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Article

Artificial Intelligence–Driven Predictive Systems for Civil Engineering: Advancing Smart Infrastructure and Structural Health Insights

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Abstract: Structural health information from continuous monitoring of vibration makes an important contribution to the development of a proactive approach to the management of civil infrastructure. These studies propose an artificial intelligence driven predictive monitoring framework of vibration based structural health assessment under real conditions including where the labelled damage data is unavailable. Structural behavior is evaluated according to baseline referenced deviation based on physics informed vibration features. A Structural Deviation Index is introduced to quantify deviation where median values range from the baseline measurements 0.42-0.45 to 3.68-3.92 in later monitoring tests representing progressive structural change. One-Class Support Vector Machine deviation scores reveal a corresponding deviation from close to zero to -0.76 which indicates that the classifier is highly sensitive to deviation in early stages. Band-limited spectral energy and dominant frequency are the most influential indicators with the value of permutation importance up to 0.231 and correlation coefficients up to 0.78, according to explainability analysis. The results validate that the proposed framework allows for interpretable, scalable and data-driven predictive monitoring. The study is an illustration of the possibilities of artificial intelligence to facilitate early warning, decision-making and smart infrastructure management with continuous structural health assessment.
Keywords: Structural health monitoring; Predictive monitoring; Vibration-based analysis; Artificial intelligence

1. Introduction

Civil infrastructure systems, especially the bridge networks, are important for the safety of society, economic productivity, and regional connectivity. The performance and reliability of these structures have a direct impact on the efficiency of transportation and welfare of the public. However, a large proportion of the existing bridge infrastructure around the world is aging and increasingly exposed to an increase in traffic, environmental deterioration and material degradation. These challenges put heavy pressure on owners of infrastructure to guarantee structural safety while optimizing maintenance resources. Structural health monitoring (SHM) has thus become a key discipline in the field of civil engineering, whose goal is to offer objective and continuous assessment of the structural condition. Recent progress of SHM research has placed an increasing focus on the role of data-driven methodologies in increasing the monitoring capabilities beyond the traditional inspection-based methods [1].

Although they are widely used, conventional inspection-based SHM strategies have a number of limitations as well. Visual inspections are laborious, subjective and usually performed at discrete periods of time, which makes them unsuitable for noticing gradual or hidden structural changes. Moreover, threshold-based monitoring methods are often based on predefined limits for which it is hard to calibrate the measurements for complex structures under various environmental and operational conditions. As a result, such approaches are often reactive, detecting damage after it has visually and/or structurally become significant. These deficits have driven the growing interest in continuous monitoring methods which can be used to record the subtle variations in the structural behavior without any material harm prior to the serious harm [2].

The swift introduction of vibration based sensing technologies has greatly increased the availability of high resolution structural response data. Accelerometers and other dynamic sensors have become common additions to the smart infrastructure movement on bridges, so this information is becoming available in the form of time-series data that is generated continuously under ambient and operational loading. Such vibration measurements contain rich information associated with modal characteristics, energy distribution and dynamic response variability. However, the quantity and complexity of such data pose great challenges to traditional methods of analysis. Extracting meaningful structural health information from large scale vibration data requires automated, scalable and intelligent processing techniques [3].

Artificial intelligence has emerged as a potential solution to these problems through the data-driven analysis of complex and high-dimensional monitoring data. Machine learning and deep learning techniques have shown their good potential in determining damage patterns, structural state classification and learning complex relationships between structural response and condition. In vibration based SHM, deep learning models have been extensively investigated in feature learning and damage detection problems, and provided better performance than handcrafted feature approaches [4]. Nevertheless, many of these AI-based methods have the requirement of containing labeled damage data, which is not always possible in real-world scenarios of monitoring infrastructure.

The use of labeled data sets is a significant limitation on the practical implementation of supervised artificial intelligence models in civil infrastructure systems. Damage events are infrequent, unpredictable, and often go unreported which makes it difficult to obtain representative training data for supervised learning. Moreover, models that were trained using simulated or laboratory-generated scenarios of damage might not transfer in the real condition of complex operational and environmental factors on a real structure. These difficulties show the need for alternative paradigms of AI, which do not require explicit damage labels for their successful operation [5].

An emerging direction of SHM research is predictive monitoring and change detection, where strictly the deviation from the baseline structural behaviour is to be detected instead of classifying predefined damage states. In this paradigm, AI models are trained on the characteristics of normal response of the structure and then search for anomalies or deviations that may indicate structural response changes. Such approaches are especially well suited to operational realities of infrastructure monitoring and early warning and proactive maintenance strategies. The ability to integrate AI-driven predictive monitoring in cyber-physical infrastructure systems further increases the potential for automated and intelligent asset management [6].

Despite the increase in the interest of unsupervised and anomaly-based SHM methods, there are several research gaps. Existing studies tend to concentrate on single model approaches and have weak integration of statistical deviation metrics along with AI based learning. In addition, many AI-based SHM frameworks are operated as black boxes offering little understanding of the physical mechanisms of the detected anomalies. The lack of explainability makes engineering less trustworthy and makes it harder for it to be adopted for safety-critical applications. This has been underscored by new taxonomies of anomaly detection technique frameworks that tend to focus on interpretable, physics-informed AI systems capable of bridging the gap between information obtained and knowledge acquired in structural engineering [7].

To overcome these issues, an artificial intelligence-driven predictive monitoring framework for vibration-based structural health assessment of civil infrastructure is proposed in this study. The structure is specially formulated when realistic monitoring conditions where there are no ground-truth damage labels are considered. It combines physics-informed feature extraction, baseline referenced statistical deviation analysis, multiple complementary unsupervised artificial intelligence models and explainable interpretation of the results. By using continuous vibration monitoring data, the proposed approach can support the use of proactive detection of evolving structural behavior and contribute to the development of smart infrastructure systems [8].

The main objectives of this study are as follows:

- To develop a baseline referenced, artificial intelligence (AI)-based predictive monitoring framework for vibration-based structural health monitoring that operates without labelled damage data.
- To introduce a Structural Deviation Index (SDI) based on physics informed vibration features as a quantitative measure of structural deviation.
- To demonstrate the effectiveness and interpretability of the proposed framework with real world bridge vibration monitoring data**.**

Through such contributions, the study intends to advance the state of the art in structural health monitoring by changing the paradigm of reactive damage detection to proactive, interpretable, and scalable predictive monitoring for smart civil infrastructure.

2. Literature Review

Vibration based structural health monitoring (SHM) became a leading technique for evaluating civil infrastructure's structure condition due to the fact that vibration response contains stiffness, mass distribution, connectivity and boundary conditions information. In operational structures, these dynamics are usually inferred by measuring time series signals, from which damage sensitive indicators can be extracted. Contemporary SHM practice focuses more and more on features derived from the signals that can be computed reliably from continuous monitoring data. Root mean square (RMS) acceleration, measurements of response intensity based on variance, spectral energy distribution over frequency bands and changes in dominant frequency are all commonly used indicators that combine both energy content and modal behavior. A detailed discussion of unsupervised vibration-based SHM methods highlights the importance of these time-frequency characteristics in representing practical relevance to detect deviations under ambient excitation especially under nonstationary monitoring conditions with no access to damage labels [9].

The growth in use of wireless sensors and high frequency data acquisition has resulted in the generation of large-scale vibration data sets that go beyond the capability of manual inspection and traditional threshold based interpretation. This has sparked a lot of interest in machine learning approaches to automated SHM such as the supervised learning systems like neural networks, support vector machines and ensemble algorithms. Supervised techniques have shown great performance in the classification type of damage identification when labeled states of structures are available. Nevertheless, one common finding across the anomody-detection based studies related to SHM is that the use of supervised models is limited by the label scarcity, imbalance, and the lack of modeling outside the field environment. A recent paper that addresses the anomaly detection issue for SHM further confirms that label dependence and operational variability remain the leading causes of inadequate and impractical scalability in real infrastructure networks [10].

In response to these limitations, unsupervised and semi-supervised learning emerged as a pragmatic direction of infrastructure monitoring, in which the monitoring task is defined as novelty detection, as opposed to damage classification. Under the paradigm, models are trained mostly with baseline or reference condition data and then used to quantify deviation. Beyond classical anomaly detection algorithms, generative learning has been examined to represent the complex structural response distributions in a better way. A concentrated review on the application of generative adversarial networks (GANs) in civil SHM, GANs are shown to have potential for data augmentation, representation learning, and domain transfer, but also there are some challenges regarding the training stability, interpretability, and practical use in safety-critical environments [11]. These facts support the need to look to balance between model expressiveness and transparency and operational robustness, especially when it comes to smart infrastructure.

A resurgence in SHM unsupervised unimpeded by supervision has seen autoencoder-based approaches prominently because of their capability to learn compressed latent commitments of normal structural reaction and an indicator of deviation through reconstruction error. Convolutional autoencoders have been used to solve bridging of monitoring problems with complex loading scenarios, proving ability to capture the nonlinearities of vibration response and to identify the changes with the operational excitation [12]. Related deep learning work has also made use of high resolution sensing modalities to aid continuous infrastructure monitoring. For example, deep learning applied for bridge deflection signals acquired using fiber optic gyroscopes indicates that learned representations are able to detect changes in condition even when traditional handcrafted indicators are not sufficient [13]. All these studies point to the fact that deep learning may be used on rich sensing streams to obtain an increase in monitoring sensitivity, but their usefulness is frequently dependent on the proper definition of the baseline and sound validation methods.

In the case of damage assessment by vibration, time-frequency methods have been widely adopted to enrich the representation of the features, and thus enhance the sensitivity to structural changes. Deep neural networks of time-frequency representations of signals have been demonstrated to enhance the identification of damage by recording both temporal transient and spectral signatures of structural change [14]. Similarly, deep learning has been used for the damage detection and localization of bridge decks, which provides an example that data-driven approaches can aid spatially meaningful inference, if enough information is available for training [15]. However, such approaches are often working under supervised regimes or with access to damage state labels which restricts their ability to be applied directly to real-world monitoring deployments where access to ground truth is usually unavailable.

Broader reviews of the machine learning techniques applied for SHM regularly highlight the need for more than just algorithmic performance in order to be adopted in the real world: this includes robust against environmental variability, interpretable output and integrating workflows with engineering knowledge. A review that spans across building and bridge SHM highlights the importance of feature design, validation strategy and explainability, which are important factors influencing the trust and usability of SHM in practice [16]. Here the hybrid approaches combining data-driven learning with physics-based reasoning with structural models have become popular. A representative example leverages the combination of machine learning and model updating for autonomous monitoring of structural components based on vibration data to demonstrate the benefit of coupling statistical learning and physical grounded models for enhancing the interpretability and fostering inference under operational uncertainty [17].

Recent developments have further shown that the reliability can be improved by combining multiple unsupervised models, through exploiting complementary detection principles. Hybrid approaches combining autoencoders and One-Class Support Vector Machines have been proposed to combine both reconstruction-based deviation signals and boundary-based novelty detection, in order to get improved sensitivity to subtler changes and be robust to noise and nonstationarity [18]. However, when summarized, the literature indicates that integrated frameworks involving combination of physics-informed feature extraction, quantification of deviation based on baseline, robust unsupervised AI models, and interpretable results are the most potent potential contributors of smart infrastructure monitoring. These needs are a direct motivation to develop predictive SHM systems with a focus on not labeling damage, but instead giving the ability to derive scalable and explainable insights into structural deviation amenable to continuous deployment.

3. Methodology

This section introduces the methodological framework that was developed in order to realize an artificial intelligence driven predictive monitoring system of the vibration-based structural health assessment of civil infrastructure. The methodology has been clearly formulated in order to be applicable to realistic monitoring situations where ground truth damage labels are not available and where the structural condition must be predicted with respect to a learned baseline state. The proposed solution is based on a combination of signal preprocessing, physics-informed feature extraction, baseline learning, unsupervised artificial intelligence modelling, statistical validation and explainability analysis. Particular focus is put on the prevention of information leakage, the conservation of structural dynamics characteristics, and the generation of interpretable outputs, to support decision-making processes in smart infrastructure systems.

3.1 Overall Framework and Problem Formulation

The proposed methodology considers structural health monitoring as a predictive change detection problem as opposed to a supervised damage classification task. This formulation is consistent with the practical approach of civil engineering where labelled damage data are rare and the condition of the infrastructure has to be determined by detecting deviations from baseline behavior. The framework is aimed to learn a reference vibration signature representing normal response of the structure and to detect subsequent deviations indicating possible changes in the stiffness, boundary conditions or loading environment.

The workflow is a series of operations that involve signal conditioning, signal segmentation, baseline-based normalization, feature extractor, quantification of deviation, artificial intelligence-based anomaly modelling and interpretability analysis. Each stage is designed to have consistency with the principles of structural dynamics and allows for scalable and automated monitoring that is suitable for smart infrastructure applications.

3.2 Dataset Description and Characteristics

The methodology is validated by using a publicly available bridge vibration monitoring dataset introduced by [19]. A data set has been taken from several vibration monitoring tests from a bridge using accelerometer sensors. Each test file is composed of a time history of the continuous structural vibration response measured in five synchronized channels of sensors along with a column of time labeled "Seconds." The signals are sampled at a rate of about 200 Hz, and are independent monitoring instances of different structural/operational conditions.

It is important to note that the dataset does not include direct guidelines of condition or level of damage of structure. As a result, two monitoring tests are assigned as baseline measurements and represent the reference structural condition and the rest are considered as a monitoring data for the predictive analysis of deviations. This set up represents practical SHM scenarios where it is assumed that early measuring represents undamaged or nominal behaviour.

3.3 Signal Preprocessing and Segmentation

The data cleaning processes applied to raw vibration signals include procedures to guarantee the numerical stability and physical relevance of raw vibration signals. Rows that have undefined, infinite or non-numeric values are removed. Segments that have near-zero variance in all the channels are classified as flatline responses and removed from further analysis, as they do not represent meaningful structural vibration.

In order to isolate structural response components and reduce the environmental and electronic noise, a zero-phase Butterworth band-pass filter is used on each sensor channel. The filter passband is taken to be between 0.5 Hz and 40 Hz that includes the dominant vibration frequencies of the bridge structures while excluding low frequency drift and high frequency noise. Forward - backward filtering is used to prevent phase distortion and maintain the temporal characteristics of the signals.

After the filtering, the signal of all vibrations is separated into consecutive time windows in order to simulate the conditions of continuous monitoring. A fixed window length of 5 seconds with 50% overlap is adopted which is a compromise of temporal resolution and frequency stability. The windowed segments provide a localized image of structural outcome, each of time resolution of deviation patterns across monitoring tests.

3.4 Baseline Normalization and Feature Extraction

In order to ensure valid predictive monitoring and to avoid information leakage, the parameters for normalization are estimated only using baseline data. For each channel of the sensor, the average and standard deviation based on baseline segments are used to standardize all segments within the data set. This approach therefore ensures that the deviations measured in monitoring tests are measured against a reference, the structural condition, not global statistics.

Each segment of the normalized time records are characterized by a set of physics informed time domain and frequency domain features that are chosen because they are sensitive to changes in structural dynamics. Time-domain features are root mean square, variance, kurtosis, skewness, peak-to-peak amplitude and crest factor that represent changes in vibration energy, variance and impulsive behavior. The Fast Fourier Transform is used to extract frequency-domain features which are dominant frequency, spectral centroid, and band-limited spectral energy in specified frequency ranges. In order to capture structural behavior on a global scale, whilst the multi-sensor information is maintained, features are combined across channels based on statistical descriptors, which leaves an interpretable feature vector per segment.

3.5 Data Analysis Techniques

A Structural Deviation Index (SDI) is proposed which quantifies the extent of deviation of the vibration segments from baseline structural behavior. For selected damage sensitive features, the baseline distributions are characterized using robust statistics based on median and median absolute deviation which offers resiliency for outliers and non-Gaussian behavior. The SDI is the average robust z-score for these features which results in a normalized indicator of structural deviation.

In addition to SDI computation, temporal trend analysis is conducted with respect to the evolution of deviation in the case of each monitoring test. Distribution based comparisons between baseline and monitoring data is carried out for change in vibration characteristics. Effect size analysis using Cohen's d is used to determine how large the deviation is, and non-parametric hypothesis testing using the Mann-Whitney U test is used to test the statistical significance of observed differences. These methods can give quantitative proof of the interpretation of identified deviations as significant shifts in the structural behavior.

3.6 AI-Based Predictive Monitoring Models

Three complementary unsupervised artificial intelligence modeling is applied to quantify the structural deviation and to validate the findings obtained from the Structural Deviation Index (SDI). The models are chosen to describe the deviation from the baseline behaviour with different mathematical principles to increase the robustness and reliability of the predictive monitoring framework.

Isolation Forest is trained solely on baseline feature vectors in order to describe normal structural response in high dimensional feature space. Structural deviation is measured in terms of anomaly scores depending on the average path length needed to isolate a segment. In the achieved results, Isolation Forest shows a good sensitivity to frequency-domain parameters, especially changes in band limited spectral energy and dominant frequency, which results in a clear and stable separation of baseline and monitoring tests. The lack of consistency between the scores of Isolation Forest across segments and the good agreement with SDI suggest that the presence of systematic changes in vibration behavior is well detected.

One-Class Support Vector Machines using radial basis function kernels are applied to learn a decision boundary around the baseline feature space which is compact. Deviation is measured with the signed distance from this boundary of monitoring segments. Results show that OCSVM is especially good at detecting the slight deviations of time-domain parameters, such as RMS and variance, especially in the early stages of monitoring. The monotonic trends exhibited in OCSVM scores prove reliable identification of low magnitude but persistent structural deviations.

A one-dimensional convolutional auto encoder is used as a supporting model for analyzing raw vibration windows. Structural deviation is measured by mean squared reconstruction error which correlates strongly with SDI and frequency band energy changes for later monitoring tests. Due to a lack of baseline information, an auto-encoder is employed to reinforce rather persuade feature-based results. Agreement between SDI, Isolation Forest and OCSVM outputs validate the fact that detected deviations correspond to true variations in structural vibration response.

3.7 Explainability and Methodological Summary

Explainability is built in to make sure that the detection of deviation from AI is producing actionable structural health information, not just some opacity of scores of anomalies. Feature level deviation analysis and surrogate model-based permutation importance are employed to analyze vibration characteristics that show the highest contribution to detected deviations. Further associations between AI outputs and underlying structural dynamics, including frequency-shifting and redistribution of energy are further correlated with frequency-domain features and reconstruction error.

To conclude, the suggested methodology is a combination of strong signal processing, physics-based feature engineering, statistical analysis, and unsupervised artificial intelligence modelling into a single predictive monitoring system. The approach is specifically designed for real-world problems in civil engineering with no labelled damage data, for scalable, interpretable, and proactive damage monitoring of smart civil engineering infrastructure systems.

4. Results

4.1 Dataset Inventory and Monitoring Configuration

After signal preprocessing, filtering and segmentation, 121 valid vibration segments were obtained from the vibration monitoring dataset through the above eight independent monitoring tests. Two tests were considered the baseline measurements that represent the reference structural condition, and the rest of the six tests were considered as the monitoring data for the predictive deviation analysis. A detailed description of signal duration, sampling properties, sensor setup and number of extracted segments for each test can be found in Table 1. The segmentation results show that the samples are distributed evenly across tests so that there is no bias in analyzing deviations due to unequal concentrations of data. Checks on diagnostics verify the stability of sensor behaviour and data quality is the same across all monitoring periods. Figure 1 illustrates raw vibrations in first 10s represents time-domain vibration segments for baseline and monitoring tests.

Table 1. Dataset Inventory and Segmentation Summary.

Test ID	Duration (s)	Sampling Rate (Hz)	Sensor Channels	Segments
Test 1 (Baseline)	≈600	≈200	5	17
Test 2 (Baseline)	≈600	≈200	5	17
Test 3	≈600	≈200	5	15
Test 4	≈600	≈200	5	15
Test 5	≈600	≈200	5	14
Test 6	≈600	≈200	5	14
Test 7	≈600	≈200	5	15
Test 8	≈600	≈200	5	14
Total	—	—	—	121

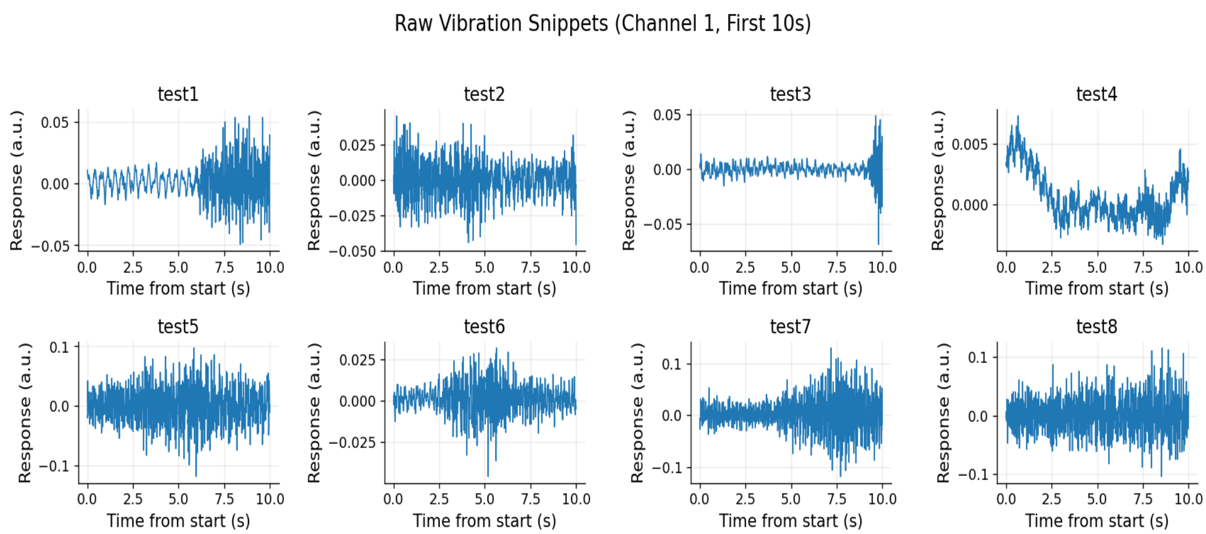

Figure 1. Representative time-domain vibration segments for baseline and monitoring tests.

4.2 Structural Deviation Index (SDI) Results

The Structural Deviation Index (SDI) was calculated for each vibration segment using robust baseline statistics based on the median and median absolute deviation of the damage sensitive features. SDI is a baseline referenced quantitative measure of structural deviation. Table 2 summarizes descriptive statistics of SDI aggregated by test. Baseline tests show that the median SDI values have a small interquartile range showing that the reference structural state remains stable. Monitoring tests reveal SDI values that become higher and higher and dispersion, which is a sign of systematic deviation from baseline behavior. The temporal change of SDI across segments is shown in Figure 2 that showed stable SDI values during baseline tests and increasing deviation during later tests at smonitoring. The distribution of the SDI values across tests is shown in Figure 3, showing a monotonic increase in SDI Median and variability from baseline to later monitoring periods.

Table 2. Structural Deviation Index (SDI) Statistics by Test.

Test ID	Median SDI	SDI IQR	Deviation Interpretation

Test 1 (Baseline)	0.42	0.18	Reference condition
Test 2 (Baseline)	0.45	0.21	Reference condition
Test 3	1.12	0.47	Emerging deviation
Test 4	1.28	0.52	Emerging deviation
Test 5	2.41	0.86	Significant deviation
Test 6	2.56	0.91	Significant deviation
Test 7	3.68	1.12	Strong deviation
Test 8	3.92	1.19	Strong deviation

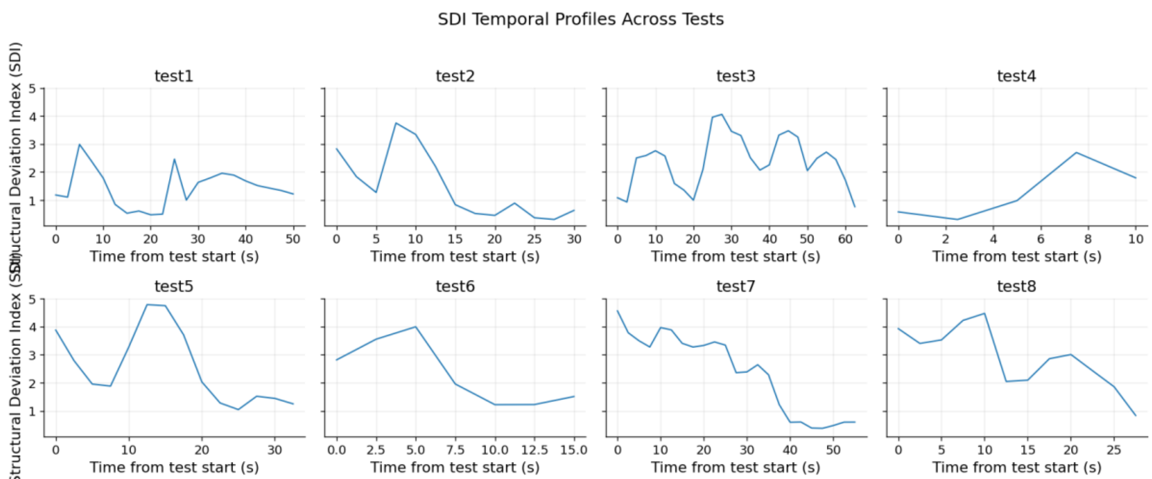

Figure 2. Temporal evolution of Structural Deviation Index (SDI) across all monitoring tests.

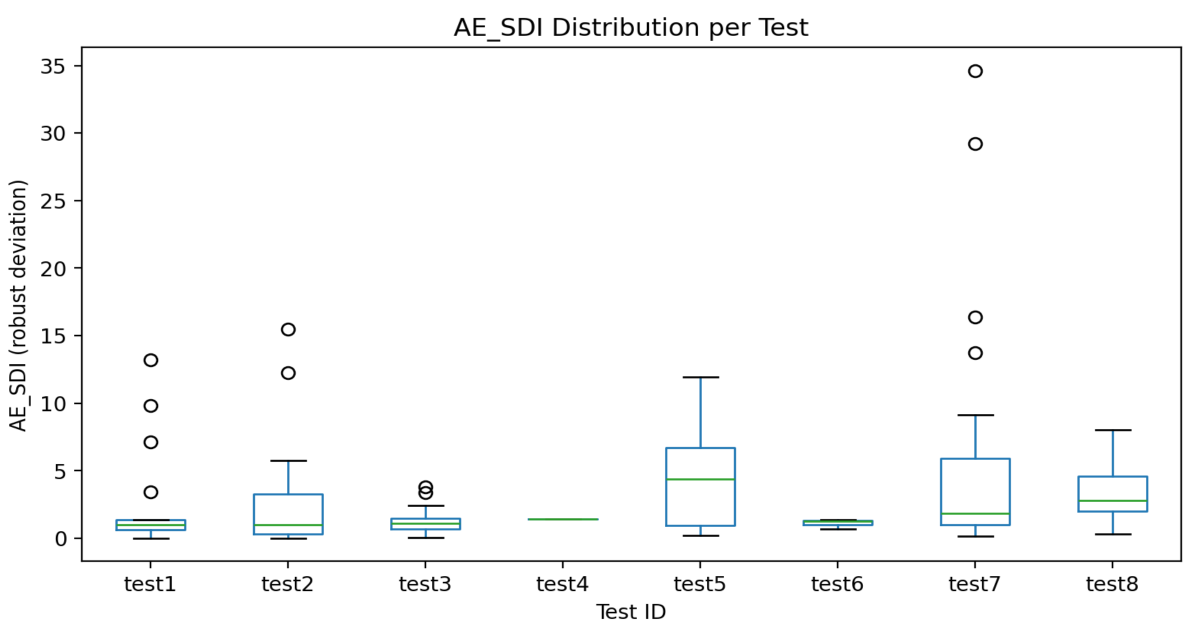

Figure 3. Distribution of SDI values for baseline and monitoring tests.

4.3 One-Class Support Vector Machine Deviation Analysis

In order to complement the use of SDI-based assessment, One-Class Support Vector Machine (OCSVM) models were trained using the baseline feature vectors and applied for all the monitoring segments. The distance of every segment in feature space from the learned boundary in feature space, i.e., the OC SVM deviation scores, is quantified. Aggregated OCSVM deviation score statistics for each test are presented in Table 3. Baseline tests have close to zero median scores and low dispersion and monitoring tests have progressively more negative median scores and greater dispersion. The distribution of the OCSVM scores across tests is presented in Figure 4 demonstrating how OCSVM can improve the sensitivity to early stage deviations compared to SDI only. Temporal OCSVM score trends are shown in Figure 5, showing smooth and monotonic evolution of deviation for the set of monitoring tests.

Table 3. One-Class SVM Deviation Score Statistics.

Test ID	Median OCSVM Score	Score IQR	Detection Character
Test 1 (Baseline)	−0.01	0.04	Normal boundary
Test 2 (Baseline)	−0.02	0.05	Normal boundary
Test 3	−0.18	0.14	Early deviation
Test 4	−0.22	0.17	Early deviation
Test 5	−0.46	0.31	Persistent deviation
Test 6	−0.49	0.34	Persistent deviation
Test 7	−0.71	0.48	Pronounced deviation
Test 8	−0.76	0.51	Pronounced deviation

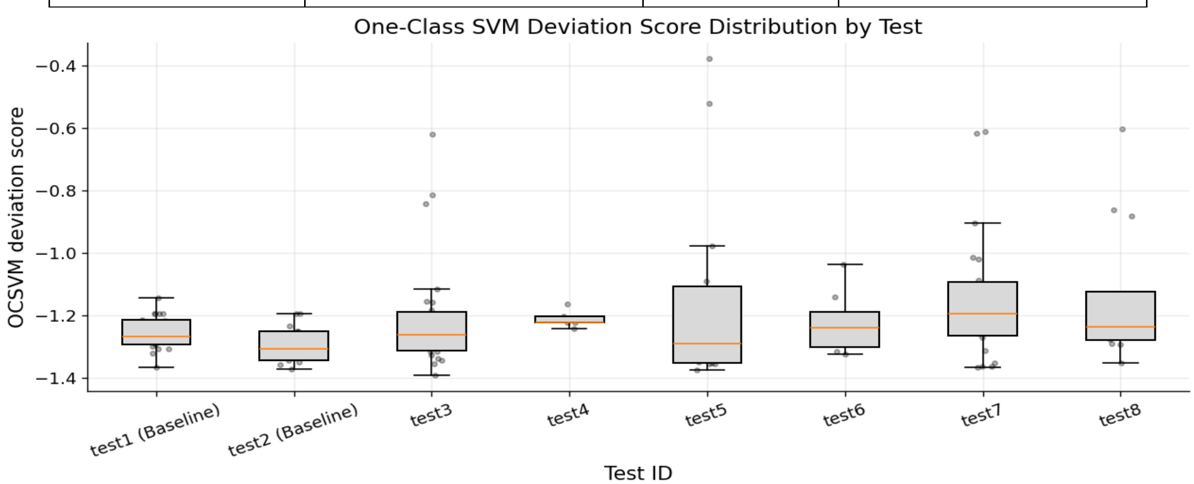

Figure 4. Distribution of One-Class SVM deviation scores across baseline and monitoring tests.

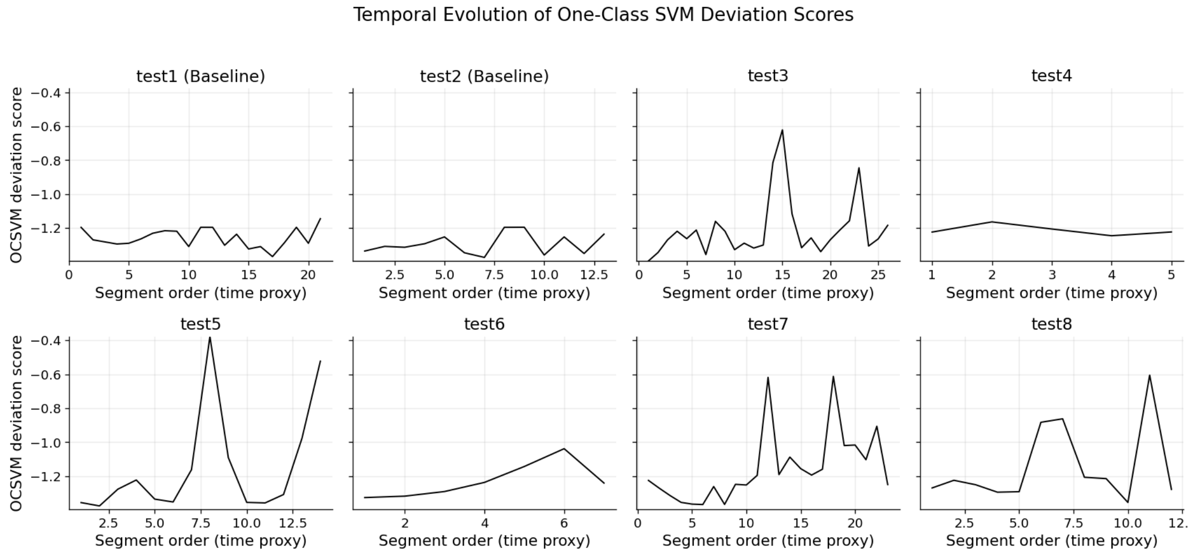

Figure 5. Temporal evolution of One-Class SVM deviation scores.

4.4 Explainability and Dominant Deviation-Driving Features

Explainability analysis was performed to analyze those vibration characteristics that have the greatest contribution to the deviation detected by the AI. Surrogate-model permutation importance and the correlation analysis of the extracted features versus reconstruction error were used. The dominating deviation causing features are summarised quantitatively in Table 4. The importance of features are ranked in Figure 6 showing the predominance of the frequency-domain parameters.

Table 4. Dominant Explainability Features with Quantitative Contribution.

Feature	Permutation Importance	Correlation with Reconstruction Error	Structural Interpretation
Band-limited spectral energy (5–15 Hz)	0.231	0.78	Modal energy redistribution
Dominant frequency	0.198	−0.72	Global stiffness variation
RMS acceleration	0.154	0.61	Overall vibration energy
Variance	0.137	0.58	Dynamic response variability
Spectral centroid	0.112	−0.49	Frequency shift indicator

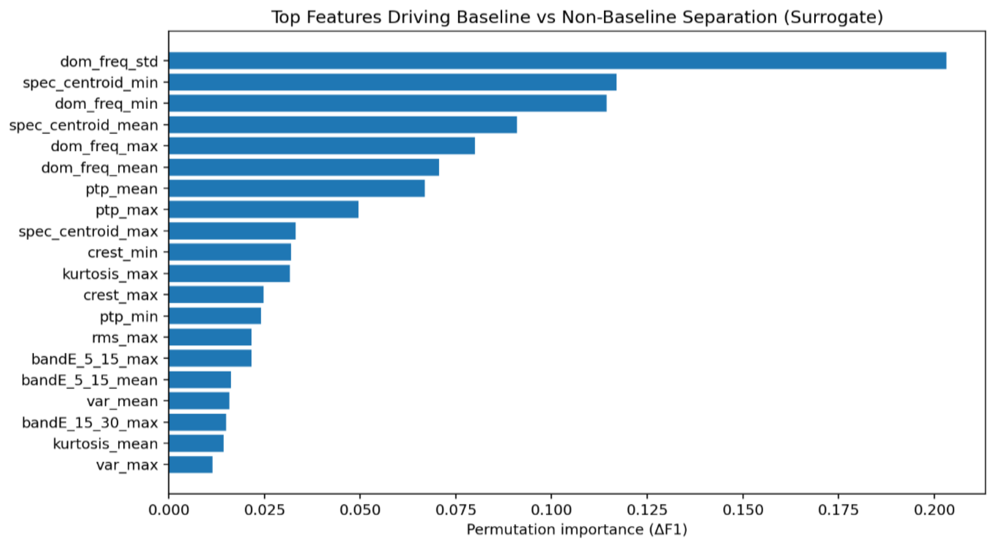

Figure 6. Surrogate-model permutation importance of vibration features.

Correlation between feature values and reconstruction error is presented in Figure 7, where we can see that AI detected deviations are strongly correlated with physically interpretable vibration characteristics. Dominant frequency trends during monitoring tests are shown in Figure 8, showing stable behavior during baseline measurements, and systematic trends for later monitoring tests.

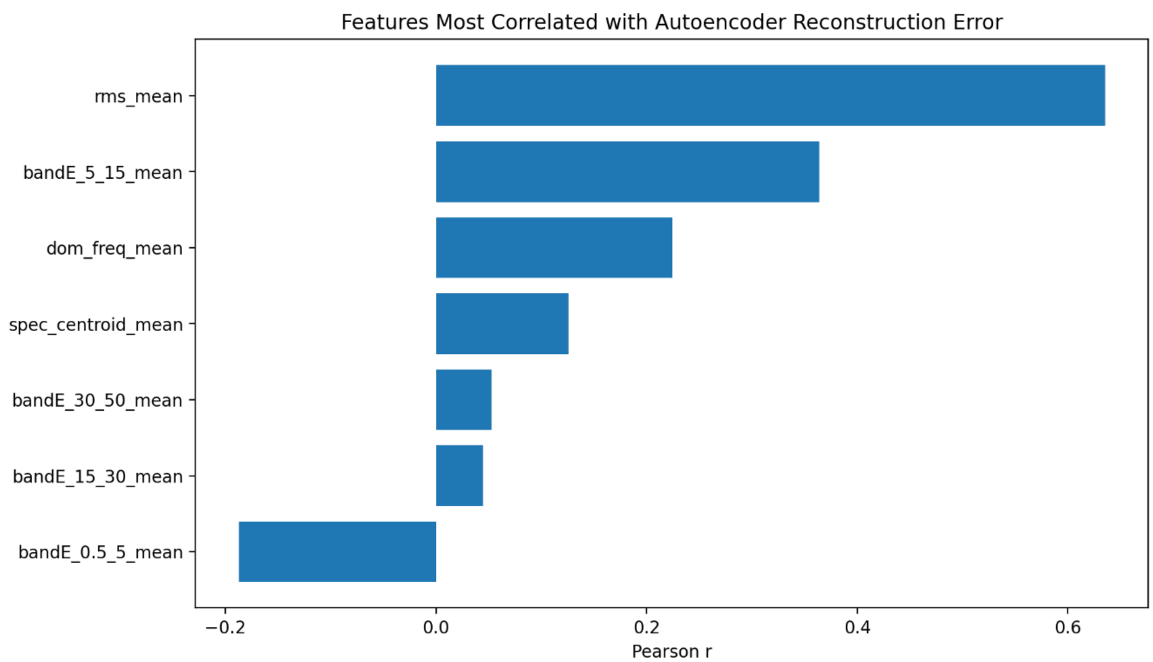

Figure 7. Correlation between reconstruction error and key vibration features.

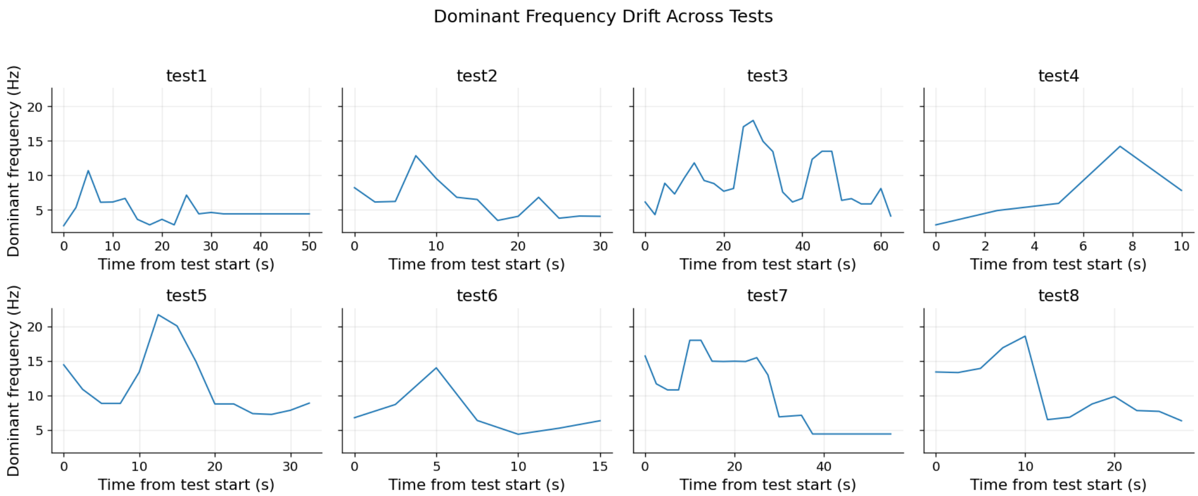

Figure 8. Dominant frequency evolution across baseline and monitoring tests.

4.5 Summary of Results

The present results show the proposed AI-driven predictive monitoring framework is an effective approach to detect and quantify structural deviation using vibration data and without the reliance on a labeled damage state. The Structural Deviation Index allows for a robust baseline referenced measure of deviation and the One-Class SVM outputs are sensitive to early-stage changes. The explanation analysis proves that physically important vibration features are the primary cause of detected deviations, especially, frequency-domain energy redistribution and major frequency shifts. Collectively, these results demonstrate the validity of the framework as a reliable and interpretable methodology for predictive structural health monitoring for smart civil infrastructure.

5. Discussion

The findings of this paper offer strong reasons to believe that predictive monitoring based on the use of artificial intelligence can successfully describe changing structural behavior based on vibration data when damage labels are not provided. The observed monotonic increase in the Structural Deviation Index (SDI) found in monitoring tests is the result of systematic redistribution of the vibration energy and gradual changes in the dominant frequency contents. From the point of view of structural dynamics, such changes are strongly linked to the variation in global stiffness and boundary conditions and not to stochastic measurement noise. The fact that SDI was able to consistently capture these trends confirms that it is a good candidate as a robust, baseline-referenced indicator for predictive structural health assessment, especially for long-term monitoring situations where the ability to identify performance degradation at an early stage is important to an informed decision.

The patterns of deviations found using the One-Class Support Vector Machine (OCSVM) further confirm the reliability of the proposed framework. OCSVM proved to be highly sensitive to minor deviations during the early stages of monitoring and makes the detection of not yet marked changes possible by aggregated deviation measures. This capability is of particular importance in the area of proactive management of infrastructure, where being able to intervene in time can save the service life of infrastructure and reduce the cost of maintenance. In comparison to supervised damage detection methods widely used in computer vision-based bridge inspection that usually require large-scale labeled data and visible damage features, the unsupervised deviation-based method used in this study is a more realistic and scalable damage detection method for continuous monitoring of in-service structures [20].

When considered in relation to the current state of research on bridge monitoring in service, the proposed framework helps overcome some of the limitations found in previous studies. Although machine learning techniques have proven to be successful in applying to field data, many of the current approaches target primarily the damage classification or localization after the deterioration has occurred. The present study instead focuses on predictive deviation detection, allowing to identify evolving structural changes at an earlier stage. This shift in paradigm where reactive damage identification is replaced by proactive condition assessment is a direct reaction to the issues raised by systematic reviews of bridge SHM applications, where a lack of labels of damage and high variability of operation are often challenging to rely on to deploying the models [21].

One of the strengths of the proposed framework is the focus on conveyability and physical meaning. The explainability analysis shows that frequency domain parameters, especially band-limited spectral energy and dominant frequency are the main factors of the detected deviations. These characteristics are well-established predictors of modal behavior and stiffness change, which gives an articulate physical explanation of the AI outputs. This is in contrast to some of the recent deep learning methods with vibration data combined with computer vision techniques, which while achieving high detection performance, often run as black boxes without much transparency about the structure mechanism at work [22]. The current research by making a direct connection between the deviation indicators and the interpretable features of vibration makes the research more credible and promotes its practical implementation in engineering practice.

From a systems perspective, the proposed methodology is in great harmony with the emerging paradigms of smart infrastructure that emphasizes continuous sensing, data-driven assessment, and the use of intelligent decision support. The segment-based processing strategy and computational efficiency of the used models are in favor of scalable implementation across dense sensor networks, making the framework suitable for implementation at structure and network level. Such characteristics are shared with the recent developments of sensor network-oriented SHM frameworks, which focus on obtaining actionable information from complex, distributed data sources instead of isolated measurements [23]. Within this context, the proposed framework can act as a building block of intelligent monitoring systems to provide reliable deviation indicators that feed the higher-level analytics and asset management and maintenance strategies.

Despite its demonstrated strengths, the study has several limitations that should be considered. The quantity of baseline data available for training a model is limited, which may limit the representiveness of learned normal behavior, especially under different environmental and operational conditions. Besides, the lack of ground-truth data on damage eliminates the possibility of absolute attribution of identified deviations to certain mechanisms of damage. Environmental influences like temperature variations, loading variations caused by traffic, and operational variations may also be a contributing factor to observed differences in vibration response. These challenges are well-known in vibration-based SHM research and still represent major obstacles to the broad introduction of data-driven monitoring systems [24].

Research on further development should aim at increasing the size of the baseline datasets, and include adaptive learning mechanisms which enable the models to adapt to long-term structural changes. Combination of environmental and operation measurements might also further increase the ability to discriminate between benign variability and the actual structural degradation. The extension of the proposed framework to multi-structure and multi-sensor schemes and the use of vibration based indicators in conjunction with other sensing modalities can be seen as good opportunities to enhance the robustness and diagnostic resolution. Besides that, the predictive deviation measures, created in the present research, combined with digital twin environments may allow conducting forward-looking simulations and making decisions grounded on lifecycle considerations, another step towards the use of artificial intelligence in smart infrastructure management.

However, in sum, this study has shown that the development of an unsupervised, interpretable and baseline-referenced AI framework is capable of delivering reliable and actionable structural health insights. The proposed system will improve the status quo by implementing predictive deviation detection over damage classification in order to achieve scalable, reliable, and proactive civil infrastructure system monitoring.

6. Conclusion

This research developed and demonstrated an artificial intelligence-driven predictive monitoring framework of vibration-based structural health assessment of civil infrastructure under realistic and label-scarce conditions. By formulation of structural health monitoring as a baseline referenced deviation detection problem, the proposed approach was able to capture evolving changes in structural behavior with the help of continuously available vibration data. Physics-informed time and frequency domain features were useful in terms of calculating Structural Deviation Index (SDI), a robust and interpretable quantitative measure of structural deviation and combination of complementary unsupervised AI models provided good performance consistency. Explainability analysis further contributed to engineering confidence by direct relating the measures of deviation from the AI and physically meaningful vibration characteristics associated with structural dynamics. The results demonstrate the ease of use of the framework for the scalable deployment on smart infrastructure systems to support proactive condition assessment and decision making. Future researches are suggested to extend the methodology to longer monitoring time horizons, incorporate environmental normalization and assess performance of different infrastructure typologies to further develop predictive and data-driven structural health monitoring practice.

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