Chapter 6
A Robust Data-Driven Algorithm for Early Damage Detection in Structural Health Monitoring

Luigi Severa, Silvia Milana, Nicola Roveri, Eleonora Maria Tronci, Antonio Culla, and Antonio Carcaterra

Abstract In the field of Structural Health Monitoring (SHM), the ability to detect and identify damage at its early stage is necessary to maintain the safety and integrity of structures. Early damage detection not only prevents catastrophic failures but also reduces maintenance costs by enabling timely interventions. Presented here is a data-driven algorithm for SHM that extracts Damage Sensitive Features (DSFs) with high sensitivity to structural damage. The proposed method leverages a model-free approach, making it highly adaptable and suitable for real-world applications where models may not be available or feasible. Central to this approach is the use of blind source separation techniques, which isolate and amplify damage indicators from the complex structural response signals. This isolation is crucial for enhancing the sensitivity and specificity of damage detection, ensuring that even minor structural anomalies are accurately identified. By integrating artificial intelligence techniques, such as machine learning algorithms, the proposed method improves the identification accuracy of damage and significantly mitigates the effects of environmental and operational variabilities on DSFs. The efficacy of the algorithm is validated through comprehensive testing on a cylinder structure subjected to various damage scenarios and loading conditions. These scenarios are designed to be representative of real-world environmental and operational influences, ensuring the practical relevance of the results, which demonstrate a significant improvement in the robustness and accuracy of SHM practices, highlighting the algorithm's potential as an effective approach for the continuous monitoring and maintenance of critical infrastructures. Furthermore, the findings suggest that the proposed method could be generalized to other types of structures, making it a versatile tool in the field of SHM.

Keywords Structural Health Monitoring · Damage Detection · Damage Sensitive Features · Principal Component Analysis · Independent Component Analysis

Introduction

Ensuring the safety and durability of structures is an important concern in engineering applications, and Structural Health Monitoring (SHM) provides a valuable means of addressing this challenge. By detecting structural anomalies at an early stage, SHM helps prevent failures and optimizes maintenance processes, thereby reducing associated costs and disruptions [1, 2].

This is relevant in several sectors, like the mechanical and aerospace industries, civil infrastructures, and pipelines. Indeed, in industrial and civil applications, pipelines are critical components since they carry fluids and gases through plants. Therefore, any malfunction in these components can result in significant environmental impacts and economic losses [3, 4].

Vibration-based SHM methods are particularly effective in this context, as they monitor the dynamic behavior using sensors that collect vibration data. These data are then used to extract specific indicators, known as Damage Sensitive Features (DSFs), which serve as a baseline to assess structural integrity. Any deviation from the baseline DSFs of a healthy structure can identify potential damage [4, 5, 6]. As far as concerns the extraction of DSFs, it traditionally involves modal

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parameters like natural frequencies and damping ratios, which are directly linked to a structure's mechanical properties [7, 8]. However, extracting these parameters can be computationally expensive and highly sensitive to environmental conditions, making them less reliable in practical applications, also because they require a great deal of expertise from the user, who interprets the data and assesses the health of the structure [9, 10]. Signal processing techniques such as the Wavelet Transform [3] and Hilbert-Huang Transform [11] have been explored as alternatives, as they decompose signals to capture distinctive patterns or signatures that indicate damage [12]. Despite their potential, these methods face limitations in automated systems due to generalization problems. In this framework, blind source separation techniques [13], including Principal Component Analysis (PCA),Independent Component Analysis (ICA), and Second-Order Blind Identification, have gained attention in SHM because they require minimal user input and are useful to extract meaningful DSFs [14, 15]. However, all the techniques employed to extract DSFs are not without limitations because they have to face the effect of EOV within the structural response. In particular, the reliability of these DSFs is related to their ability to distinguish between structural changes caused by damage and those caused by Environmental EOV. Sensitivity to damage and robustness to EOV are critical for minimizing false alarms. A pre-processing stage of the data recorded by sensors is typically performed to address this. This activity is generally performed in a pre-processing stage, where various machine learning techniques have been employed to achieve this. Among them, PCA stands out as particularly effective, compared with auto-associative neural networks, factor analysis, Mahalanobis distance, and singular value decomposition [16]. PCA projects data into lower-dimensional subspaces, focusing on the components least affected by EOVs, thereby improving the reliability of the extracted DSFs [9, 17]. In particular, projecting data onto the Minor Components (MCs) subspace has proven effective in enhancing the robustness of DSFs. This paper proposes an SHM approach that leverages the combined strengths of PCA and ICA to extract non-modal-based DSFs. Unlike most traditional methods, this approach is data-driven, relying solely on measured structural response data, making it suitable for real-world monitoring applications. The proposed method offers sensitivity to low-magnitude damage and demonstrates resilience to variable loading conditions, thanks to the use of MCs projection. To validate this approach, we applied it to a Finite Element model of a pipe structure, where damage was simulated by reducing the cross-sectional area at various locations. The results validate the method's capability to detect damage at early stages while remaining robust to EOV.

Background

The proposed methodology is based on the cascading application of PCA and ICA. The theoretical foundations of these techniques are presented in the following paragraphs.

Principal Component Analysis

Principal Component Analysis (PCA) is a powerful multivariate statistical technique commonly used to identify and extract the most significant patterns hidden within a dataset [18]. By reducing the dimensionality of the problem, PCA minimizes information loss while preserving as much variance as possible. This makes it especially valuable in the analysis of large datasets, where eliminating redundancy is mandatory to focus on the most relevant signals and trends and so to ensure that the most critical insights are retained.

PCA achieves this by transforming a set of potentially correlated variables into a new set of uncorrelated variables, called Principal Components (PCs), which represent the directions of maximum variance in the data, capturing the essential information in a more compact form. This is performed through an orthogonal transformation since the PCs' orthogonality ensures that each component captures unique information [18].

Given a data-acquisition matrix $\mathbf{Z} \in \mathbb{R}^{N \times N_s}$, its rows are the N observations, while its columns ($\mathbf{z_n}$) are the N variables available. The implementation of the PCA encounters several stages, as following listed [19]:

1. Data Standardization. In the beginning, data ($\mathbf{z_n}$) are standardized in order to ensure that variables with different measurement scales do not disproportionately influence the analysis. Without standardization, variables with larger scales could dominate the variance and skew the results. Generally, this stage consists of two sub-stages, giving the Z-score normalization, as in Eq. (1), which are:

   (a) Centering: each variable is set to zero-mean, otherwise the first PC would capture the mean (μ_n) of the data instead of their variance.

   (b) Scaling: each variable is divided by its standard deviation (σ_n) in order to ensure that all variables contribute equally to the process, which is not biased by different data magnitude.

$$\mathbf{x_n} = \frac{\mathbf{z_n} - \mu_n}{\sigma_n} \tag{1}$$

2. Covariance Matrix Computation. Starting from the standardized data collected in the $\mathbf{X}$ matrix, a covariance matrix is evaluated, as in $\mathbf{C} = \dfrac{\mathbf{X}^T\mathbf{X}}{N}$, to quantify the degree of correlation between the variables and how the co-vary with each other to identify the direction of maximum variance in the dataset.
3. Covariance Matrix Eigenproblem. This is the key step of the PCA algorithm, and it consists of an eigenvalue decomposition of the covariance matrix, as expressed in $\mathbf{Cv} = \lambda\mathbf{v}$. It is performed in order to find the eigenvectors ($\mathbf{v}$), or PCs, and their corresponding eigenvalues (λ). The eigenvectors represent the directions in which the data varies the most, and the corresponding eigenvalues indicate the amount of variance captured by each component. Each eigenvector corresponds to a PC, and the eigenvalues are ranked in descending order to prioritize the directions that capture the most variance. Since the eigenvalues are often referred to as active energies [12], representing the proportion of total variance explained by each component, PCs with larger eigenvalues capture more variance and are, therefore, more energetic and relevant to the data.
4. Dimensionality Reduction. Subsequently, which components to keep and to discard are selected. This selection process is guided by a threshold, typically based on the proportion of variance to retain or the mean of the eigenvalues, as in Eq. (2) [19].

$$\lambda_i > \frac{1}{N_s}\sum_{j=1}^{N_s}\lambda_j. \tag{2}$$

where λ_i is the eigenvalue of the $i-th$ component. Components with eigenvalues that exceed the mean eigenvalue are traditionally considered significant, while the others are the so-called Minor Components (MCs), which are the ones that exhibit less variability.
5. Projection onto Principal Components. Once the PCs are identified, the data can be projected into the new subspace, effectively reducing its dimensionality and making them more manageable for analysis or further processing.. The transformed data matrix $\mathbf{Y}$ is obtained as in $\mathbf{Y} = \mathbf{X}\ \mathbf{V_k}$, where $\mathbf{V_k}$ is the matrix of the previously selected k eigenvectors.

Thanks to this framework, PCA enhances the interpretability of the data, making it a suitable tool in data analysis for feature extraction, revealing relationships, and patterns that may not be immediately apparent in the original variable space. Additionally, PCA can improve the performance of ML algorithms by eliminating noise and redundant features.

Despite its strengths, PCA assumes that the components are linear combinations of the original variables. As a result, it may not capture complex nonlinear relationships present in the data. Additionally, while PCA is effective for variance-based feature selection, it does not explicitly consider the underlying distribution of the data, which may lead to the loss of important information, especially in cases with significant non-Gaussian characteristics.

Independent Component Analysis

Independent Component Analysis (ICA) is a computational technique that seeks to decompose multivariate data into statistically independent non-Gaussian components [13]. While similar to other dimensionality reduction techniques like PCA and factor analysis, ICA goes a step further by aiming to extract signals that are not only uncorrelated but also independent, meaning that the presence of one signal provides no information about the presence of the others. Thanks to this property, ICA is particularly useful in applications involving the analysis of mixed signals, such as in BSS, where the goal is to recover original source signals from observed mixtures without prior knowledge of the mixing process. One of the most classic examples is the cocktail party problem, in which multiple people are speaking simultaneously in a room, and ICA is used to isolate each individual voice from a set of mixed recordings captured by several microphones.

Assuming that the observed data are linear mixtures of statistically independent and non-Gaussian source signals, ICA aims to recover these unknown sources by finding components that are as far from Gaussian as possible, using measures like kurtosis (a measure of the ”tailedness” of the distribution) or negentropy (a measure of how far a distribution is from Gaussianity).

To illustrate the underlying principles of ICA, consider the following mathematical formulation. Let $\mathbf{s} = \left(s_1, s_2, \ldots, s_{N_s}\right)^T$ represent the unknown source signals and $\mathbf{x} = \left(x_1, x_2, \ldots, x_{N_s}\right)^T$ represent the observed mixed signals. The mixing process can be expressed as in Eq. (3) [13], where $\mathbf{A}$ is the unknown mixing matrix.

$$\mathbf{x} = \mathbf{As} \tag{3}$$

Therefore, the challenge lies in estimating both $\mathbf{s}$ and $\mathbf{A}$ from the observable signals $\mathbf{x}$. This is achieved through various optimization techniques, commonly based on maximizing the non-Gaussianity of the estimated signals or minimizing the mutual information among them, like FastICA, kurtosis maximization ICA, Infomax and joint approximate diagonalization of eigenmatrices [13, 20, 21]. After the unmixing coefficients have been computed, the original Independent Components (ICs) are reconstructed from the mixed signals, using the relation $\mathbf{s} = \mathbf{W}\mathbf{x}$, where $\mathbf{W}$ is the estimated unmixing matrix. ICA's ability to leverage higher-order statistics and maximize non-Gaussianity makes it especially effective in scenarios where independence, rather than variance, is the primary concern. However, despite its effectiveness, ICA comes with certain limitations due to the unknown nature of both $\mathbf{s}$ and $\mathbf{A}$. One primary challenge is that the variances of the ICs remain indeterminable. This is because any scalar multiplier present in one of the source signals s_i can be compensated by adjusting the corresponding column $\mathbf{a_i}$ in the mixing matrix. To address this issue, a common approach is to assume unit variance for the sources. Additionally, a sign ambiguity exists: multiplying an IC by -1 does not violate the model, but this ambiguity is often inconsequential in most applications [20]. Another challenge is that the sequence of the ICs cannot be uniquely determined. The order of terms in the summation in the mixing equation allows for any IC to be designated as the primary one. A permutation matrix $\mathbf{P}$ can be introduced into the model, in this way $\mathbf{x} = \mathbf{A}\mathbf{P}^{-1}\mathbf{P}\mathbf{s}$, where the components of $\mathbf{P}\mathbf{s}$ are the original independent variables s_i but rearranged. Consequently, the matrix $\mathbf{A}\mathbf{P}^{-1}$ becomes an unknown mixing matrix that ICA algorithms must resolve [20]. This is one of the more important distinctions between ICA and PCA.

Overview and Description of the Technique

The proposed methodology, outlined in Fig. 1, involves several phases designed to enhance the detection of early-stage damage while remaining robust against variations of loading and operative conditions [22]. The first phase involves the application of PCA, with the data standardization outlined in Eq. (1), to the raw data collected by sensors. This step aims to reduce the dimensionality of the data and to isolate the most significant components that capture the underlying structural behavior [10]. As a result, the selected components are the Minor Components (MCs) [9].

Following PCA, ICA is applied to separate further the mixed signals recorded by the sensors, isolating the Independent Components (ICs). This step distinguishes the effects of structural damage from confounding factors such as noise or external environmental influences. Once the ICs are extracted, the next step is transforming these signals from the time domain to the frequency domain using the Fourier Transform (FT). Indeed, the frequency domain offers several advantages over the time domain when detecting damages, above all at their early stage: it simplifies the complexity of the raw vibratory data, making it easier to identify patterns associated with structural anomalies. Additionally, analyzing the frequency characteristics of the ICs helps reduce the impact of noise and other temporal variations, thereby improving the accuracy of the damage detection process.

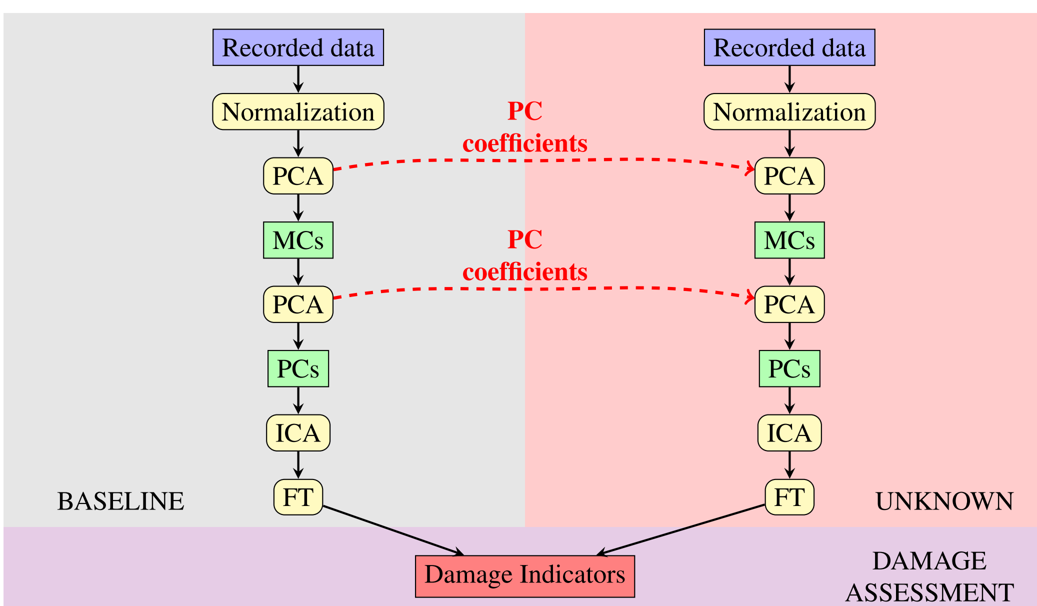


Fig. 1 Block diagram resuming the algorithm workflow [22]

In the final phase, the method compares the frequency spectra of ICs obtained from measurements taken at different time intervals, corresponding to the baseline and the actual states of the structure. The differential area (A), as in Eq. (4), is employed to quantify the overall difference between the spectra $x(f)$ and $y(f)$ of two signals, where the frequency vector f spans the bandwidth $[f_{min}, f_{max}]$. For this metric, larger values indicate more significant alterations in the structural response, thus warning for potential damage [22].

$$A(x, y) = \int_{f_{min}}^{f_{max}} |y(f) - x(f)| \, df \tag{4}$$

Analysis

This section is dedicated to the description of the structure to which the proposed methodology is applied, as well as the presentation of the results obtained.

Case Study: A Randomly Excited Cylindrical Pipe

The structure under investigation is a steel pipe, numerically modeled using the finite element software ANSYS, as detailed in [3]. The cylindrical structure has a length of $5m$, with a circular cross-section of $0.2m$ in radius and a uniform thickness of $0.01m$, and it is clamped at both ends to simulate fixed boundary conditions.

This study focuses on only one damage type, involving a 10% reduction in the section's thickness at six different locations along the cylinder's length, as detailed in Table 1. The type of damage was chosen to simulate a condition that affects the dynamic behavior of the pipe. Indeed, a reduction in thickness will impact the flexural stiffness of the cylinder, which in turn affects its frequency response.

Nine measurement points were selected on the test bed's external surface. These points, illustrated in Fig. 2, are evenly spaced along the cylindrical axis to cover the entire pipe, while their angular positions are evenly spaced along half of the cylinder's section to capture possible asymmetries in its behavior. These sensors collect the displacement time histories at the nodes where they are installed.

To evaluate the dynamic behavior of the pipe under a randomly distributed load ($p(x, t)$, a modal analysis is performed on ANSYS, identifying the first N_M natural mode shapes (ϕ_n). Then, using the modal superposition techniques, as in Eq. (5), the displacement at any point (x_0), where sensors are positioned, has been computed. In this approach, the displacement is evaluated as a combination of the single modal contributions, and the amplitude of each mode is governed by the modal coordinates (q_n), which can be calculated by solving the system of differential equations in Eq. (6) [11], where the natural

Table 1 Damage location along the longitudinal axis of the pipe for each scenario

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Description	Undamaged	Damaged	Damaged	Damaged	Damaged	Damaged
Damage intensity	-	10%	10%	10%	10%	10%
Damage location	-	$1.5m$	$2.0m$	$2.5m$	$3.0m$	$3.5m$

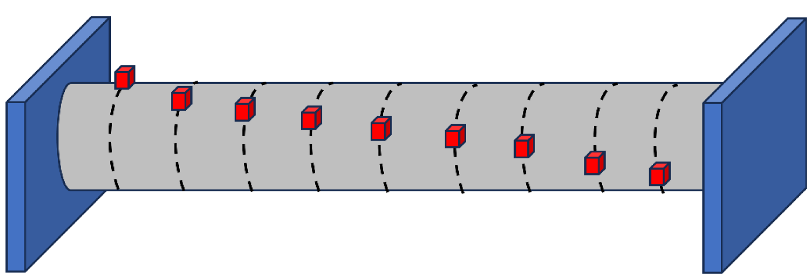


Fig. 2 Case study: the cylindrical pipe with sensors mounted on it (red cubes)

frequencies of each mode (f_n), ranging from $93.96Hz$ to $234.20Hz$ are given by the finite element model; while the the damping ratios (ζ_n) were then introduced in the system's response computation.

To better simulate the variability and uncertainty present in real-world conditions, random numerical noise is introduced into the computed displacements. This noise is proportional to 5% of the standard deviation of the displacement signal.

$$w(x_0, t) = \sum_{n=1}^{N_M} \phi_n(x_0)\, q_n(t) \tag{5}$$

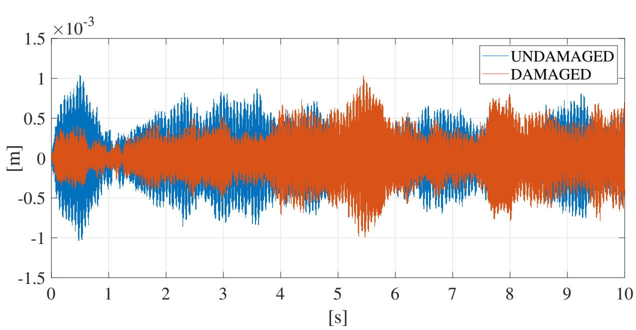
$$\ddot{q}_n(t) + 2\zeta_n\omega_n\dot{q}_n(t) + \omega_n^2 q_n(t) = \int_0^L \phi_n(x)p(x,t)\, dx \tag{6}$$

Results and Discussion

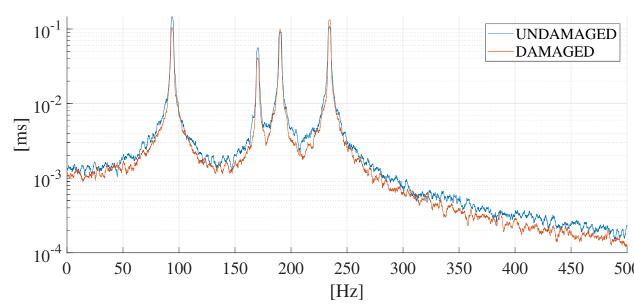
The goal of this analysis is to evaluate how well the proposed method performs in assessing structural damage. For clarity and conciseness, the damage considered in all the figures is scenario 2 in Table 1, except for the illustration of the final result. The general behavior of the signal recorded by sensors is illustrated in Fig. 3a, where the damage influence in the pipe's response is barely noticeable. To gain deeper insights, its corresponding frequency spectrum is provided in Fig. 3b, where damage effects are typically more evident.

However, only a slight shift in modal peaks can be observed in this case. The analysis begins by applying PCA to data recorded by the N_s sensors. In this step, the most significant MCs are identified based on the formulation in Eq. (2). PCA is then reapplied on them to reduce the problem's dimensionality further, selecting the PCs from the application of Eq. (2). Subsequently, ICA is performed on the selected components, using the FastICA and the kICA algorithm [20], to extract the ICs. Figure 4 shows the spectra of the most damage-sensitive PC and IC, which are identified by the greater differential area. Notably, damaged IC's spectrum shows a pronounced increase in amplitude within the frequency band close to the first mode when the structure is damaged, demonstrating the algorithm's ability to highlight structural changes. In contrast, as sensors, PCA alone fails to reveal substantial differences between damaged and undamaged states, underlining the added value of ICA in improving the detection of structural anomalies (as illustrated in Fig.4b).

The next step involves the evaluation of the differential area, as in Eq. (4), which serves as a damage indicator. This is done for all damage scenarios in Table 1, within a damage detection framework [22], Specifically, for the evaluation of the differential area for each damage scenario j in Table 1, the ICs' spectra of the j^{th} are compared against the first undamaged scenario (scenario 1). The results, depicted in Fig. 5, clearly demonstrate that the combination of PCA and ICA is more effective in detecting damage than PCA alone. Indeed, these findings highlight the presence of structural anomalies, confirming the occurrence of damage. Therefore, the method proves effective even in identifying damage at an early stage, where the damage intensity is as low as 10%.

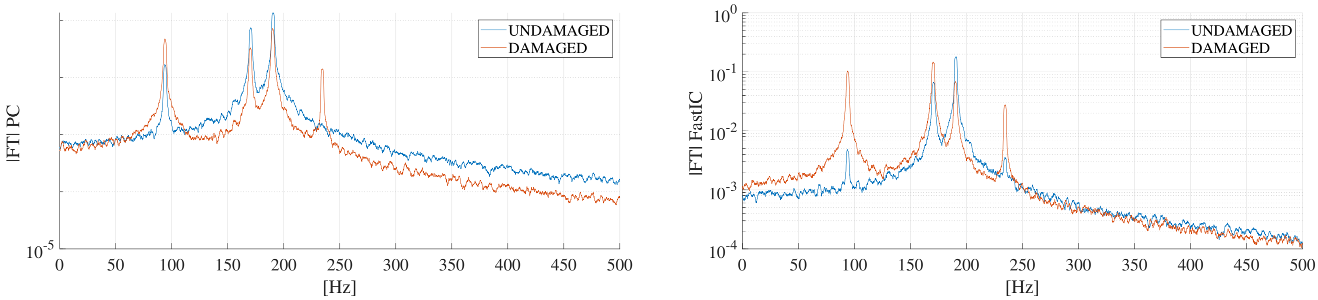


(a) Time histories of the displacement



(b) FT of the normalized displacement

Fig. 3 Signals recorded (and their FT) in the undamaged (blue) and damaged (orange) cases by the sensor placed at the midpoint of the cylinder axis on its surface



(a) PC (b) FastIC

Fig. 4 Best PC's FT and best FastIC's FT in the undamaged (blue) and damaged (orange) cases

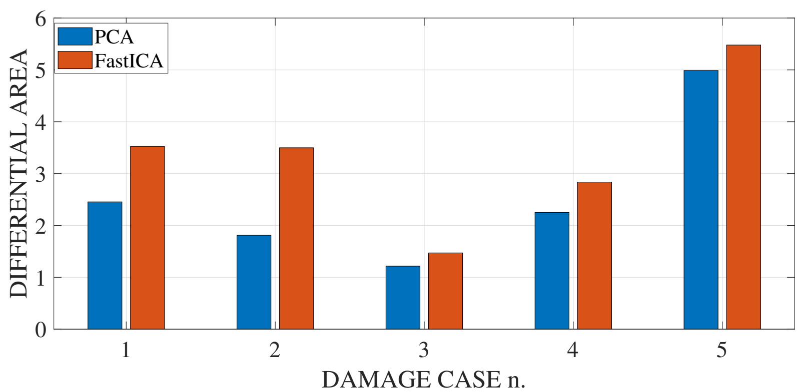


Fig. 5 Differential area for both PCs and ICs evaluated for damage detection for all the scenarios in Table 1

Conclusion

This research explores the ability of the proposed methodology, which integrates PCA and ICA, to detect early-stage damage. This is performed using the differential area as a key damage indicator. Applied to a FEM model of a pipe with simulated damage, the algorithm demonstrates superior performance when compared to PCA alone. Even under conditions where the structure is subjected to a randomly distributed load, the algorithm efficiently filters the noise by analyzing the Minor Components identified through PCA. The encouraging results suggest that this approach could be applied to various structural scenarios.

Future work will expand this analysis, considering multiple damage scenarios and locations to test the method further. Additionally, several environmental factors, such as temperature and humidity variations, will be included to evaluate how sensitive the damage indicator is under different conditions and the ability of PCA to filter out them.

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