30.32	28.76	36.60	35.02
f_2	99.95	NA	93.81	NA	103.39	N.A

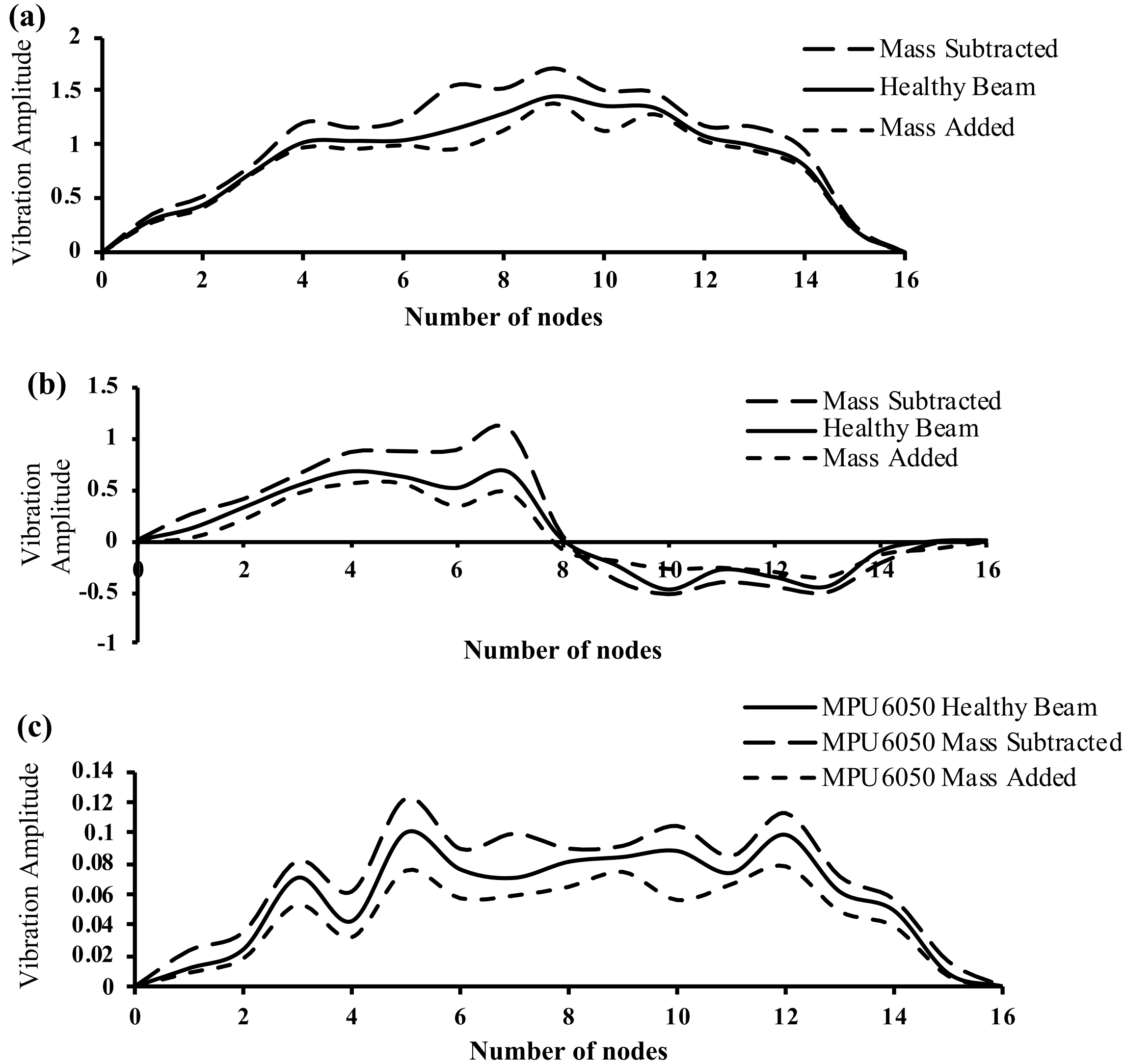


Fig. 9 Fixed beam: conventional accelerometers (**a**) 1^{st} and (**b**) 2^{nd} mode shapes; (**c**) MPU6050 1^{st} mode shape

observed. Figures 9a and 9b represent the first two mode shapes obtained from the fixed beam using conventional accelerometers, while Fig. 9 (c) depicts the first mode shape obtained from MPU6050. Scenario exhibited a 13.78% shift in f_1 and a 6.13% shift in f_2, whereas the mass-subtracted case showed a 4.07% shift in f_1 and a 3.44% shift in f_2. Due to the higher frequency exceeding 90 Hz, only a single frequency was detectable by the MPU6050. For the MPU6050, the mass-added scenario had a 14.53% shift, and the mass-subtracted scenario had a 4.07% shift.

Figures 10a and 10b showcase the results of employing the change in curvature of the mode shape method to identify the location of the damage. Interestingly, in the case of added mass, the highest peak is observed at 500 mm from the support, while in the case of subtracted mass, it is found at 350 mm from the fixed end. This demonstrates the efficacy of the MPU6050 IoT sensor in accurately detecting and pinpointing structural damage, as depicted in Fig. 10c. These findings highlight the sensor's capability to contribute to SHM by precisely identifying the damage location based on changes in curvature within the mode shape.

Several studies have investigated the precision of accelerometers compatible with vibration-based SHM either based on Arduino boards or similar electronic boards in various settings. In a study conducted by Rossi et al. [46], a Raspberry Pi and a MEMS accelerometer were used to detect the vibrations of a fan blade for the wind turbine. The mean absolute percentage error (MAPE) that was reported was consistently <5% which was indicative of good accuracy. Comparing the findings of a low-cost accelerometer (LARA) with those of high-precision commercial sensors, Komarizadehasl et al. [47] observed maximum discrepancies of 3.3% in eigenfrequencies for low-cost wireless Arduino-based accelerometers with a sampling frequency of 333 Hz for

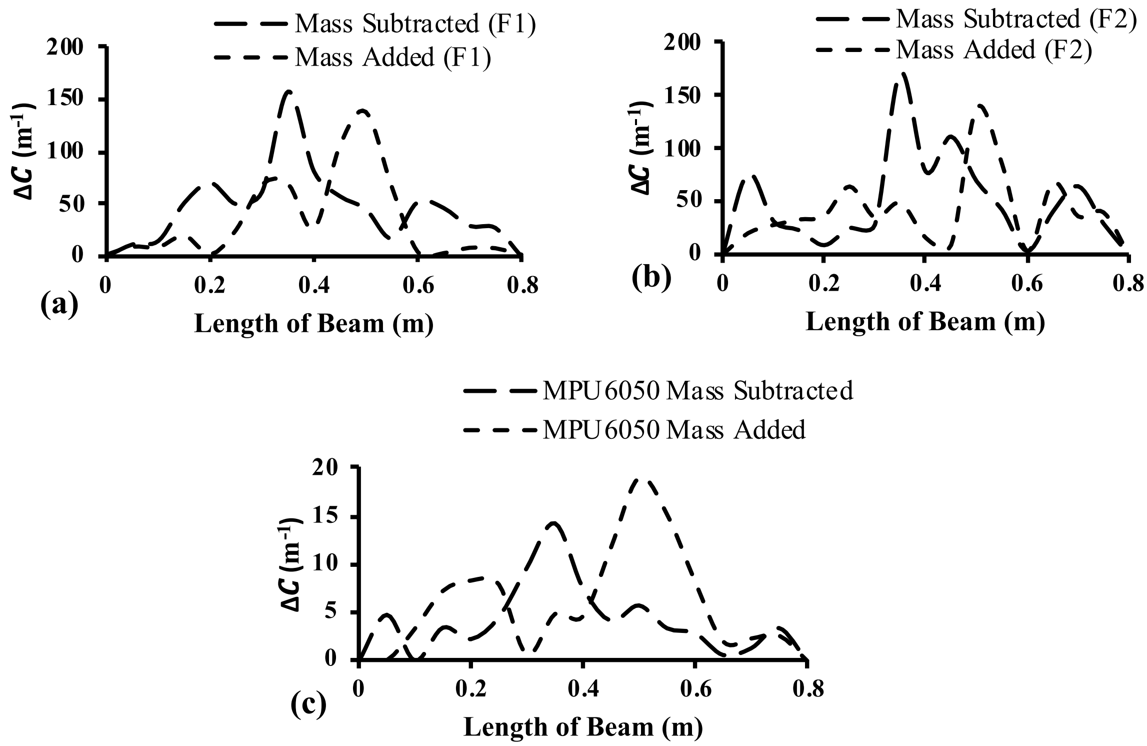


Fig. 10 Curvature change graph (fixed beam) for reading of conventional accelerometers (**a**) 1st and (**b**) 2nd mode shapes; (**c**) MPU6050 1st mode shape

a case study bridge in Barcelona. Ali et al. [48] discovered that the frequency of outcomes obtained from experiments and finite element analyses (FEM) varied by approximately 10% for reinforced concrete pedestrian bridge. An IoT system was verified using Pro-Trinket, an NRF module, a WiFi module, and Raspberry Pi. The system achieved error rates of 1% and 9% for detection of damage location and damage width detection, respectively [49]. Peng et al. [36] in their developed IoT system for footbridge SHM obtained relative error in mean value and maximum relative error in standard deviation ranging from 0.006% and 1.5%. In this study, an error of <6 % was obtained with respect to the conventional accelerometer, which is in agreement with the reported findings. However, the difference between IoT-based and conventional accelerometers varied from 1.3%−14.3% over the various frequencies captured.

Discussion

This study used an IoT-based accelerometer, specifically the MPU6050, for detecting structural damage in a cantilever beam and a fixed-fixed beam. A prototype damage detection system based on the IoT paradigm was developed, incorporating a "NODE MCU" electronic board with sensors to capture vibration data (acceleration-time history of healthy and damaged beams). The performance of the IoT-based system was compared against industry-standard accelerometers and a good agreement was obtained for the frequency range captured. However, the proposed solution can be used for prototype systems with desirable accuracy.

Implementing IoT-based SHM can effectively mitigate economic losses and casualties from natural disasters. The findings of this study suggest that IoT-based sensors can be a viable option for detecting and locating structural damage, with potential advantages in terms of cost, ease of use, and accessibility. This technology enables timely identification of necessary repairs, thereby improving the resilience of such infrastructures and contributing to the development of smart and sustainable cities.

In this study, the sampling frequency of the MPU6050 accelerometer was set to 180 Hz, that is, it can only capture the first and second frequencies of the system considered in this study. This limitation can be particularly relevant for structures or systems that primarily exhibit low-frequency motion or vibration. For instance, buildings or bridges often experience low-frequency oscillations caused by wind or traffic. Analyzing and capturing the first and second frequencies in these scenarios can provide valuable insights into the structural response and help assess whether corrective measures are required. The first mode represents the fundamental frequency, while the second mode corresponds to the first harmonic frequency, which is typically significant in these structures. However, it is important to note that for structures with higher-frequency motion or vibration characteristics, capturing only the first and second frequencies may not be adequate. In such cases, employing a sensor with a higher sampling frequency becomes essential to accurately capture the higher modes and frequencies in the system. This can ensure a comprehensive analysis of the structural behavior and enable timely action based on the findings. Furthermore, edge/extreme edge processing solution was not used in this study to save energy as sensor data were measured only during laboratory testing but not over a long time.

Conclusions

This study delved into the innovative infrastructure SHM solutions based on IoT technologies for structural damage detection and maintenance. The novelty of this study is in real-time prediction and localization of damage using a low-cost IoT-based sensor node in two case study civil engineering structures. The IoT system demonstrated the ability to detect changes in natural frequency and mode shapes and pinpoint the exact location of damage, providing invaluable insights into the system's structural integrity. This approach has far-reaching potential in various industries because it ensures safety while significantly reducing SHM costs. Moreover, the outcomes of this research are poised to provide cost-effective solutions for SHM, which is critical for maintaining infrastructure safety even on limited budgets. Therefore, this study provides significant contributions for the development of next-generation IoT-based sensors for real-time SHM. It is a step forward in implementing a circular economy in the construction sector through building maintenance.

Despite the remarkable benefits of IoT and sensor technologies, some drawbacks exist in their applications. For instance, measurement accuracy, sampling frequency, high noise levels, battery life, and data transmission challenges have limited their commercial applications. In this study, accelerometer data were downloaded from the cloud and processed using MATLAB; however, the high cost of real-time analysis limits its application. Future technological advancements could allow for the direct measurement of modal and real-time analyses, making IoT more accessible and cost-effective for use in buildings. This would require further evaluation and consideration of specific use cases and requirements to ensure successful implementation. Lastly, validation tests on real structures need to be carried out to further strengthen the validity of the system in real-world scenarios as this study is limited to the laboratory scale.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval Presented results do not contain studies with human or animal subjects.

Informed consent For this type of study, formal consent is not required.

References

1. Arcadius Tokognon C, Gao B, Tian GY, Yan Y (2017) Structural health monitoring framework based on internet of things: A survey. IEEE Internet Things J 4(3):619–635
2. Liang R, Guo Y, Zhao L, Gao Y (2021) Real-time monitoring implementation of pv/t façade system based on iot. J Build Eng 41:102451
3. Mishra M, Lourenço PB, Ramana GV (2022) Structural health monitoring of civil engineering structures by using the internet of things: A review. J Build Eng 48:103954
4. Namhoon Ha, Han-Sol Kim, Han-Seung Lee, and Songjun Lee (2021). Monitoring concrete compressive strength using iot-based wireless sensor network. In *2021 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia)*, pages 1–3. IEEE,
5. Miller D, Ho N-M, Talebian N, Javanbakht Z (2023) Real-time monitoring of early-age compressive strength of concrete using an iot-enabled monitoring system: an investigative study. Innov Infrastruct Solut 8(2):75
6. Sarkar D, Pandya K, Dave B, Jha KN, Dhaneshwar D (2022) Development of an integrated bim-erp-iot module for construction projects in ahmedabad. Innov Infrastruct Solut 7:1–19
7. Bapat H, Sarkar D, Gujar R (2021) Application of integrated fuzzy fcm-bim-iot for sustainable material selection and energy

management of metro rail station box project in western india. Innovat Infrastruct Solut 6:1–18
8. Ramakrishnan Raman, Mehul Gor, R Meenakshi, GM Jayaseelan, Abhay Chaturvedi, Syed Noeman Taqui, P Ganeshan, Mohamed Ouladsmane, and MA Kalam (2023). Solar energy measurement and monitoring model by using internet of things. *Electric Power Compon Syst*, pages 1–12,
9. Yang X, Yantao Yu, Shirowzhan S, Li H et al (2020) Automated ppe-tool pair check system for construction safety using smart iot. J Build Eng 32:101721
10. Chung WWS, Tariq S, Mohandes SR, Zayed T (2023) Iot-based application for construction site safety monitoring. Int J Constr Manag 23(1):58–74
11. Scuro C, Lamonaca F, Porzio S, Milani G, Olivito RS (2021) Internet of things (iot) for masonry structural health monitoring (shm): Overview and examples of innovative systems. Constr Build Mater 290:123092
12. Uva G, Sangiorgio V, Ruggieri S, Fatiguso F (2019) Structural vulnerability assessment of masonry churches supported by user-reported data and modern internet of things (iot). Measurement 131:183–192
13. Jianfeng Cao, Ruichuan Zhao, Liqiang Hu, Qing Liang, and Zhenhua Tang (2022) Application of internet of things based on wireless sensor in tunnel construction monitoring. *J Sensors*, 2022,
14. Wang D, Ren B, Cui B, Wang J, Wang X, Guan T (2021) Real-time monitoring for vibration quality of fresh concrete using convolutional neural networks and iot technology. Autom Constr 123:103510
15. Gurunath Kampli, Satyadhyan Chickerur, and MV Chitawadagi (2023). Real-time in-situ strength monitoring of concrete using maturity method of strength prediction via iot. *Mater Today: Proc*,
16. Woubishet Zewdu Taffese and Ethiopia Nigussie (2023). Automated concrete curing and assessment of strength and durability using iot system. *Mater Today: Proc*,
17. Coulby G, Clear AK, Jones O, Godfrey A (2021) Low-cost, multimodal environmental monitoring based on the internet of things. Build Environ 203:108014
18. AbdelRaheem M, Hassan M, Mohammed US, Nassr AA (2022) Design and implementation of a synchronized iot-based structural health monitoring system. Internet of Things 20:100639
19. Mohan SC, Maiti DK, Maity D (2013) Structural damage assessment using frf employing particle swarm optimization. Appl Math Comput 219(20):10387–10400
20. Du D-C, Vinh H-H, Trung V-D, Hong Quyen N-T, Trung N-T (2018) Efficiency of jaya algorithm for solving the optimization-based structural damage identification problem based on a hybrid objective function. Eng Optim 50(8):1233–1251
21. Parsa Ghannadi and Seyed Sina Kourehli (2020) Multiverse optimizer for structural damage detection: Numerical study and experimental validation. Struct Design Tall Spec Build 29(13):e1777
22. Ashraf Tahat, Azmi Al-Zaben, Lubna Saad El-Deen, Sara Abbad, and Chamseddine Talhi (2022). An evaluation of machine learning algorithms in an experimental structural health monitoring system incorporating lora iot connectivity. In *2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, pages 1–6. IEEE,
23. Harms T, Sedigh S, Bastianini F (2010) Structural health monitoring of bridges using wireless sensor networks. IEEE Instrum Measure Mag 13(6):14–18
24. Noel AB, Abdaoui A, Elfouly T, Ahmed MH, Badawy A, Shehata MS (2017) Structural health monitoring using wireless sensor networks: A comprehensive survey. IEEE Commun Surv Tutorials 19(3):1403–1423
25. Sofi A, Regita JJ, Rane B, Lau HH (2022) Structural health monitoring using wireless smart sensor network–an overview. Mech Syst Signal Process 163:108113
26. Azimi M, Dadras Eslamlou A, Pekcan G (2020) Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review. Sensors 20(10):2778
27. John ST, Sarkar P, Davis R (2022) Energy-efficient long range wide area network for construction industry applications. Autom Constr 136:104150
28. Hafidz A, Kinoshita N, Yasuhara H, Tsuzuki S (2023) Development and applications of slope and river monitoring system using low-power wide-area network technology. J Civ Struct Heal Monit 13(1):83–100
29. Hsieh KH, Halling MW, Barr PJ (2006) Overview of vibrational structural health monitoring with representative case studies. J Bridg Eng 11(6):707–715
30. Sungheetha DA et al (2020) Real time monitoring and fire detection using internet of things and cloud based drones. J Soft Comput Paradigm 2(3):168–174
31. Muttillo M, Stornelli V, Alaggio R, Paolucci R, Di Battista L, de Rubeis T, Ferri G (2020) Structural health monitoring: An iot sensor system for structural damage indicator evaluation. Sensors 20(17):4908
32. Tuan Ta Duc, Tuan Le Anh, and Huong Vu Dinh (2018). Estimating modal parameters of structures using arduino platform. In *Proceedings of the International Conference on Advances in Computational Mechanics 2017: ACOME 2017, 2 to 4 August 2017, Phu Quoc Island, Vietnam*, pages 1095–1104. Springer,
33. Reddy C, Shenoy S, Sharma RS (2019) Vibration analysis of cantilever beam in time domain and frequency domain using arduino platform. Vibroeng Procedia 29:1–5
34. Muhammad Hassan, Amr Nassr, Usama S Mohammed, and Mohamed AbdelRaheem (2021). An iot based structural health monitoring system for critical infrastructures. In *2021 IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT)*, pages 130–135. IEEE,
35. Chilamkuri K, Kone V (2020) Monitoring of varadhi road bridge using accelerometer sensor. Mater Today: Proc 33:367–371
36. Peng Z, Li J, Hao H (2023) Development and experimental verification of an iot sensing system for drive-by bridge health monitoring. Eng Struct 293:116705
37. Koene I, Klar V, Viitala R (2020) Iot connected device for vibration analysis and measurement. HardwareX 7:e00109
38. Danish A, Tayyab F, Salim MU (2020) Health assessment based on dynamic characteristics of reinforced concrete beam using realtime wireless structural health monitoring sensor. J Struct Integr Maint 5(3):204–210
39. Jafarkhani R, Masri SF (2011) Finite element model updating using evolutionary strategy for damage detection. Comput-Aided Civil Infrastruct Eng 26(3):207–224
40. Alkayem NF, Cao M, Zhang Y, Bayat M, Zhongqing S (2018) Structural damage detection using finite element model updating with evolutionary algorithms: a survey. Neural Comput Appl 30:389–411
41. Mirjalili S, Jangir P, Saremi S (2017) Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems. Appl Intell 46:79–95
42. Mishra M, Barman SK, Maity D, Maiti DK (2019) Ant lion optimisation algorithm for structural damage detection using vibration data. J Civ Struct Heal Monit 9:117–136
43. Pandey AK, Biswas M, Samman MM (1991) Damage detection from changes in curvature mode shapes. J Sound Vib 145(2):321–332
44. Sampaio RPC, Maia NMM, Silva JMM (1999) Damage detection using the frequency-response-function curvature method. J Sound Vib 226(5):1029–1042

45. Guilherme Ferreira Gomes and Rafael Simões Giovani (2022) An efficient two-step damage identification method using sunflower optimization algorithm and mode shape curvature (msdbi-sfo). Engineering with Computers 38(2):1711–1730
46. Rossi A, Bocchetta G, Botta F, Scorza A (2023) Accuracy characterization of a mems accelerometer for vibration monitoring in a rotating framework. Appl Sci 13(8):5070
47. Komarizadehasl S, Huguenet P, Lozano F, Lozano-Galant JA, Turmo J (2022) Operational and analytical modal analysis of a bridge using low-cost wireless arduino-based accelerometers. Sensors 22(24):9808
48. Ali A, Sandhu TY, Usman M (2019) Ambient vibration testing of a pedestrian bridge using low-cost accelerometers for shm applications. Smart Cities 2(1):20–30
49. Ahmed Abdelgawad and Kumar Yelamarthi (2016) Structural health monitoring: Internet of things application. In *2016 IEEE 59th international midwest symposium on circuits and systems (MWSCAS)*, pages 1–4. IEEE,