Journal of Trends in Computer Science and Smart Technology (ISSN: 2582-4104)
www.irojournals.com/tcsst/

Comparative Multi Domain Vibration Analysis of Dual Sensors for Structural Health Monitoring

Gowri Shankar Manivannan[1*], Guruprasath Jeevajothi[2], Sanjoy Deb[3], Venkateswara Rao Kolli[4], Deepika K C.[5], Santhosh Kumar K B.[6]

[1]Associate Professor, Department of Electrical and Electronics Engineering, Malnad College of Engineering, Hassan, Karnataka, India.
[2]Research Scholar, [3]Professor, Department of Electronics and Communication Engineering, Bannari Amman Institute of Technology, Sathyamangalam, India.
[4,5,6]Associate Professor, Department of Electronics and Communication Engineering, Malnad College of Engineering, Hassan, Karnataka, India.

E-mail: [1*]mshankar065@gmail.com, [2]jgurukpt@gmail.com, [3]sanjoydeb@bitsathy.ac.in, [4]vrk@mcehassan.ac.in, [5]kcd@mcehassan.ac.in, [6]kbs@mcehassan.ac.in

Orcid ID: [1*]0000-0002-0293-6393, [2]0009-0004-8694-9360, [3]0000-0002-0186-3938, [4]0000-0003-3168-2449, [5]0000-0002-2873-7624, [6]0000-0003-4132-1823

Abstract

Vibration-based Structural Health Monitoring (SHM) is a powerful technique to monitor the health of engineering structures and identify possible anomalies. In this paper, the vibration signal received using HG24HS and HG07U sensors in Python on Google Colab is thoroughly analyzed. The approach combines time-domain, frequency-domain, statistical, and clustering-based techniques to assess how similar sensor responses are and identify possible structural changes. The time-domain and frequency-domain analyses indicate that the signals have similar amplitudes and spectral properties. Statistical testing, T-test and Mann-Whitney U test, show that there is no significant difference in mean and median behavior, whereas the Kolmogorov-Smirnov test demonstrates on the level of distribution that there are slight variations. The analysis of variance indicates that there is a slight difference in the dispersion of vibration energy in the HG07U sensor. The similarity in vibration patterns with a partial overlap is further supported by clustering analysis. Overall, the findings indicate that the system works in stable conditions and there is no strong indication of structural damage, but slight variations can be noticed that can be explained by localized effects or differences in the sensitivity of the sensors.

Keywords: Cluster, Sensors, Structural Health Monitoring, Statistical Testing, Vibration Signals.

1. Introduction

Structural Health Monitoring (SHM) is an important aspect of ensuring the safety, reliability, and longevity of engineering structures, as it allows for the continuous evaluation

* Corresponding Author

DOI: https://doi.org/10.36548/jtcsst.2026.2026.3.013
Received: 08.05.2026, received in revised form: 14.06.2026, accepted: 06.07.2026, published: 16.07.2026

of their state. Vibration-based methods have become some of the most popular SHM techniques because they are non-destructive, cost-effective, and offer real-time information on structural behavior. The information carried by vibration signals is very useful in determining a structure's dynamic nature, where even small variations can reflect possible alterations or anomalies in the structure [1]. Vibration-based monitoring is used extensively in civil and mechanical structures since it can continuously monitor their condition in real time without needing to access interior structural components or interrupt normal structural function. As infrastructure ages and monitoring needs become more demanding, there is a growing need for sensing approaches that are easy to use and do not require high costs, specialized equipment, or significant previous knowledge of infrastructure damage history. Low-cost geophone sensors are a viable option for recording the vibration response of structures, but further studies are needed to investigate their ability to accurately and repeatedly obtain the same response signal from different sensors under real ambient conditions. The need for comparative studies, in which a larger number of low-cost vibration sensors are installed on the same structure to build confidence in the data produced by these sensors before they can be used reliably for long-term structural health monitoring, is thus evident. Although vibration-based SHM has many benefits, it is not widely and effectively deployed for several reasons. First, the data from different sensors, even if they are of the same specification, can be inconsistent as a result of variations in sensor sensitivity, calibration or manufacturing tolerances, which may make it hard to detect structural changes from within the sensor measurements. Second, variations in the duration of recordings and the number of samples recorded between different sensors makes it difficult to compare them directly without appropriate pre-processing to make them comparable. Third, most current SHM studies involve single-sensor measurements or access to large labeled datasets with known damage scenarios that are not available in the early stages of developing, deploying, and testing monitoring systems on actual in-service structures. Fourth, the physical meaning of frequency domain features is generally not obvious without separate modal analysis or structural modeling, and this make it difficult to associate apparent vibration characteristics seen in the data with actual structural behavior. Finally, there is no common comparative model of consistency analysis under real, uncontrolled, ambient conditions for multiple vibration sensors in the current literature.

To address these challenges, this study proposes a comparative analysis framework for analyzing the vibration signals acquired by two high-sensitivity geophone sensors (HG24HS and HG07U) in real time on the floor of the building structure. The proposed framework consists of time domain feature extraction, frequency domain analysis, statistical hypothesis testing, and unsupervised clustering algorithms to evaluate the consistency and variability between the two sensor sets. The goal of this study is to assess if the two sensors have consistent vibration characteristics under nominally identical operating conditions, as well as to establish the degree of similarity between the sensors and confirm if the differences are due to sensor specific behavior, local environment effects, or actual structural variance. The results of this study help advance the design of practical, low-cost multi-sensor vibration monitoring systems for preliminary structural condition assessment when there is no benchmark or labelled damage dataset to use.

This paper is organized as follows: Section 2 summarizes the existing research on vibration based structural health monitoring. In Section 3, the experimental setup, sensor specifications, data acquisition procedure, and the analytical methods applied to vibration signals such as time domain feature extraction, frequency domain analysis, and statistical testing and clustering based evaluation are described. The results of each analytical phase are presented in Section 4, and implications within the context of structural condition assessment are discussed. Section 5 further specifies the scope and limitations of the proposed framework. Finally, Section 6 presents the conclusions of the study and recommends further research.

2. Related Works

Vibration based SHM has been widely studied in recent literature on structural evaluations and damage detection. SHM is an essential method of infrastructure evaluation based on vibration. Rabi et al. [2] review vibration-based methods for localizing damage and predicting the lifetime of a bridge during monitoring, highlighting the non-destructive and real-time nature of these systems. Mardanshahi et al. [3] introduced a systematic approach to assessing sensing technologies in SHM, emphasizing vibration analysis as one of the most common and popular techniques for evaluating structural conditions. Ayankoso et al. [4] performed a comparative study of vibration and current signals in fault diagnosis, which showed that vibration signals were incredibly accurate (almost 100%), in detecting mechanical faults. Gonen and Erduran [5] designed a hybrid system that uses both traditional accelerometers and computer vision-based measurements, demonstrating the possibility of multi-sensor fusion to improve damage detection. Altaf et al. [6] used statistical characteristics such as skewness, kurtosis, average, and root mean square values of time and frequency domain vibration signals achieving a 99.13% accuracy rate by combining statistical analysis with machine learning.

Kuo and Lee [7] employed statistical analyses such as mean, standard deviation, and scatter plots in sensor performance analysis, which proves statistical methods to be effective in SHM. Zhou et al. [8] present an extensive overview of signal processing methods with a focus on non-parametric time-frequency analysis (such as the short-time Fourier transform and wavelet transform methods). Bazaz et al. [9] compared frequency response functional and power spectral density functional and concluded that PSD methods were more precise and robust in identifying damage. Laha et al. [10] suggested a framework based on spectral distance and t-SNE-GMM clustering to detect structural damage, which proved the efficiency of clustering algorithms in detecting anomalous patterns. Dang et al. [11] examined semi-supervised methods of integrating deep graph learning and contrastive learning in structural damage detection by vibration signals from several sensors. Lydakis et al. [12] covered the sensor fault diagnosis of vibration-based SHM and suggested ways to identify and isolate faulty sensors based on vibration response data. Buckley et al. [13] showed that smaller sets of univariate features measured by individual acceleration sensors can effectively differentiate the presence of more than one damage state, indicating that sensor-specific attributes are essential to comprehend. Li et al. [14] presented indicators to measure abnormal vibrations and structural health, showing that even in seemingly stable conditions, a slight change in the parameters of vibrations may indicate a transition to other structural states.

Even though a lot of research has been done in the area of vibration based SHM, a number of gaps still exist. Current vibration-based SHM research is predominantly based on machine learning models, sensor fusion, or complex signal processing methods and usually uses labeled data and demands high computational costs. Minimal effort has been made on a simple and unified statistical model that integrates parametric, non-parametric, distribution-based, and clustering schemes of sensor comparison and structural evaluation without a model.

Figure 1 represents the block diagram of the proposed work. This paper proposes a multi-domain, model-free framework that combines time-domain, frequency-domain, statistical testing, distribution analysis, and clustering for vibration-based SHM. It allows the stable evaluation of structural condition and comparison of dual sensors without labeled data or machine learning models. The comparative analysis of the two vibration signals indicates that both sensors exhibit similar behavior in terms of statistical and frequency-domain characteristics, as confirmed by the T-test, Mann–Whitney test, and spectral analysis. Variance analysis, however, shows that there is a slight amount of variability in one sensor and that it is more sensitive to any changes in small vibrations, whereas the other sensor has more stable and consistent readings. This implies that the two sensors can be used in structural health monitoring, with one being more appropriate for stability and the other for detecting subtle variations in vibration patterns.

3. Methodology

High-sensitivity geophone sensors (HG24HS and HG07U) for structural health monitoring were used to record data from the structural vibration of a building floor in the Electronics Laboratory, Department of Electronics and Communication Engineering, Bannari Amman Institute of Technology, Tamil Nadu. The two sensors were surface-mounted on a laboratory floor at fixed points in order to rigidly couple the vibration signal to the structural surface and to receive an accurate signal from it. The data was collected at an ambient temperature of 34°C and relative humidity of 47% under real-time conditions and manually-created impact excitation forces. All sensors operated at the same sampling rate (10Hz), which provided similar temporal resolution between all datasets. The HG24HS sensor recorded 24,673 samples while the HG07U sensor recorded 23,931 samples, yielding approximate recording times of 2467.2 seconds and 2392.8 seconds, respectively. The minor difference in the number of samples is due to the difference in triggering and recording times at each of the two independent acquisition channels, and not to sensor performance.

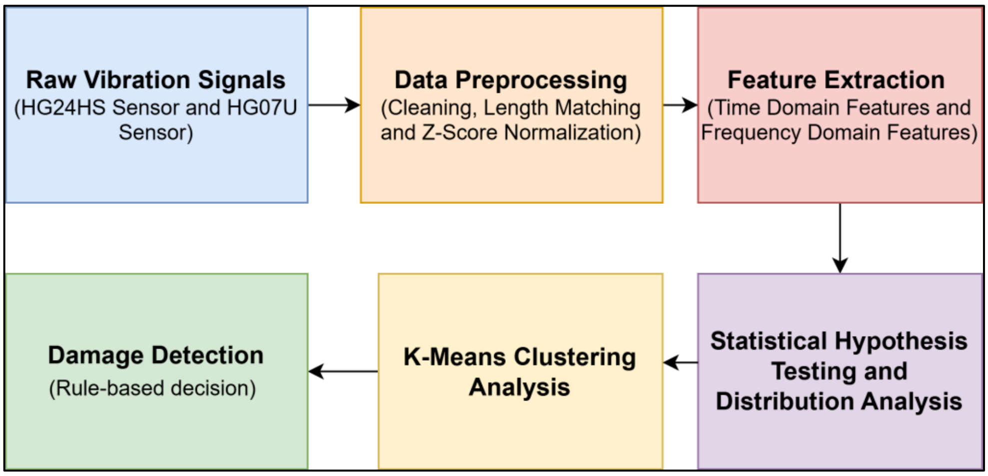

Figure 1. Schematic diagram of the work

To ensure sample-wise temporal alignment, the two signals were first truncated to a common length, the shorter of the two for comparative analysis. Z score normalization technique was used to independently standardize each signal separately, in order to preserve each signal's statistical variance so as to allow for fair comparison. A 10Hz sampling frequency was used to create a time vector to facilitate time-domain visualization and interpretation. Both raw and normalized signals were kept for further analysis; the raw signals were analysed for distributional and statistical comparison, and the normalised signals were analysed for spectral analysis and unsupervised clustering to find potential variations in structural dynamic behavior.

3.1 Data Preprocessing

The vibration signals obtained with HG24HS and HG07U sensors were preprocessed to achieve uniformity, eliminate scale dependence, and render the data ready to extract features and conduct statistical analysis. The preprocessing phase involves signal alignment, handling missing values, and Z-score normalization. Assume that the raw signals of the two sensors are:

$$p_1[q], \quad q = 1,2, \dots . Q_1 \tag{1}$$

$$p_2[q], \quad q = 1,2, \dots . Q_2 \tag{2}$$

Where $Q_1 = 24673$ and $Q_1 = 23931$. Both signals are truncated to an equal length to facilitate consistent comparison:

$$Q = min(Q_1, Q_2) \tag{3}$$

$$p_1'[q] = p_1[q] \tag{4}$$

$$p_2'[q] = p_2[q] \tag{5}$$

This is done to ensure that the signals are analyzed within the same time period so that variations in sample lengths, which introduce bias to statistical and spectral comparisons, are eliminated. To ensure that the HG24HS (24,673 samples) and HG07U (23,931 samples) datasets were of a common length, truncation rather than interpolation was used. This decision was made for the following reasons. The difference in the number of samples collected by the two datasets is relatively small (742 samples, about 3% of the total length) due to minor differences in the timing of the triggers and the duration of recordings, and not due to a different sampling frequency, since the two sensors use the same sampling frequency of 10 Hz. Truncating to this shorter common length (23,931 samples) therefore, does not lose much information, except that the originally recorded and unaltered sensor measurements are still temporal and aligned. Second, interpolated sample values would need to be synthetically generated within one of the datasets, potentially skewing the true amplitude, frequency content, and statistical properties of the signal; this is especially important in this study, where spectral analysis and statistical/distributional comparisons are key parts of the analysis. Adding interpolated values could introduce bias into these metrics and invalidate the comparison between sensors. To ensure that all analyses are conducted with actual sensor data, not estimated data, truncation was therefore preferred as a conservative approach. Any missing or undefined values in the signals are eliminated before analysis:

$$p[q] = p[q] \setminus \{NaN\ Values\} \tag{6}$$

Removal of the missing values avoids distortion of statistical statistics like mean, variance and spectral estimation. The time axis corresponding to each sample is defined as:

$$t[q] = \frac{q}{f_s}, \quad q = 0,1,2, \dots . Q - 1 \tag{7}$$

Where $f_s = 10\ Hz$ indicates the sampling frequency. This enables the visualization and physical interpretation of vibration signals in the time domain.

Figure 2 shows the raw vibration readings of HG24HS and HG07U sensors. The amplitude variations of the two signals are similar within a constant range, and there are no sudden disturbances or structural shocks. The similarity in the signals indicates a similar structural dynamic response to operating conditions. Z-score normalization is used to remove the effects of amplitude scaling between sensors [15]:

$$p_{norm}[n] = \frac{p[n]-\frac{1}{Q}\sum_{q=1}^{Q} p[q]}{\sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\left(p[q]-\frac{1}{Q}\sum_{q=1}^{Q} p[q]\right)^2}} \tag{8}$$

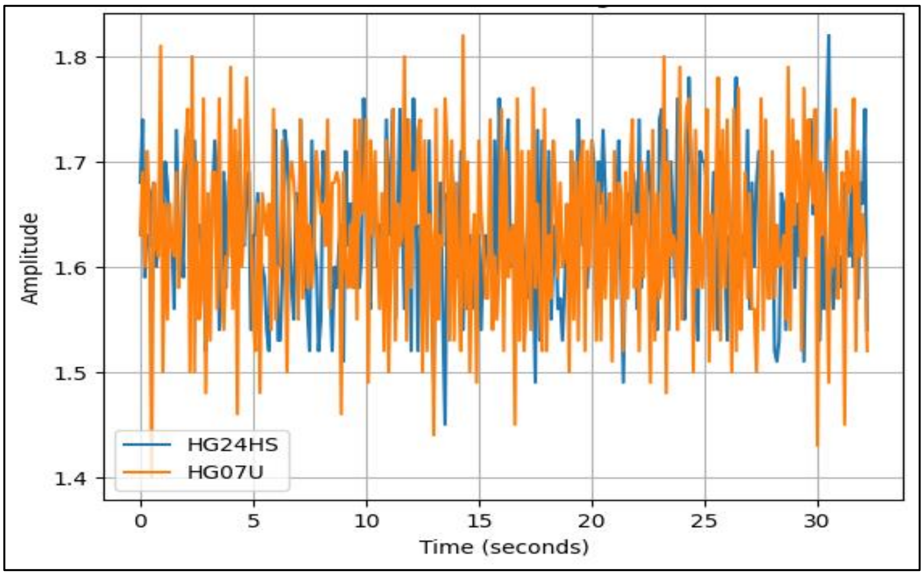

Figure 2. Raw time series signals

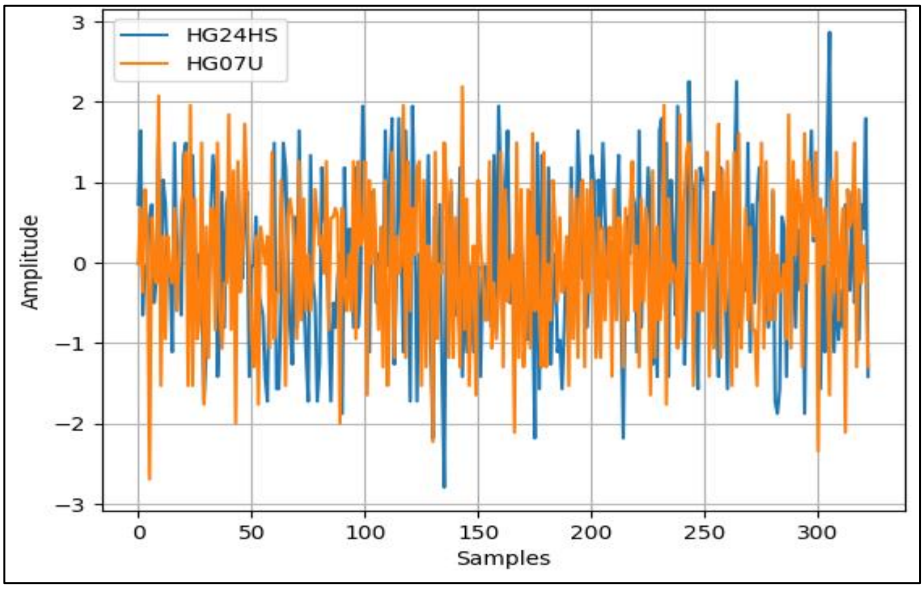

Figure 3. Normalized time series signals

Where $\mu = \frac{1}{Q}\sum_{q=1}^{Q} p[q]$ indicates the mean and $\sigma = \sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\left(p[q]-\frac{1}{Q}\sum_{q=1}^{Q} p[q]\right)^2}$ represents the standard deviation. Normalization ensures that the mean is zero and variance is one, enabling fair comparison of the sensor signals of various sensors and enhancing the performance of machine learning and statistical analysis.

Figure 3 shows the normalized vibration signals of HG24HS and HG07U following Z-score transformation. The signals are centered about a zero mean with unit variance, so their dynamic behavior can be directly compared. Despite the similarity in the patterns of both signals, small changes in the level of fluctuations denote subtle changes in the structural response that cannot be clearly seen in the original raw signals. The preprocessing phase provides data consistency, eliminates scale bias, and improves the validity of further analyses. It is essential for properly determining structural variations because it ensures that observed differences result from structural behavior and not data inconsistencies.

3.2 Feature Extraction

Raw vibration signals are processed to extract features to achieve numerical descriptors of structural behavior in both the time and frequency domains [13]. Such characteristics allow for quantitative comparison of the HG24HS and HG07U sensor responses and are from foundation of statistical analysis and unsupervised learning.

Tim-Domain Feature Extraction: The time-domain feature extraction procedure consists of deriving a set of statistical parameters from the vibration signal $p[q], \ q = 1,2, \dots . Q$, to describe the structural behavior. The mean is the average level of vibration, which provides an idea of the e signal's on average magnitude whereas the standard deviation represents the variability or dispersion of the signal around the mean.

$$\mu = \frac{1}{Q} \sum_{q=1}^{Q} p[q] \tag{9}$$

$$\sigma = \sqrt{\frac{1}{Q} \sum_{q=1}^{Q} (p[q] - \mu)^2} \tag{10}$$

Root mean square (RMS) value is used to indicate the effective energy content of a vibration signal, making it one of the main indicators of structural activity.

$$RMS = \sqrt{\frac{1}{Q} \sum_{q=1}^{Q} p^2[q]} \tag{11}$$

Peak value is used to capture the highest absolute amplitude, which is the highest vibration of the structure.

$$p_{peak} = max|p[q]| \tag{12}$$

The crest factor, which is the ratio of peak value to RMS, measures the impulsiveness of the signal and finds application in detecting abnormal or irregular structural conditions.

$$Crest\ factor = \frac{p_{peak}}{RMS} \tag{13}$$

Also, skewness is applied to measure the asymmetry of the signal distribution (i.e. whether the signal is skewed toward higher or lower values), whereas kurtosis measures the peakedness of the signal distribution and is useful in identifying sudden spikes or impulsive events.

$$\text{Skewness} = \frac{1}{Q} \sum_{q=1}^{Q} \left(\frac{p[q] - \mu}{\sigma} \right)^3 \tag{14}$$

$$\text{Kurtosis} = \frac{1}{Q}\sum_{q=1}^{Q}\left(\frac{p[q]-\mu}{\sigma}\right)^4 \tag{15}$$

The statistical features selected were widely used and efficient descriptors to compute for a vibration SHM. These features are effective in characterizing the amplitude, variability, energy, impulsiveness, and distribution of vibration signals, with low computational complexity.

Frequency Domain Features: The spectral properties of the vibration signals and the identification of underlying structural dynamics are conducted by frequency-domain feature extraction. Fast Fourier Transform (FFT) is used to transform the signal from the time domain, to the frequency domain where the magnitude spectrum $|P[k]|$ can be used to identify the most common frequency content within the signal vibration [16].

$$P[k] = \sum_{q=0}^{Q} p[q]e^{-j2\pi kq/Q} \tag{16}$$

This is used to determine resonance frequencies and potential structural behavior changes. Moreover, the Power Spectral Density (PSD) is approximated based on the Welch method, which splits the signal into numerous blocks and calculates the averaged spectral power.

$$PSD(f) = \frac{1}{S}\sum_{i=1}^{S}|P_i(f)|^2 \tag{17}$$

Where S represents the number of segments, and $P_i(f)$ indicates each segment's Fourier transform. Finally, PSD represents signal power distribution over frequencies. The PSD was calculated with a segment length of 256 samples, a Hann window, 50% overlap (128 samples) and an FFT length of 256 samples. With a 10 Hz sampling frequency, this gives a frequency resolution of ~0.039Hz and a segment duration of 25.6 seconds, in order to obtain a good compromise between the spectral resolution and the variance reduction of the low-frequency content of the structure.

3.3 Statistical Hypothesis Testing

The statistical hypothesis testing [1] involves the determination of whether the two sensor signals (HG24HS and HG07U) have a statistically significant difference in their behavior. These tests can be used to confirm that the two sensors are recording similar structural conditions or recording different vibration characteristics.

Independent T-Test: An independent t-test is used to compare the means of two independent sets of data.

$$t = \frac{\mu_1-\mu_2}{\sqrt{\frac{\sigma_1^2}{Q_1}+\frac{\sigma_2^2}{Q_2}}} \tag{18}$$

Where μ_1, μ_2 indicates the mean of the HG24HS sensor and HG07U sensor, σ_1^2, σ_2^2 represents the variance of two signals, and Q_1, Q_2 indicates the number of samples in each sensor dataset. The t-test hypothesis is the comparison of the mean vibration response of the two sensors. The null hypothesis (H_0) will be: no significant difference in the means $(\mu_1 = \mu_2)$ whereas the alternative hypothesis (H_1) will be: there is a significant difference in the means $(\mu_1 \neq \mu_2)$. When the p-value exceeds 0.05, the two sensors are said to possess similar average vibrations. When the p-value is below 0.05, there is a significant difference, which indicates that there may be a structural variation or sensor-related effects.

Mann-Whitney U Test: The Mann Whitney U test is applied when the data is not normally distributed. It is used to compare the median or rank distribution of two datasets.

$$U = min(U_1, U_2) \tag{19}$$

Where U_1, U_2 are calculated based on rank sums of both groups. Small U value indicates the distributions are different and Large U value indicates the distributions are similar.

Kolmogorov-Smirnov (KS) Test: KS test is used to compare the whole distribution shape of two datasets.

$$D = sup_p|F_1(p) - F_2(p)| \tag{20}$$

Where F_1, F_2 represents the Cumulative Distribution Functions (CDFs) and sup indicates the maximum vertical distance between two CDF curves. $D \approx 0$ indicates identical distributions, and a larger D indicates the robust difference between sensor behavior. This test measures differences at a distribution level.

Variance Analysis: Variance is used to measure the spread of signal dispersion or vibration energy around the mean.

$$Var(p) = \frac{1}{Q}\sum_{q=0}^{Q}(p[q] - \mu)^2 \tag{21}$$

Where $p[q]$ indicates the samples of the vibration signal, μ indicates the mean of the vibration signal and Q represents the total number of samples. Higher variance implies increased vibration energy, which is usually related to structural abnormalities.

3.4 Unsupervised K-Means Clustering

A K-Means clustering algorithm is used to process vibration patterns with no labels. This allows structural response patterns to automatically cluster with each other, and the approach is appropriate when structural health is applied in the real world and labeled datasets are not always available [16]. The K-Means algorithm is used to divide the data into K clusters by minimizing:

$$J = \sum_{i=1}^{K}\sum_{p\in C_i}||p - \mu_i|| \tag{22}$$

Where C_i indicates the cluster and μ_i represents the centroid. This helps identify patterns in structural behavior.

4. Results and Discussion

This section discusses of vibration measurements obtained with HG24HS and HG07U sensors, which are implemented in Python in Google Colab. The similarity of signals is analyzed using time-domain, frequency-domain, statistical, and clustering methods to detect possible structural differences.

4.1 Time Domain and Frequency Domain Analysis

Table 1 shows a statistical comparison of HG24HS and HG07U sensor signals. The sensors have a close-to-zero mean and the same standard deviation and RMS, which signify that the sensors are well-normalized and the signals are of similar magnitude. There are small changes in peak and minimum values, indicating small shifts in extreme responses. The values of skewness and kurtosis indicate almost symmetric and flatter distributions of both signals. In general, the vibration properties of both sensors are similar with minor differences in signal distribution and peak behavior.

Table 1. Statistical comparison of different sensor signals

Features	HG24HS	HG07U
Mean	1.70E-15	3.12E-15
Standard Deviation	1.0000	1.0000
RMS	1.0000	1.0000
Peak	2.8652	2.6968
Min	-2.7984	-2.6968
Skewness	0.0415	-0.1141
Kurtosis	-0.5327	-0.8019
Crest Factor	2.8652	2.6968

Figure 4 shows the FFT spectrum of the HG24HS and HG07U signals. The two sensors record similar frequency components, which validates the similar dynamic characteristics of the structure. HG07U has a dominant peak value at a certain frequency, which implies that it has a stronger response at that mode, whereas HG24HS has a more distributed amplitude pattern over frequencies.

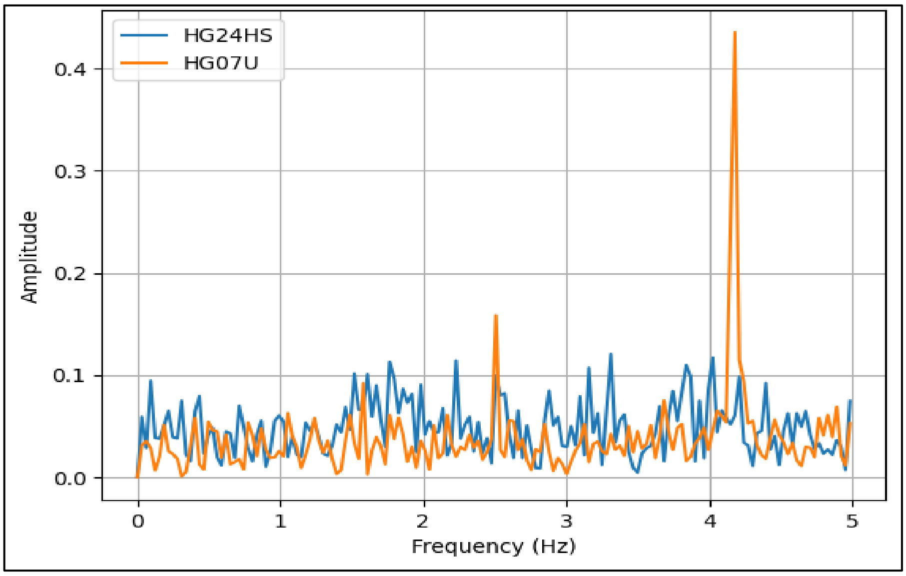

Figure 4. FFT spectrum of HG24HS and HG07U signals

The comparison of the Power Spectral Density (PSD) of the HG24HS sensor and the HG07U sensor is shown in Figure 5. The spectral distribution of both sensors is similar throughout the frequency range, which means there is consistency in the energy behavior of the system. However, the HG07U has some local high peaks, which indicates that the energy is more concentrated at certain frequencies than in the HG24HS.

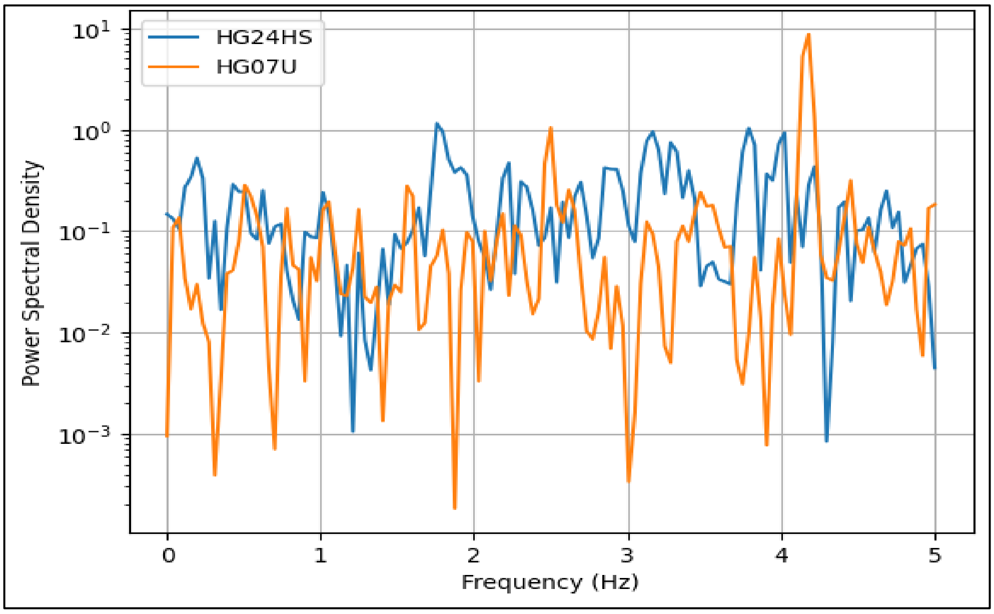

Figure 5. PSD comparison between HG24HS and HG07U sensors

Overall, dominant peaks found in the FFT spectrum are related to the main vibration frequencies of the monitored structure. Likewise, the PSD shows how the energy of the vibration is distributed over the frequency bands. Changes in the magnitude or energy distribution of the spectrum can suggest stiffness, damping or dynamic changes in the structure. Hence, frequency domain analysis is useful in addition to statistical analysis to give other insights into the structural response.

4.2 Statistical Hypothesis Analysis

Table 2 shows the statistical analysis of HG24HS and HG07U sensor signals using the T-test, Mann-Whitney test, Kolmogorov-Smirnov test, and variance analysis.

Table 2. Statistical hypothesis analysis of HG24HS and HG07U sensor signals

Statistical Hypothesis Test	Values
T-Test	0.1647
P-value	0.8693
Mann-Whitney U Test	51991.5
P-value	0.9420
Kolmogorov-Smirnov Test (D)	0.1084
P-value	0.0450
Variance HG24HS	0.0043
Variance HG07U	0.0074

According to the statistical findings, the T-test value (0.1647) with a high p-value (0.8693) indicates no significant difference in the average vibration levels of HG24HS and HG07U sensors, which proves the occurrence of similar average behavior. Likewise, the Mann-Whitney test ($U = 51991.5$, $p = 0.9420$) implies that the median or rank distributions are not significantly different, suggesting a common central tendency in both sensors. The Kolmogorov-Smirnov Test ($D = 0.1084$, $p = 0.0450$) however, shows a statistically significant difference in the overall shape of the distribution, which suggests slight variations in vibration patterns between the two sensors. Moreover, the variance values indicate that the variability of HG07U (0.0074) is greater than that of HG24HS (0.0043), representing a slight difference in the vibration dispersion or sensitivity of HG07U. Overall, while mean and median behaviors are equal, differences at the distribution level indicate localized changes in sensor responses.

4.3 Distribution Analysis

Figure 6 shows a comparison of the vibration amplitudes of the HG24HS and HG07U sensors, presented as a histogram of their distributions. The two signals have overlapping distributions, indicating similar overall amplitude ranges. Nevertheless, minor variations exist in their spread and shape, with the HG07U exhibiting a broader distribution. This implies small differences in structural response that are not apparent under mean-based tests but are reflected under distribution-based tests.

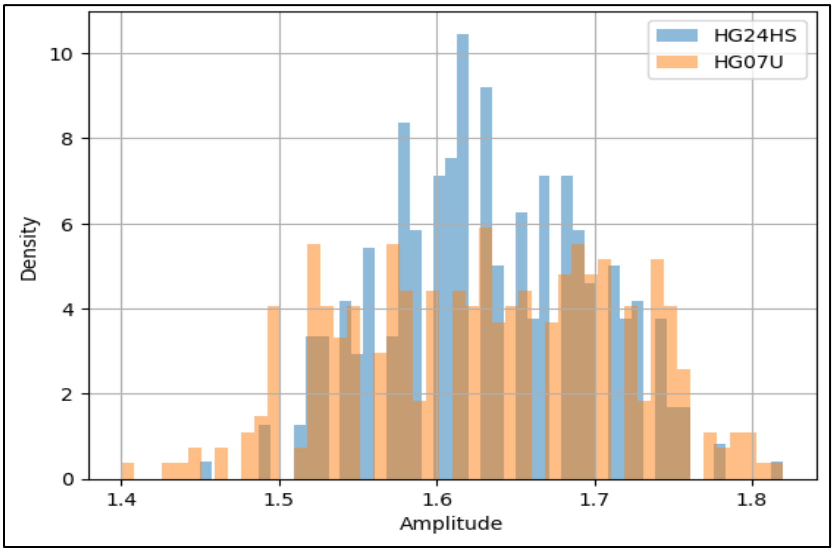

Figure 6. Histogram based distribution analysis of HG24HS and HG07U sensor signals

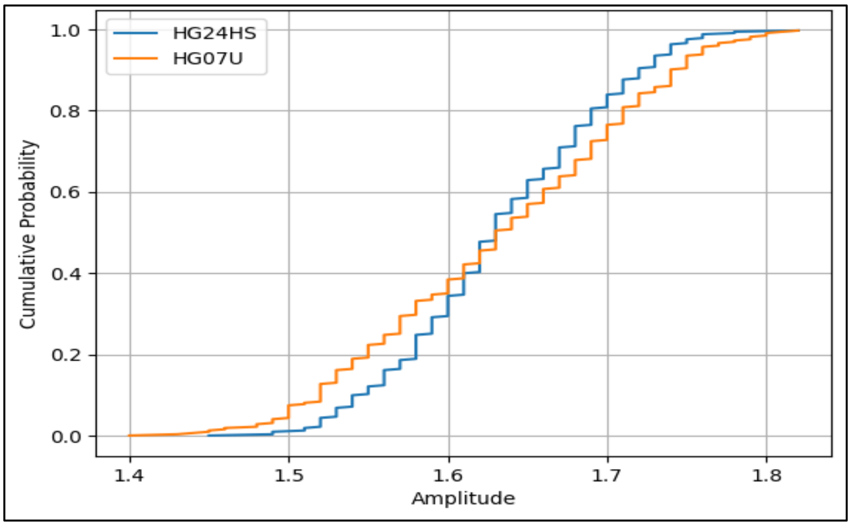

Figure 7. CDF based distribution analysis of HG24HS and HG07U sensor signals

Figure 7 depicts the CDF comparison between sensor signals of HG24HS and HG07U. The cumulative distribution of both sensors is similar, which means that both sensors exhibit similar statistical behavior. The slight movement of the curves indicates slight variations in the distribution of amplitude, whereby HG24HS attains higher cumulative probabilities a bit earlier than HG07U. Overall, similar distributions are observed, which proves the similarity of signals from the two sensors.

4.4 K-Means Clustering Analysis

The validity of the K-means clustering results was quantitatively evaluated by calculating the silhouette score for a clustering with two clusters (k = 2) for the combination of the normalized HG24HS and HG07U signals. The silhouette score was 0.5915 which is considered a good score and shows that the clusters were well separated and compact with a small amount of overlap between them. The K-means clustering of the vibration signal is performed into two clusters (k = 2) for the combination of the normalized vibration signals and shown in Figure 8. The data points are clustered around the zero value of the normalized amplitude with the positive (above zero) normalized amplitude data points in one cluster and the negative (below zero) normalized amplitude data points in another cluster. There is no overlap between the two clusters, with a silhouette score of 0.5915. Most importantly, data from both HG24HS and HG07U sensors are spread across each cluster and across the entire spectrum of samples, which suggests that a clustering characteristic is not unique to either of the sensors but rather a natural property of the vibration signals. This indicates that there is a common vibration characteristic associated with each sensor, and that the differences are due to amplitude level changes, but not a difference in the underlying pattern of the vibration.

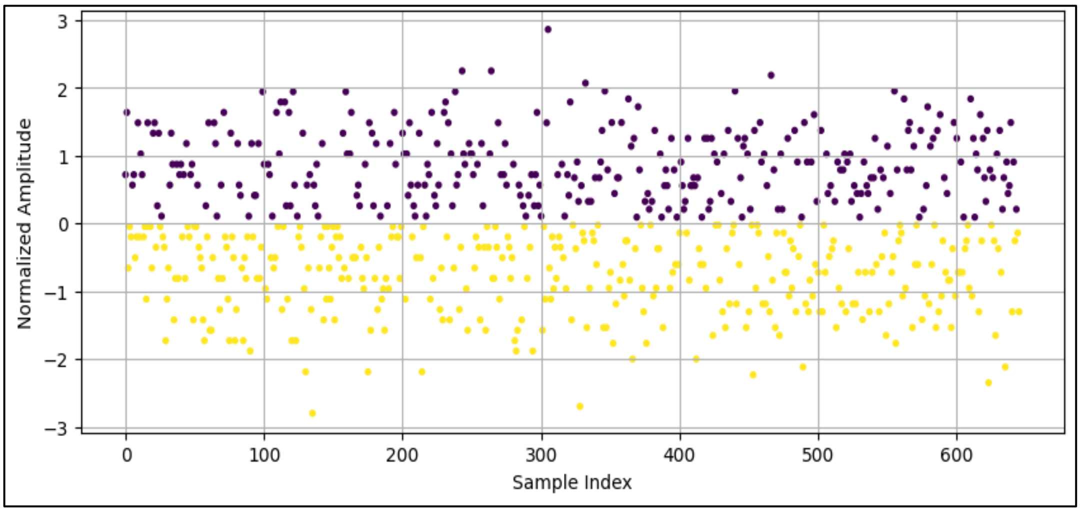

Figure 8. K-means clustering of the normalized vibration signals into two groups

Damage Detection criterion: A rule-based decision is defined as:

$$Damage = \begin{cases} Yes, \ if p_{ks} < 0.05 \ and \ Var_2 > Var_1 \\ No, \qquad otherwise \end{cases} \tag{23}$$

Where p_{ks} indicates the p-value of the Kolmogorov-Smirnov Test and Var_1, Var_2 indicates the variance of the signals. The ultimate damage decision is obtained by combining the output of statistical hypothesis tests, variance analysis, and distribution-based analysis. T-test (p = 0.8693) and Mann-Whitney U test (p = 0.9420) show that there is no significant difference between the mean and median behavior of HG24HS and HG07U sensor signals and this proves that there are similar central tendencies. Nevertheless, the Kolmogorov-Smirnov test (p = 0.0450) indicates statistical significance in the overall distribution which indicates the existence of minor changes in the vibration patterns. Moreover, variance analysis shows that the HG07U has a greater variance than HG24HS, which implies that the dispersion of vibration energy is slightly higher. These combined observations suggest that the system has no clear indicators of structural damage, but it has a small amount of distribution-level variability that can be attributed to local vibration variations or sensor sensitivity variations.

5. Limitation of the Present Work

The damage detection criterion is a rule-based approach that has not been validated on real damaged structures or benchmark SHM databases. These two datasets are obtained in ambient conditions, and thus the difference in observations can only be attributed to sensor/operational variability, not to damage. The framework will be validated with damage scenarios in the future. Additionally, sensors will be added to the network for damage localization, and machine learning-based methods will be investigated to enhance the framework's robustness and achieve a more accurate assessment than the current threshold-based approach.

6. Conclusion

Time and frequency domain, statistical, and clustering-based methods were used to analyze the vibration signals generated by the HG24HS and HG07U sensors. According to the findings, both sensor signals show consistent behavior in terms of mean values, frequency content, and statistical properties (rank order). Some minor variations were observed in the distribution level and the variation in the HG07U signal, but these differences fall within the range of sensor-to-sensor and operational variations and are not significant of structural damage. It is important to note that this conclusion is based on a single operating condition recorded under undamaged, real-time ambient conditions and not compared to other data acquired from a known or induced damaged state. Therefore, it is not a validated confirmation of structural integrity, but rather an indication of steady-state structural behaviour under the tested condition. The observed variations are more likely due to local effects or differences in individual sensor sensitivity due to structural change. Overall, the proposed framework shows that statistical and signal processing methods can be used to provide a valid comparative basis for the initial structural condition assessment, but further validation with damaged-state or benchmark data is required before the framework can be used for definitive damage detection. Future studies will include more sensors and higher sample rates for increased sensitivity to structural changes, as well as data collected under controlled or induced damage conditions and benchmark SHM datasets for testing and validation of the proposed framework against ground truth damage labels. The use of supervised machine learning models based on labeled data, and the development of real-time monitoring systems, will also be discussed to improve the accuracy and robustness of damage detection.

Acknowledgement

The authors acknowledge the financial support extended by DST-SERB through the Core Research Grant (Reference No. CRG/2023/005596) for carrying out the technology development.

References

[1] Eltouny, Kareem, Mohamed Gomaa, and Xiao Liang. "Unsupervised Learning Methods for Data-Driven Vibration-Based Structural Health Monitoring: A Review." Sensors 23, no. 6 (2023): 3290.

[2] Rabi, Raihan Rahmat, Marco Vailati, and Giorgio Monti. "Effectiveness of Vibration-Based Techniques for Damage Localization and Lifetime Prediction in Structural Health Monitoring of Bridges: A Comprehensive Review." Buildings 14, no. 4 (2024): 1183.

[3] Mardanshahi, Ali, Abhilash Sreekumar, Xin Yang, Swarup Kumar Barman, and Dimitrios Chronopoulos. "Sensing Techniques for Structural Health Monitoring: A State-of-the-Art Review on Performance Criteria and New-Generation Technologies." Sensors 25, no. 5 (2025): 1424.

[4] Ayankoso, Samuel, Ananta Dutta, Yinghang He, Fengshou Gu, Andrew Ball, and Surjya K. Pal. "Performance of Vibration and Current Signals in the Fault Diagnosis of Induction Motors Using Deep Learning and Machine Learning Techniques." Structural Health Monitoring 25, no. 1 (2026): 196-212.

[5] Gonen, Semih, and Emrah Erduran. "A Hybrid Method for Vibration-Based Bridge Damage Detection." Remote Sensing 14, no. 23 (2022): 6054.

[6] Altaf, Muhammad, Tallha Akram, Muhammad Attique Khan, Muhammad Iqbal, M. Munawwar Iqbal Ch, and Ching-Hsien Hsu. "A New Statistical Features Based Approach for Bearing Fault Diagnosis Using Vibration Signals." Sensors 22, no. 5 (2022): 2012.

[7] Kuo, Chien-Chih, and Ching-Hung Lee. "An Enhanced Structural Damage Identification Approach Using Statistical Analysis and Optimization." IEEE Sensors Journal 23, no. 24 (2023): 31082-31097.

[8] Zhou, Yixin, Zepeng Ma, and Lei Fu. "A Review of Key Signal Processing Techniques for Structural Health Monitoring: Highlighting Non-Parametric Time-Frequency Analysis, Adaptive Decomposition, And Deconvolution." Algorithms 18, no. 6 (2025): 318.

[9] Hadizadeh-Bazaz, Mehrdad, Ignacio Javier Navarro Martínez, and Víctor Yepes Piqueras. "Performance Comparison of Structural Damage Detection Methods Based on Frequency Response Function and Power Spectral Density." (2022).

[10] Laha, S. K., B. Swarnakar, and S. Kansabanik. "Anomaly Detection in Structural Health Monitoring Using Spectral Distance and t-SNE–GMM Framework Under Ambient Excitation." Asian Journal of Civil Engineering 25, no. 4 (2024): 3711-3727.

[11] Dang, Viet-Hung, Khuong Le-Nguyen, and Truong-Thang Nguyen. "Semi-Supervised Vibration-Based Structural Health Monitoring via Deep Graph Learning and Contrastive Learning." In Structures, vol. 51, Elsevier, 2023, 158-170.

[12] Lydakis, Emmanouil, Holger Koss, Rune Brincker, and Sandro DR Amador. "Data-Driven Sensor Fault Diagnosis for Vibration-Based Structural Health Monitoring Under Ambient Excitation." Measurement 237 (2024): 115232.

[13] Buckley, Tadhg, Bidisha Ghosh, and Vikram Pakrashi. "A Feature Extraction & Selection Benchmark for Structural Health Monitoring." Structural Health Monitoring 22, no. 3 (2023): 2082-2127.

[14] Li, X. Y., Y. H. Guan, S. S. Law, and W. Zhao. "Monitoring Abnormal Vibration and Structural Health Conditions of an In-Service Structure from Its SHM Data." Journal of Sound and Vibration 537 (2022): 117185.

[15] Ye, Xijun, Yongjie Cao, Airong Liu, Xinwei Wang, Yinghao Zhao, and Nan Hu. "Parallel Convolutional Neural Network Toward High Efficiency and Robust Structural Damage Identification." Structural health monitoring 22, no. 6 (2023): 3805-3826.

[16] Dolui, Cherosree, Dipanjan Bose, and Debabrata Roy. "Analysis of FFT and K-Means Clustering for Structural Health Monitoring." In 2024 IEEE Calcutta Conference (CALCON), IEEE, 2024, 1-5.