*Environmetrics*

WILEY

SPECIAL ISSUE Exploring Statistical Strategies for Addressing Complex Environmental Challenges Involving Spatial-Temporal Data

REVIEW OPEN ACCESS

# A Functional Principal Component Analysis Framework for Vibration-Based Structural Condition Assessment of Highway Bridge Spans

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**Received:** 29 May 2025 | **Revised:** 27 June 2026 | **Accepted:** 15 July 2026

**Keywords:** bootstrap inference | FPCA | functional subspace comparison | principal angles | structural anomaly detection

## ABSTRACT

The management of lifespan and safety performance, aimed at ensuring the structural integrity and durability of highway infrastructure, has become an increasingly important area of research. In civil engineering, traditional methods for evaluating dynamic behavior, such as Operational Modal Analysis and the Peak Picking technique, often fall short in detecting subtle signs of damage. This study proposes a novel approach based on Functional Principal Component Analysis (FPCA) to enhance the sensitivity of vibration-based structural condition and anomaly assessment. A preliminary analysis based on classical PCA applied to the same dataset was previously presented in Agrò et al. (2025a). That study highlighted the capability of PCA to capture dominant variance patterns in the vibration signals. However, PCA operates on discretized time series and does not explicitly account for their functional nature. In contrast, the FPCA framework proposed in this study models the signals as continuous functions, enabling a more refined characterization of temporal variability and improving sensitivity to subtle structural differences. By comparing the optimal functional subspaces derived from FPCA for both intact and potentially compromised bridge spans, we quantify structural differences through the cosine of principal angles. The approach is applied to a real case involving a viaduct on the Palermo–Catania highway, demonstrating its potential to reveal anomalies not evident through conventional modal analysis.

## 1 | Introduction

Monitoring the structural health of bridges is vital for public safety and infrastructure management. Vibration-based Structural Health Monitoring (SHM) techniques are widely employed because dynamic responses are highly sensitive to structural degradation, anomalous behavior, or changes in operational conditions. Typically, ambient vibration testing employs a specified number of uniaxial piezometric accelerometers connected to a control unit to acquire environmental acceleration data over a defined time span. Conventional SHM approaches commonly transform these time-series data into the frequency domain using a Fast Fourier Transform (FFT) and utilize the "Peak Picking technique" to extract modal parameters, such as natural frequencies, mode shapes, and damping ratios.

However, conventional methods operating on discretized vectors or spectral descriptors face significant limitations in real-world applications. Several studies have shown that environmental and operational variability—including temperature, humidity, traffic, and wind conditions—can significantly influence the dynamic response of monitored structures, often masking early-stage structural changes. To isolate damage from environmentally induced effects, traditional multivariate techniques such as Principal Component Analysis (PCA), Mahalanobis-distance-based monitoring, and clustering approaches are frequently adopted (Farrar and Worden 2012). Recent advances have shown that PCA applied directly to time-domain data can detect subtle changes in structural response by comparing suspected damaged and undamaged structures (Agrò 2022).

In recent years, the background of damage identification methods has significantly evolved, increasingly benefiting from artificial intelligence (AI) and deep learning techniques for automated damage detection and structural condition assessment. Convolutional neural networks, autoencoders, recurrent neural networks, and hybrid AI-based frameworks have demonstrated promising performance in identifying structural anomalies directly from vibration signals and high-dimensional monitoring data (Cha et al. 2024; Malekloo et al. 2022; Zinno et al. 2023). Nevertheless, many supervised and deep learning frameworks require large, labeled datasets representative of different damage scenarios, extensive training procedures, and significant computational resources. In practical applications involving existing bridges and civil infrastructures, such requirements are often difficult to satisfy due to the scarcity of damaged-state data, the limited availability of controlled experimental conditions, and the challenge of ensuring robust generalization capabilities under environmental and operational variability (Ataei et al. 2026; Bao et al. 2025).

Consequently, unsupervised, computationally efficient, and statistically interpretable methods remain highly relevant and attractive for operational vibration-based SHM. Among them, PCA-based techniques and their functional extensions provide efficient dimensionality reduction capabilities and enable the extraction of dominant structural patterns directly from ambient vibration measurements, without requiring prior labeling of damage conditions. However, reducing continuous signals to discrete features or spectral descriptors may still lose critical temporal information and smooth out dynamic patterns that contain relevant structural signatures.

Because time-domain vibration measurements are intrinsically continuous, correlated, and often affected by noise, they are better modeled as functional data rather than discrete data points. Functional Data Analysis (FDA), and in particular Functional Principal Component Analysis (FPCA), provides a more natural and informative framework for SHM by treating each observation as a smooth function over time. This approach fully exploits the functional nature of ambient vibration signals, retaining the continuous temporal information that traditional discretization discards.

This paper explores the application of FPCA for structural condition and anomaly assessment, detailing its advantages and implementation through a case study of a Sicilian highway bridge. The study highlights the benefits of FDA in managing the lifespan and safety performance of highway infrastructure. Furthermore, we describe a new procedure for identifying structural dynamic discrepancies, delving into its inferential aspects and presenting significance tests derived from bootstrap methods.

The remainder of this paper is organized as follows. Section 2 contextualizes the study within the current literature by reviewing FDA and FPCA applications in SHM, contrasting them with conventional frequency-domain approaches, and defining the specific research gap addressed by this work. Section 3 provides a short overview of FDA and FPCA, elucidating its application in real contexts and highlighting the advantages offered in the context of managing the lifespan and safety performance of highway infrastructure. Moreover, the new procedure for structural condition and anomaly assessment is described, also delving into the inferential aspects of the analysis and presenting significance tests derived from bootstrap methods. In Section 4 the case study is presented together with results obtained by static and dynamic testing performed by experts in the field of structural engineering. Section 5 presents the application of the proposed procedure to data related to highway spans in Sicily, showcasing the promising results in identifying spans with anomalous dynamic behavior. Section 6 summarizes our findings, emphasizing the enhancements in analytical capabilities achieved through the implementation of our procedure. Finally, in Section 7 we draw some conclusions and outline some ideas for future developments.

## 2 | Functional Data Analysis and FPCA in Structural Health Monitoring: A Review

In recent years, Functional Data Analysis (FDA) has emerged as a powerful paradigm for analyzing continuous structural response measurements in Structural Health Monitoring (SHM) applications. Unlike conventional methodologies that handle measured signals as finite-dimensional vectors, FDA treats them as realizations of continuous stochastic functions, thereby fully preserving their intrinsic temporal continuity and correlation structures. Comprehensive foundations of FDA can be found in Ramsay and Silverman (2005) and Gertheiss et al. (2024), while a dedicated review of its early adoption within the SHM domain is provided by Momeni and Ebrahimkhanlou (2022).

Within this functional framework, Functional Principal Component Analysis (FPCA) extends classical Principal Component Analysis (PCA) to functional observations by decomposing the covariance structure of the monitored signals into orthogonal eigenfunctions and associated scores. To date, FPCA has been successfully evaluated for dimensionality reduction, denoising, environmental variability compensation, outlier detection, and change-point analysis in diverse SHM problems. Specifically, Chen et al. (2026) proposed FDA-based methodologies for distributional regression and missing-data reconstruction in monitoring systems, whereas Lei et al. (2023) validated functional approaches for outlier and change-point identification in damage-sensitive data. Furthermore, Jiang et al. (2021) effectively coupled FPCA with warping-based FDA methods to filter out seasonal temperature-induced structural effects.

When applied to ambient vibration monitoring, FPCA offers substantial advantages over conventional PCA-based or Factor Analysis techniques operating on frequency-domain descriptors obtained by FFT. While frequency-domain approaches coupled with statistical or AI-based discrimination methods are widely adopted for structural identification, they present limitations under operational conditions (Poncelet et al. 2006). First, FPCA naturally accounts for time-dependent correlations within raw vibration signals without requiring pre-processing transformations. Second, it yields a compact, low-dimensional functional representation of dominant dynamic patterns while filtering out high-frequency measurement noise. Third, it preserves subtle, smooth temporal variations and local transient features that are often attenuated or smoothed out when signals are converted into spectral representations via Fast Fourier Transform (FFT) algorithms, particularly under stochastic ambient excitation conditions. Consequently, operating directly in the time-domain through an FDA framework prevents the loss of local, transient structural information that spectral peaks alone cannot fully capture.

Despite these recent advancements, the literature reveals a significant research gap regarding the use of FPCA for the comparative analysis of span-dependent dynamic behavior in multi-span highway bridges. The vast majority of past contributions have focused on long-term environmental compensation or temporal anomaly detection on a single structure. Conversely, critical evaluations of FPCA as a comparative tool to assess dynamic variability and detect anomalies among nominally identical, repetitive bridge spans under operational conditions remain scarce.

The present study directly addresses this gap, building upon preliminary investigations conducted on the same experimental dataset where classical PCA was applied directly to acceleration time histories (Agrò 2022; Agrò et al. 2025a). This work extends those previous findings by transitioning into the FDA framework. By leveraging ambient vibration measurements acquired from a multi-span Sicilian highway bridge, this paper explores the deployment of FPCA as a natural functional extension of classical PCA. The proposed framework is evaluated not only to analyze vibration signals as continuous functional observations but also to systematically identify span-to-span structural dynamic variability and localized anomalous response patterns under operational traffic.

## 3 | Methods

### 3.1 | Functional Data Analysis

FDA is a statistical framework that treats data as smooth functions rather than discrete observations, offering a more natural framework for analyzing ambient vibration data. Unlike traditional data analysis, where observations are typically scalar or vector values, FDA focuses on data that vary over a continuum, such as time or space; it enables the modeling of smooth curves, enhancing the ability to capture dynamic trends (Ramsay and Silverman 2005). This approach is particularly useful in fields such as medicine, environmental science, and economics, where measurements are often collected over intervals or across different conditions (Ramsay and Silverman 2002). A brief overview of FDA, covering the most frequently used statistical analysis methods and their corresponding software tools is reported in Wang et al. (2016). Practical examples and recent advances in the area are reported in Gertheiss et al. (2024).

In this framework, each environmental acceleration signal is represented as a continuous curve defined over time. These functions are typically represented on a chosen basis—such as B-splines or Fourier series—with the goal of preserving the temporal structure of the data while reducing noise.

Then, to convert discrete time series data into functional form a smoothing procedure is applied using basis expansion:

$$x_i(t) = \sum_{m=1}^{M} c_{im}\psi_m(t) + \epsilon_i(t),$$

where $\psi_m(t)$ are basis functions (e.g., B-splines), $c_{im}$ are coefficients, and $\epsilon_i(t)$ represents noise. The data are considered as discrete realizations of an underlying continuous process (signal plus noise). This step reduces dimensionality and improves robustness to noise.

### 3.2 | Functional Principal Component Analysis

FPCA is an extension of PCA where eigenfunctions replace eigenvectors, and the covariance is treated as an operator on functions. The goal is to decompose the variability of a set of functional data $\{\boldsymbol{x}_i(t)\}_{i=1}^{n}$ into orthogonal principal components.

Given functional observations $x_i(t)$, the mean function is estimated as:

$$\mu(t) = \frac{1}{n}\sum_{i=1}^{n} x_i(t).$$

The covariance function is estimated as follows:

$$C(s,t) = \frac{1}{n}\sum_{i=1}^{n}\left(x_i(s) - \mu(s)\right)\left(x_i(t) - \mu(t)\right).$$

The FPCA involves solving the eigenvalue problem.

$$\int C(s,t)\phi_k(t)\,dt = \lambda_k\phi_k(s),$$

that yields eigenfunctions $\phi_k(t)$ and corresponding eigenvalues $\lambda_k$.

Each functional observation $x_i(t)$ can then be approximated by a finite number of basis functions:

$$x_i(t) \approx \mu(t) + \sum_{k=1}^{K}\xi_{ik}\phi_k(t),$$

where the principal component scores $\xi_{ik}$ are computed by:

$$\xi_{ik} = \int \left(x_i(t) - \mu(t)\right)\phi_k(t)\,dt.$$

This decomposition captures the main modes of variation in the functional data, facilitating interpretation and further analysis.

FPCA has a variety of applications; the advantages of FPCA include its ability to handle large datasets efficiently and its capability to reveal complex structural information inherent in functional data.

In conclusion, FDA and FPCA offer powerful tools for analyzing and interpreting complex data that vary over a continuum. The integration of FDA and FPCA into various disciplines promises to enhance our understanding of dynamic processes across diverse domains, allowing us to uncover deeper insights and patterns that may not be apparent through traditional data analysis techniques.

### 3.3 | Advantages of FPCA in Structural Health Monitoring

FPCA offers several advantages over classical PCA when applied to structural health monitoring using ambient vibration data:

1. Continuity of Data: FPCA treats ambient vibration signals as continuous functions, enabling a more faithful representation of the system's dynamic behavior than discrete PCA.
2. Dimensionality Reduction: By projecting onto a functional subspace, FPCA captures essential dynamic characteristics while reducing noise and irrelevant variation.
3. Noise Handling: FPCA incorporates smoothing techniques that mitigate the influence of environmental noise and measurement error, improving the robustness of the analysis.
4. Interpretability: Functional principal components (FPCs) or harmonics are continuous functions representing major modes of variation, allowing clearer physical interpretation of structural changes.
5. Enhanced Subspace Comparison: Distances between functional subspaces provide more nuanced insight into structural differences, particularly for detecting anomalies that may be subtle or localized.

### 3.4 | Proposed Procedure for Structural Condition and Anomaly Assessment

The proposed method for assessing structural dynamic variations is based on comparing the optimal functional subspaces extracted from vibration data of different spans.

To analyze the structural dynamic behavior of a highway bridge span, environmental acceleration data are recorded over time from each of the $p$ sensors. For each sensor, the recorded time series is treated as a realization of a continuous function, leading to a dataset composed of $p$ functional observations, one per sensor.

In FPCA framework, the $p$ discrete time series are first smoothed and expressed as functional objects $\left\{x_1(t), \dots, x_p(t)\right\}$, defined over a common time domain $\mathcal{T}$.

FPCA aims to reduce the dimensionality of the system by projecting the functional observations onto a $k$-dimensional functional subspace, where $k < p$. The resulting FPCs are orthogonal functions $\left\{\phi_1(t), \dots, \phi_k(t)\right\}$, ranked by their associated eigenvalues, which represent the proportion of total variance captured by each component.

The eigenfunctions $\phi_k(t)$ of $\mathcal{K}$ define the optimal basis capturing the main modes of variability in the data.

This methodology is applied to two functional datasets: one representing a structurally healthy system, and the other representing a potentially damaged state. After applying FPCA to both sets, we obtain two functional subspaces of dimension $k$, denoted by $\mathcal{H}_k$ and $\mathcal{D}_k$, for Healthy and Damaged (suspected), respectively.

The assessment of structural dynamic discrepancies is performed by comparing the functional subspaces $\mathcal{H}_k$ and $\mathcal{D}_k$ through the calculation of principal angles (Nguyen et al. 2012). As in the multivariate case, the cosines of the principal angles between these subspaces quantify the degree of similarity or divergence. More formally (Golub and Van Loan 1996):

Let $\theta_1, \dots, \theta_k \in \left[0, \frac{\pi}{2}\right]$ be the principal angles between $\mathcal{H}_k$ and $\mathcal{D}_k$, defined recursively as:

$$\cos(\theta_i) = \max_{\substack{h_i \in \mathcal{H}_k \\ d_i \in \mathcal{D}_k}} \langle h_i, d_i \rangle \quad \text{subject to } \| h_i \| = \| d_i \| = 1,$$

$$\left\langle h_i, h_j \right\rangle = \left\langle d_i, d_j \right\rangle = 0 \text{ for } j < i,$$

where the vectors $\left\{d_1, \dots, d_k\right\}$ and $\left\{h_1, \dots, h_k\right\}$ are called the principal vectors of $\mathcal{D}_k$ and $\mathcal{H}_k$; the principal angles satisfy $0 \leq \theta_1 \leq \theta_2 \dots \leq \theta_k \leq \frac{\pi}{2}$.

The largest principal angle is related to the notion of distance between subspaces, then:

$$\delta = \text{dist}\left(\mathcal{H}_k, \mathcal{D}_k\right) = \sqrt{1 - \cos\left(\theta_k\right)^2}. \tag{1}$$

If the largest principal angle $\theta_k$ is not zero, then the compared subspaces differ, suggesting that the system represented by $\mathcal{D}_k$ may have structural damage in comparison to the healthy reference $\mathcal{H}_k$.

### 3.5 | Inferential Framework via Bootstrap

To evaluate whether the observed differences between functional subspaces are statistically significant, a hypothesis test is formulated. The null hypothesis $H_0$ assumes that the subspaces represent the same dynamic behavior, implying that the maximum principal angle between them is zero.

Since the theoretical distribution of principal angles under $H_0$ is not analytically known, it must be estimated empirically. For this purpose, a conventional bootstrap procedure is inadequate because it assumes independent random resampling; it would destroy the temporal autocorrelation within each signal and the cross-series dependencies between different sensors, thereby altering the dynamic characteristics of the structure. To overcome this limitation and ensure reliable inference, we employ the Moving Block Bootstrap (MBB) approach (Efron and Tibshirani 1994; Lahiri 2003). The MBB framework is uniquely suited for vibration-based Structural Health Monitoring (SHM) applications because it resamples contiguous blocks of observations rather than individual samples, effectively preserving both the intra-series temporal correlation and the inter-series structural dependencies where vital modal information is embedded (Zhang et al. 2019).

In practice, the multivariate time series data, represented as an $n \times p$ matrix X (where $p$ corresponds to distinct sensor measurements over n time steps), is segmented into overlapping blocks of length $l$. This forms a collection of submatrices:

$$\mathcal{B}_j = \left(X_{j:j+l-1,:}\right), \quad j = 1, 2, \ldots, n - l + 1$$

Each block $\mathcal{B}_j$ captures $l$ consecutive time steps for all $p$ series simultaneously, safeguarding the complete dependency structure of the system.

A bootstrap sample is constructed by randomly selecting $\lceil n/l \rceil$ blocks with replacement from the set $\left\{\mathcal{B}_1, \ldots, \mathcal{B}_{n-l+1}\right\}$ and concatenating them to form a resampled matrix $X^*_{n \times p}$. If needed, the final sample is truncated to match the original length $n$.

This procedure is repeated $B$ times to generate an ensemble of bootstrap replicates $\left\{X^{*(1)}, X^{*(2)}, \ldots, X^{*(B)}\right\}$.

The choice of the number of blocks, and consequently the block length, in MBB is essential for obtaining reliable estimates and for accurately capturing temporal or spatial dependence on the data. An empirical rule is to divide the data into approximately $\sqrt{n}$ blocks, where $n$ is the sample size. Cross-validation techniques allow for assessing the stability of the estimates with different numbers of blocks.

FPCA is applied to each bootstrap sample; the statistic of interest—for example, the maximum principal angle between the original functional subspace and each bootstrap replicate is calculated, yielding an empirical distribution under $H_0$.

From this empirical distribution, confidence intervals and $p$-values can be derived.

The MBB thus ensures that both autocorrelation within each series and cross-series correlations are accounted for, making it particularly suitable for inference on high-dimensional functional data in structural health monitoring applications.

## 4 | Case Study: A Viaduct on the Palermo–Catania Highway

The case study focuses on a concrete viaduct located along a Sicilian highway, which consists of two structurally independent, separate carriageways.

Each carriageway comprises 10 simply supported spans, as shown in the overall panoramic view in Figure 1.

Each typical span features a total length of 35.00 m and a deck width of 10.00 m. To provide a comprehensive geometric description and detail the vibration measurements, Figure 2 illustrates the engineering longitudinal elevation of a typical span, while Figure 3 displays the corresponding top view (plan layout) of the bridge deck along with the exact spatial deployment of the six uniaxial accelerometers.

**FIGURE 1** | Panoramic photographic view of the multi-span concrete viaduct.

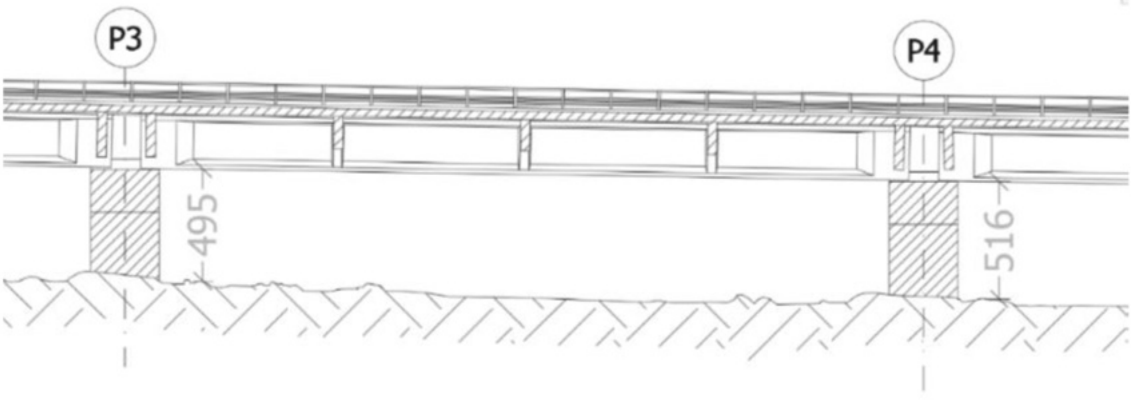


**FIGURE 2** | Longitudinal elevation of a typical span between piers P3 and P4.

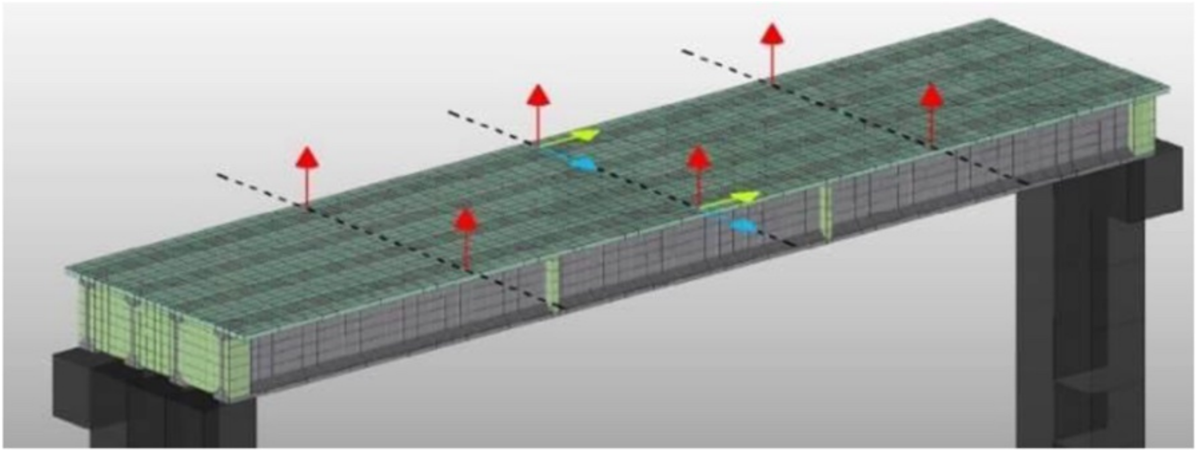

**FIGURE 3** | Location of the sensors on the bridge deck.

These sensors were installed on the reinforced concrete curbs along the external girders at both mid-span and quarter-span locations to properly capture the main dynamic vibration modes.

The raw ambient vibration data were collected by DISMAT (Laboratory for Structural and Construction Materials Testing, officially authorized pursuant to Article 20 of Italian Law No. 1086/71 by Ministerial Decree No. 415 of December 1, 2020), using high-sensitivity sensors and subsequently provided to the authors. Standard pre-processing, including baseline correction and a band-pass filter, was performed to eliminate environmental and electrical noise prior to the Operational Modal Analysis (OMA).

A preliminary assessment of these raw measurements was presented by Agrò et al. (2025a). In the present work, a more advanced processing framework is implemented.

Since the spans are structurally separated by expansion joints, their dynamic responses are independent. Consequently, acceleration data were acquired and processed for each span individually over a 30-min period at a sampling frequency of 100 Hz.

This process yielded a total of $n = 180{,}000$ data points by sensor. Consequently, each acquisition matrix has dimensions $180{,}000 \times 6$, representing the dynamic functioning of the system.

According to the investigation program proposed by the Commissioning party to DISMAT, all 10 spans were subjected to ambient vibration monitoring to assess their dynamic behavior, while static testing under controlled loading was limited to four selected spans due to high operational costs (Technical Report n° 51216–2 2017). Although preliminary visual inspections revealed generalized signs of degradation across the entire bridge, visual assessment alone was insufficient to provide a quantitative ranking of defect severity or differentiate structural capacity among the spans.

To gain deeper insights, midspan deflections recorded during the static tests were evaluated, as summarized in Table 1. The results indicate that Span 1 and Span 3 suffered from the most pronounced degradation, whereas Span 5 exhibited the lowest deflection values among the tested segments. These findings suggest that Span 5 is less statically compromised, making it the most suitable candidate to serve as the reference (benchmark) span in the procedure proposed in Section 3.4.

**TABLE 1** | Static load test results.

| Span | Max deflection (mm) |
|---|---|
| 1 | 9.445 |
| 3 | 7.640 |
| 5 | 6.280 |
| 8 | 6.948 |

By employing Operational Modal Analysis (Brincker and Ventura 2015), the first five natural frequencies of each span were identified. These parameters are reported in Table 2 along with their respective coefficients of variation. Notably, all coefficients of variation remained consistently below 10%, indicating low variability across the structure under ambient excitation conditions. Despite some span-to-span variability in individual frequencies, the overall modal parameter set did not provide a consistent ranking of structural condition and was not fully aligned with the static-test evidence (Lo Giudice and Mantione 2019).

This apparent inconsistency underscores the limitations of traditional diagnostic tools and highlights the need for a more sensitive approach. Traditional modal indicators may not be sufficiently sensitive to subtle structural variations; to address this limitation and capture the underlying dynamic differences, the FPCA–based subspace comparison methodology described in Section 3.4 is herein applied to the continuous time-domain signals.

## 5 | FPCA-Based Subspace Comparison

To further investigate potential damage that was not clearly identified through conventional dynamic indicators, the same matrices analyzed by Operational Modal Analysis were examined following the proposed procedure described in Section 3.4. All data analysis was carried out using R (R Core Team 2025).

**TABLE 2** | Dynamic test results.

| Freq [Hz] | Span 1 | Span 2 | Span 3 | Span 4 | Span 5 | Span 6 | Span 7 | Span 8 | Span 9 | Span 10 | CV (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| f1 | 4.44 | 4.15 | 4.25 | 4.25 | 4.15 | 4.20 | 4.20 | 4.30 | 4.20 | 4.20 | 1.92 |
| f2 | 4.59 | 4.93 | 5.57 | 5.32 | 5.18 | 5.76 | 4.88 | 4.44 | 4.88 | 4.98 | 7.77 |
| f3 | 11.52 | 11.18 | 11.04 | 11.62 | 10.84 | 10.84 | 10.89 | 10.74 | 11.28 | 12.06 | 3.63 |
| f4 | 14.80 | 14.45 | 14.45 | 13.72 | 13.87 | 14.01 | 14.99 | 13.77 | 14.55 | 13.18 | 3.75 |
| f5 | 22.22 | 22.95 | 22.95 | 22.80 | 21.44 | 21.83 | 22.90 | 22.31 | 21.00 | 22.66 | 2.92 |

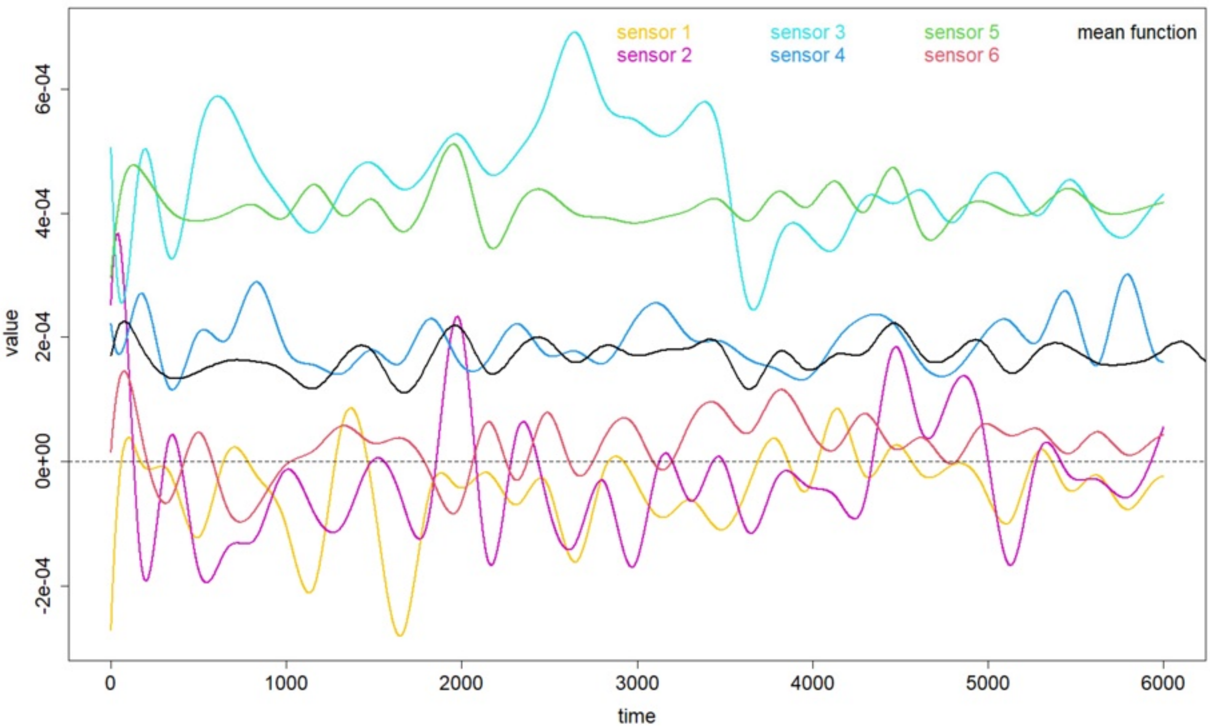


**FIGURE 4** | Functional data for Span 5.

The fda package (Ramsay 2024) was utilized to perform FDA and FPCA (Ramsay et al. 2009).

Time series are first converted into functional objects for each span by means of cubic B-spline basis functions selected due to their suitability for modeling non-periodic signals; they offer flexible approximation capabilities, allowing for the capture of local variations and sharp transitions within the data.

A total of $M = 999$ basis functions were employed, corresponding to approximately one basis function every 180 observations (or every 1.8 s). This choice balances the need to accurately represent the main features of the signal while avoiding issues related to over-parameterization or overfitting. Preliminary experiments with a smaller basis number, starting from $M = 99$, resulted in excessive smoothing, which diminished the fidelity of the signal's features.

Regarding the smoothing parameter, we set $\lambda = 0$ to omit additional smoothing, thereby preserving the original signal characteristics without further regularization.

Figure 4 shows, as an example, temporal series already converted into functional ones, and the related mean function, for Span 5.

In Figure 5, the mean functions for all considered spans are represented.

Then, FPCA was performed separately on each functional data set. The first principal component curve is plotted in Figure 6 for each span.

To improve readability, the curves in Figures 4–6 are plotted over the first minute.

The proportions of overall variation the FPCs account for, indicating the total amount of variability captured by the principal components, are reported in Table 3 for each span.

For each case, the leading $k = 3$ FPCs were retained, forming a reduced-dimensional subspace that captures the dominant structural response characteristics.

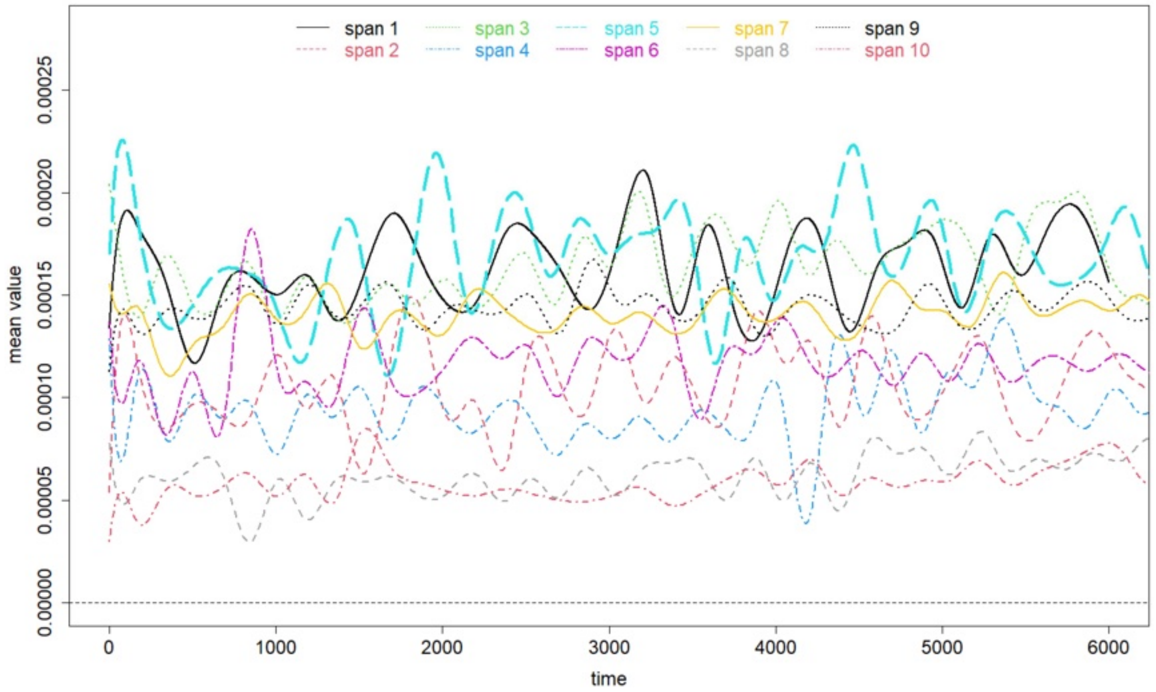


**FIGURE 5** | Functional mean.

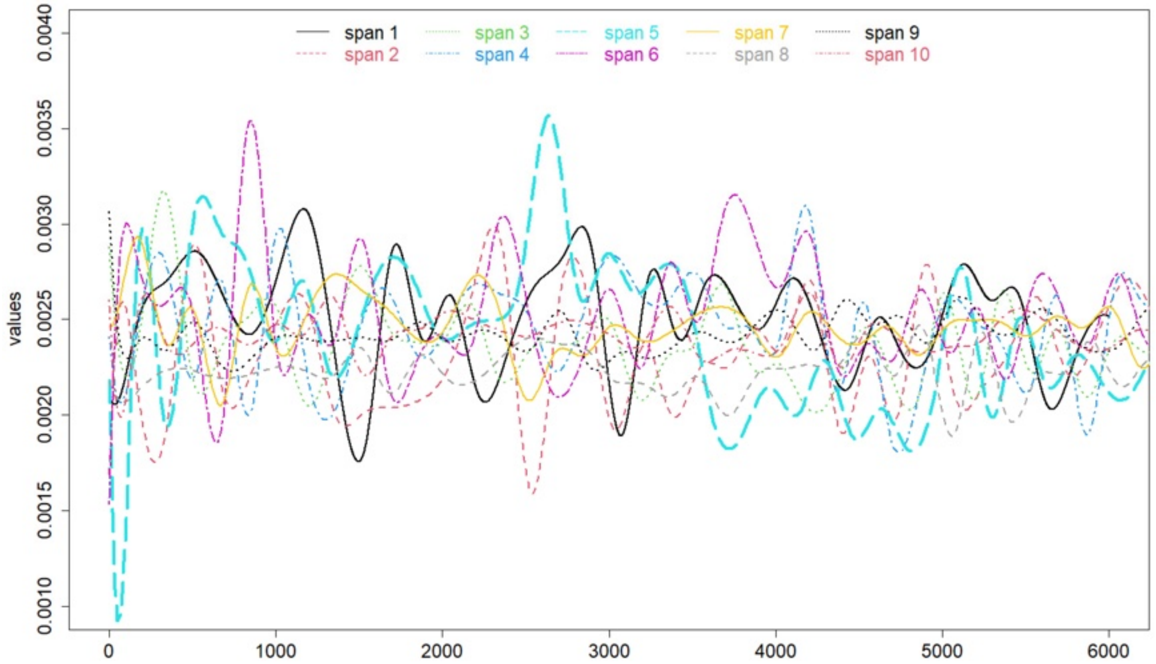


**FIGURE 6** | First harmonic.

As explained earlier in Section 3.4, the generated subspaces are compared in pairs with reference Span 5 by calculating the distance (1).

In Table 4, the cosines between the subspaces related to Spans 2 and 5 are provided as an example. The maximum among these cosines is highlighted in bold.

The angles, measured in degrees and radians, of the maximum cosines between each span and Span 5 are displayed in the first two columns of Table 5 in ascending order. The smaller the angle, the more similar the dynamic behavior of the span under consideration is to that of Span 5.

As described in Section 3.5, the MBB is conducted on the reference span to generate the simulated distribution of principal angles, allowing us to determine when the magnitude of the angle can be considered significantly different from zero.

The distribution of angles (measured in radians) was initially constructed by selecting a total of $\sqrt{M} = \sqrt{999} \cong 32$ blocks. The

**TABLE 3** | Cumulative variance explained by FPCs.

| FPC | Span 1 | Span 2 | Span 3 | Span 4 | Span 5 | Span 6 | Span 7 | Span 8 | Span 9 | Span 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.34 | 0.58 | 0.48 | 0.59 | 0.41 | 0.31 | 0.55 | 0.60 | 0.56 | 0.33 |
| 2 | 0.62 | 0.77 | 0.74 | 0.77 | 0.61 | 0.58 | 0.77 | 0.75 | 0.83 | 0.59 |
| 3 | 0.87 | 0.92 | 0.86 | 0.90 | 0.73 | 0.71 | 0.85 | 0.86 | 0.90 | 0.75 |
| 4 | 0.96 | 0.95 | 0.94 | 0.96 | 0.84 | 0.83 | 0.91 | 0.94 | 0.95 | 0.87 |
| 5 | 0.99 | 0.98 | 0.97 | 0.99 | 0.94 | 0.93 | 0.96 | 0.99 | 0.98 | 0.94 |
| 6 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

**TABLE 4** | Cosines between the subspaces of Spans 2 and 5.

| Span 2 vs. Span 5 | FPC1 | FPC2 | FPC3 |
|---|---|---|---|
| FPC1 | **−0.99699095** | 0.05769400 | 0.00248947 |
| FPC2 | 0.01786760 | −0.02379598 | −0.27202766 |
| FPC3 | 0.05697763 | 0.97042676 | 0.21543532 |

**TABLE 5** | Angle between subspaces of each span and Span 5.

| Span | Angle (deg) | Angle (rad) | $p$ |
|---|---|---|---|
| Span 2 | 4.445934 | 0.077596 | 0.604600 |
| Span 10 | 5.123380 | 0.089419 | 0.476400 |
| Span 9 | 7.742707 | 0.135135 | 0.134800 |
| Span 8 | 15.865161 | 0.276898 | 0.000000 |
| Span 3 | 18.166503 | 0.317064 | 0.000000 |
| Span 4 | 19.702738 | 0.343876 | 0.000000 |
| Span 7 | 27.861982 | 0.486281 | 0.000000 |
| Span 1 | 28.211906 | 0.492389 | 0.000000 |
| Span 6 | 32.911857 | 0.574418 | 0.000000 |

95th percentile ($\alpha = 0.05$) of this distribution was found to be 0.149242. To ensure robustness of our results, we ultimately chose a total of 6 blocks. Figure 7 illustrates the resulting distribution after this selection, with the corresponding 95th percentile value being 0.1660763. This demonstrates the stability of our results across different block sizes.

Based on the distribution shown in Figure 7, $p$-values were calculated for each span comparison and are presented in the last column of Table 5. As reflected by these $p$-values, all angles were found to be significantly different from zero, except for Spans 2, 10, and 9.

The scores obtained for Span 5 (healthy) and for example, Span 6 (damaged), both projected onto the healthy PC1-PC2 subspace, are shown in Figure 8, illustrating an approximate angle of 33° between them.

## 6 | Discussion

The analysis revealed that when the conventional Operational Modal Analysis struggled to identify any span as distinctly anomalous, the FPCA-based subspace comparison proposed can be useful to identify significant deviations in the vibrational behavior. These deviations were quantified via the maximum cosine of principal angles between subspaces and validated through bootstrap inference. The $p$-values derived from the bootstrap distributions confirmed the statistical significance of the observed differences, supporting the hypothesis of structural irregularity. Interestingly, Spans 8, 3, and 1, showing higher deflections in the static tests, exhibit a pronounced subspace divergence, following the same ranking also in our results. This agreement with static assessments reinforces the reliability of the proposed methodology. It is important to emphasize that static tests are very expensive and time consuming, unlike the approach we propose, which is based exclusively on the analysis of acceleration data.

The results underscore the sensitivity of FPCA to subtle changes in structural behavior that may not manifest in frequency-domain analyses alone. By leveraging the full temporal resolution of vibration signals, FPCA enables a richer and more nuanced interpretation of the data.

While the highway bridge case study demonstrates the framework's capability to detect severe, asymmetric operational degradation, the inherent sensitivity of the proposed FPCA approach to subtle and evolving damage scenarios has been further validated across different structural contexts. Specifically, the method has been successfully applied to numerical benchmarks featuring progressive structural damage (Agrò et al. 2025b), as well as to experimental data from controlled destructive tests on prestressed reinforced concrete beams with known, incrementally induced damage, as presented in our preliminary findings at Agrò et al. (2026). Both investigations confirm that the FPCA framework can capture localized structural variations well before they manifest as macro-scale shifts in conventional natural frequencies. These findings position the proposed approach as a promising advancement for SHM, particularly for tracking early-stage potential anomalies in infrastructures where conventional modal analysis may be inconclusive.

## 7 | Conclusion and Future Work

This study has demonstrated the effectiveness of the procedure "FPCA-Based Subspace Comparison" as a tool for structural condition and anomaly assessment in highway bridge spans using ambient vibration data. Unlike traditional techniques such

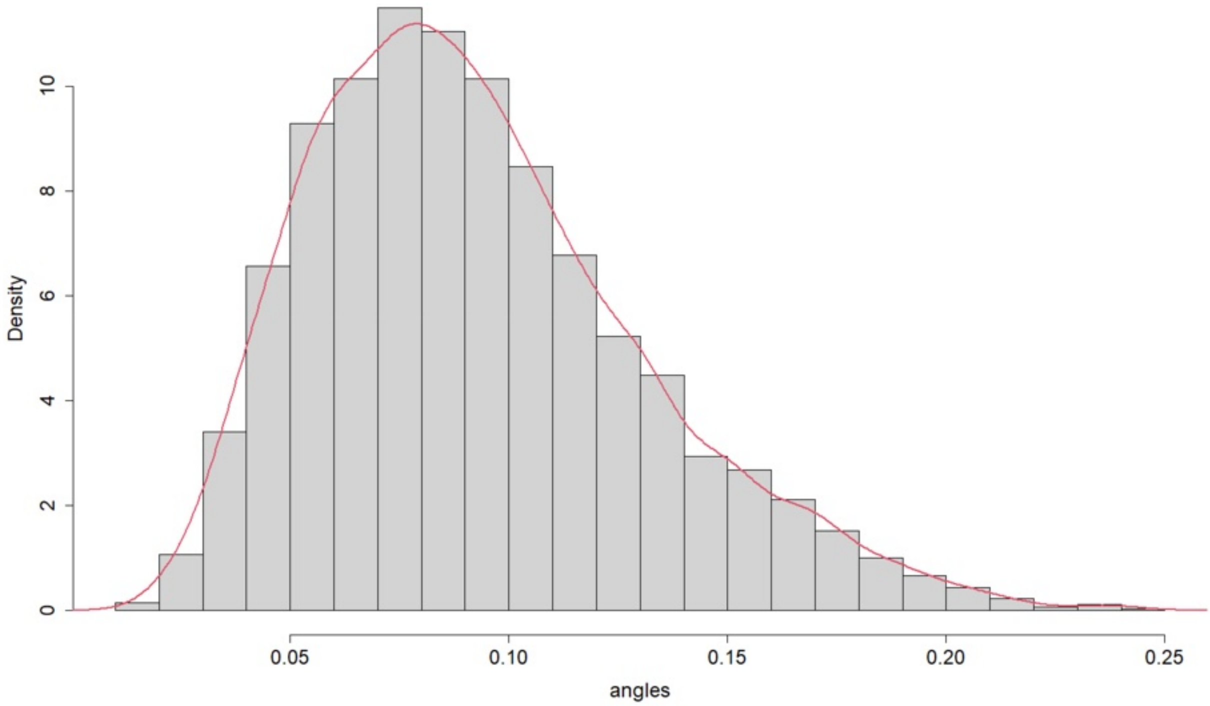


**FIGURE 7** | Bootstrap distribution of angles (rad).

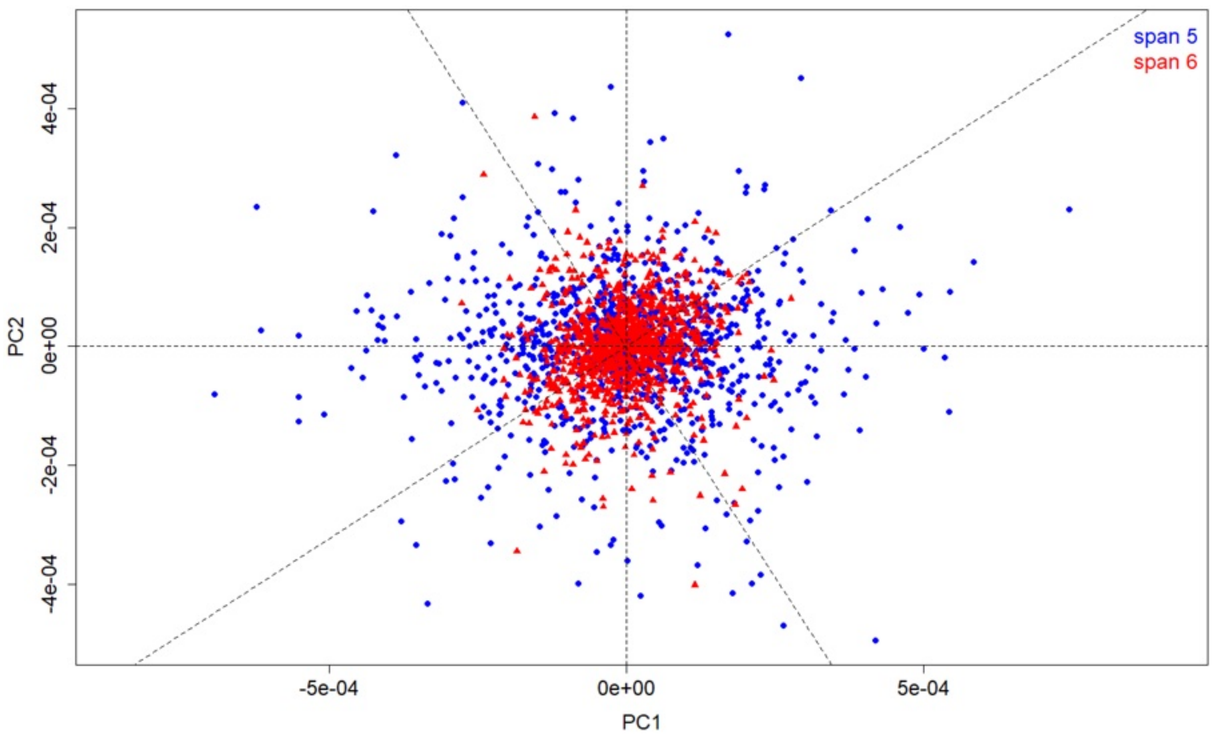


**FIGURE 8** | Span 6 vs. Span 5 scores.

as the Operational Modal Analysis and Peak Picking method, our proposal offers a time-domain approach that captures the continuous nature of structural vibrations and allows for a more detailed comparison of dynamic behavior.

By applying FPCA to functional representations of sensor data, the analysis enables the extraction of reduced-dimensional subspaces that effectively characterize structural states. Comparisons between these subspaces—quantified through principal angles—provide strong indicators of structural anomalies. The methodology was validated through a case study involving a viaduct on the Palermo–Catania highway; FPCA highlighted structural differences that were less evident when considering conventional modal frequencies alone.

Building upon the numerical and experimental validations on progressive damage (Agrò et al. 2025b; Agrò et al. 2026), future work will focus on expanding the application of this approach to a broader range of structural typologies and exploring its integration with other statistical and machine learning techniques. Specifically, combining FPCA with anomaly detection, clustering, and classification algorithms may enhance the robustness and automation of structural health monitoring systems. In this context, further research will investigate the integration of established discrimination approaches, such as Discriminant Analysis of Principal Components (DAPC), Mahalanobis Square Distance (MSD), Discriminant Analysis for Factor analysis Loadings (DAFL), and multivariate statistical process control indicators including Hotelling's $T^2$ and $Q$-statistics (Squared Prediction Error), within the Functional Data Analysis framework, with the aim of improving automated structural condition assessment and damage-sensitive monitoring strategies. Such methods could be applied to the functional principal component scores to provide complementary damage identification and classification capabilities. A systematic comparison of their relative performance in terms of sensitivity, robustness, and interpretability represents a promising direction for future research. Furthermore, long-term monitoring campaigns could benefit from this methodology to track progressive changes in structural behavior over time.

**Acknowledgments**

The Authors thank the director of the DISMAT laboratory, Eng. Elio Lo Giudice, for providing the data and sharing the results of the dynamic and static tests that offered the opportunity for comparison with the method proposed here. AI tools were used to refine the English language and improve readability. The authors maintain full responsibility for the content. Open access publishing facilitated by Universita degli Studi di Palermo, as part of the Wiley - CRUI-CARE agreement.

**Funding**

The authors have nothing to report.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**Data Availability Statement**

The datasets generated and analyzed during the current study are not publicly available due to confidentiality agreements with the bridge authority. However, the processed data and relevant modal identification results are available from the corresponding author upon reasonable request.

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