A hybrid unsupervised learning method for structural health monitoring by artificial neural networks and k-means clustering

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Abstract:

This article addresses the challenges of environmental variability and damage detection in structural health monitoring by introducing a hybrid unsupervised learning approach. The method combines a novel two-level artificial neural network (TLANN) for data normalization to mitigate environmental variations and employs k-means clustering (KMC) for damage detection. In the TLANN algorithm, feature samples are processed through two neural networks to generate a residual matrix used as the primary input for KMC. The Silhouette value technique is applied to determine the number of clusters. The key contribution of this article is the development of an innovative hybrid unsupervised learning method that effectively handles environmental variability and enhances damage detection. The method's performance is validated using the Z24 bridge and compared favorably with classical techniques, demonstrating its effectiveness in detecting damage and mitigating environmental variations.

Keywords: Structural health monitoring; early damage detection; environmental variability; artificial neural network; k-means clustering; full-scale bridge

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1. Introduction

Civil infrastructures are vital components of society but are susceptible to various forms of damage, including aging, natural disasters, and wear and tear. Structural health monitoring

(SHM) is an interdisciplinary research field that offers a practical approach for detecting and evaluating damage in civil engineering structures [1-3]. One effective method within SHM is vibration-based damage detection, which assesses the structural health of buildings and infrastructure by analyzing vibration parameters [4]. Vibration-based structural health monitoring can be categorized into two approaches: model-driven and data-driven. Model-driven methods involve creating detailed finite element models and using dynamic theories, inverse problems, and model updating techniques. In contrast, data-driven methods rely solely on raw vibration data without constructing numerical models or employing model updating strategies. Data-driven approaches offer advantages in handling uncertainties in damage detection and are considered to complement and improve upon model-driven techniques [5].

In structural health monitoring (SHM), the data-driven approach aligns with statistical pattern recognition, involving two primary steps: feature extraction and feature classification [3]. Feature extraction is a data analysis method aimed at uncovering meaningful information (features) from raw system data [6, 7]. This process can utilize techniques such as time series analysis, operational modal identification (particularly in novel frameworks), and time-frequency signal processing [8, 9]. Feature classification involves statistically analyzing these extracted features using machine learning techniques to assess the condition of a civil structure and determine whether it has sustained damage or remains in normal behavior [10-12]. It needs to clarify before feature extraction and feature classification, sensor deployment and data measurement are mandatory for data-driven SHM. Recent advancement in sensor technologies allow civil engineers to benefit different sensor systems such as non-contact optical sensors [13], remote sensors [14], and even smartphones [15].

Machine learning is a field that involves analyzing training data to build a model (classifier or detector) for making decisions using test data, a methodology beneficial not only in structural health monitoring (SHM) but also across various aspects of structural engineering [16]. In SHM, two types of machine learning algorithms are employed: supervised and unsupervised learning. Supervised learning requires training data containing features from both normal and damaged states of a structure, necessitating information about damaged conditions. Conversely, unsupervised learning relies solely on features from the normal condition, making it more practical, especially in complex and costly civil engineering infrastructures where introducing additional damage for training data is unreasonable [17-20]. While supervised machine learning can be applied to SHM, unsupervised learning is often preferred for damage detection and health assessment of full-scale civil structures [21].

Unsupervised machine learning involves training a statistical model using features extracted exclusively from the normal/undamaged condition as training data. This process utilizes various statistical models, including artificial neural networks [22-24], clustering algorithms [25-26], and statistical distance measures [27-29]. Once the model is trained, features extracted from vibration data related to the current or unknown state of the structure are inputted into the model for decision-making and feature classification, which is essentially damage detection. To perform this procedure, an initial threshold level is determined using the model's outputs based on the training data. Any deviation in the model's output using test data beyond this threshold is indicative of the presence of damage [30]. The described procedure for damage detection faces significant challenges, primarily stemming from environmental and operational variations caused by factors like temperature and humidity fluctuations, wind speed fluctuations, live loads, additional masses, and human activities [31]. These challenges are substantial because they can lead to changes in structural properties and vibration responses, similar to those caused by actual damage. Consequently, in such cases, any structural change might be incorrectly interpreted as damage, resulting in a false positive (Type I). Conversely, environmental and operational variations may sometimes produce changes of greater magnitude than actual damage, making it challenging to accurately detect damage occurrences, leading to false negatives (Type II) [32]. To address these issues, it's crucial to perform data (feature) normalization to mitigate the impact of environmental and operational effects on the extracted features [31].

In the field of bridge structure health monitoring, Sarmadi conducted a comprehensive study comparing various machine learning algorithms, categorizing them as non-parametric, semi-parametric, or parametric based on their suitability for different bridge types and sizes [33]. It was found that non-parametric algorithms perform well when environmental and operational variability is low, while semi-parametric and parametric methods are more suitable when dealing with higher variability, requiring careful determination of hyperparameters to address these effects. Several techniques have been introduced to mitigate environmental and operational variability. Shi et al. [34] used cointegration analysis for detrending nonstationary time series data. Silve et al. [35] introduced a deep principal component analysis to normalize data by extracting salient features, irrespective of environmental variations. Sarmadi et al. [36] proposed an unsupervised feature normalization method using a hybrid feature weighting-selection algorithm and a concept called natural neighbors. Entezami et al. [37] employed empirical learning to develop a non-parametric unsupervised learning method for bridge health assessment under severe environmental variability. Daneshvar and Sarmadi [21] introduced an innovative information-based anomaly detection method inspired by density peaks clustering for assessing damage in civil structures. Their approach is applicable to both short- and long-term monitoring programs, considering different environmental variations in dynamic and statistical features. Entezami et al. [38] proposed a novel double hybrid learning methodology consisting two steps with double learning algorithm for damage assessment under different environmental variation patterns.

In structural health monitoring (SHM), effectively classifying features for damage detection is a challenging task. While unsupervised models based on artificial neural networks, clustering algorithms, and statistical distance measures can be used individually, they may produce erroneous results. Hybrid unsupervised learning methods have emerged as a promising solution to address poor performance and reduce errors. Several innovative hybrid methods have been proposed in this context: Entezami et al. [39] developed an online hybrid learning method for SHM using spaceborne remote sensing technology and an online transfer learning model based on auto-associative neural networks to eliminate environmental effects from displacement responses of a masonry bridge. Daneshvar et al. [40] introduced a locally unsupervised hybrid learning method based on a discriminative reconstruction-based dictionary learning model to remove environmental effects from bridge modal frequencies. Wang et al. [41] presented a hybrid approach combining principal component analysis and Gaussian mixture models for bridge damage detection, particularly in scenarios involving temperature variations. Daneshvar et al. [42] introduced two innovative hybrid methods, one combining the Gaussian mixture model with Mahalanobis distance and another incorporating an artificial neural network for early damage detection. Entezami et al. [43] proposed a novel hybrid learning method based on unsupervised meta-learning for damage assessment in bridge structures. In a separate study, Entezami et al. [44] developed an unsupervised hybrid learning method using the concept of multi-task learning for continuous health monitoring of various bridges under severe environmental variability.

This study introduces a novel hybrid unsupervised learning approach, named TLANN-KMC, for damage detection in the presence of environmental variability. The key innovation lies in the data normalization process achieved through a two-level artificial neural network (TLANN). In the first level, a multiple feedforward neural network learns to predict features of the normal condition based on training data. In the second level, predicted features are used as new inputs to train another neural network, yielding final features for damage detection.

The same process is applied to features from the current state (test data) using the trained networks to obtain final features. For feature classification and damage detection, the normalized features from both normal and current conditions are inputted into the k-means clustering technique (KMC). The number of clusters is determined using the normalized features from the normal condition, and a damage index (DI) based on the Euclidean norm is calculated to detect damage in the current state. Damage detection relies on a threshold limit established using a generalized extreme value distribution and the block maxima method. The proposed TLANN-KMC method excels in addressing the adverse effects of environmental variability. It utilizes natural frequencies of the Z24 bridge as dynamic features for damage detection and outperforms several existing methods, demonstrating its capability to detect structural damage even in the presence of significant environmental variations.

2. Multiple feedforward neural network

Artificial Neural Networks (ANNs) are computational models inspired by biological neural networks. They aim to approximate unknown functions by mapping inputs to desired outputs. ANNs consist of layers and neurons, with each neuron resembling a simplified biological cell body, involving weights, biases, summation, and transfer functions. Typically, the network's architecture, including the number of layers and neurons, as well as summation and transfer functions, is defined before training. During training, the primary objective is to estimate or adjust the weights and biases to enable the network to perform its desired function.

2.1. Network architecture

This article employs a multilayer feedforward neural network as its chosen architecture to address the impacts of operational and environmental variability. A key advantage of this network is its unsupervised learning capability, enabling it to reconstruct input data, which, in turn, mitigates operational and environmental variability. The multilayer feedforward neural network consists of an input layer, multiple hidden layers, and an output layer [45]. The normal condition's structural features serve as input data, which are fed into the input layer. Simultaneously, reconstructed or output data are obtained from the output layer, mirroring the input data's size. Essentially, the output layer acts as a filtered version of the input data, aiding in reducing variability [46].

The main part of the multilayer feedforward neural network is hidden layers. These are composed of mapping and de-mapping layers as well as a bottleneck layer. The mapping layer often uses a transfer function, which is non-linear like sigmoid function, to map the input data into the next (bottleneck) layer. The bottleneck layer plays a prominent role in the functionality of the multiplayer feedforward network. This layer limits an internal encoding/compression of the input data with a subsequent decoding/decompression after the bottleneck to make the output data of the network. Finally, the de-mapping layer exploits a non-linear transfer function (e.g. sigmoid function) to decode/de-map the compressed data in the bottleneck layer and then extract the output data. Fig. 1 illustrates the general view of the neural network used in this article for data normalization, where n_m, n_b, n_d are indicative of the numbers of neurons regarding the mapping layer, bottleneck layer, and de-mapping layer, respectively.

The multilayer neural network employs a feedforward architecture, which distinguishes it from recurrent neural networks. Unlike recurrent networks, a feedforward algorithm propels data in a unidirectional manner without any cycles or loops. Consequently, a feedforward network configuration involves transmitting information from input neurons through hidden neurons to output neurons in a forward direction. The network's weights and biases for each layer are unknown parameters that must be properly estimated. Various learning techniques are employed in multilayer networks, with back-propagation being the most widely used method. This technique aims to iteratively adjust the weights to minimize the error between input and output, ultimately achieving the desired output. Further details on different aspects of artificial neural networks (ANNs) can be found in reference [47], but are not covered within the scope of this current research study.

2.2. Selection of neuron sizes

In a multilayer feedforward neural network, while the number of layers is known, it is crucial to accurately determine the sizes of neurons in each hidden layer. The selection of these neuron numbers must strike a balance to avoid underfitting and overfitting issues. Underfitting occurs when the neuron numbers are insufficient for the layer, necessitating an increase. Overfitting, on the other hand, means that the network performs well with training data but exhibits unreliable performance with validation data [47]. Therefore, it is vital to choose neuron sizes based on a reliable criterion. In this article, the criterion used is the mean-squared error (MSE) between network inputs and outputs. To determine the neuron numbers in hidden layers, a grid search algorithm is applied based on this criterion. It's worth noting that when dealing with a small number of hyperparameters, grid search is considered the most effective and efficient hyperparameter optimization algorithm [48]. Given the need to determine two types of neuron numbers, the choice of the grid search algorithm in this paper is reasonable.

This process involves splitting the input data into training and validation sets. The primary goal is to train a neural network using the training data, considering a substantial number of sample neurons. Each sample neuron is used to train a neural network solely on the training data (the network input). After obtaining the network's output, the Mean Squared Error (MSE) between the input and output is calculated. The same procedure is applied to the validation data (new input fed into the network) without training a new neural network. Instead, the pre-trained network is used to generate the new output, and the MSE between the new input and output data is computed. To facilitate this process, MSE values are stored in a matrix. Rows in this matrix correspond to neuron numbers for the mapping and de-mapping layers, while columns represent neuron numbers for the bottleneck layer. By calculating the direct difference between the MSE matrices for training and validation data, one can determine the optimal neuron sizes for the hidden layers. The rows and columns associated with the minimum value of this direct MSE difference (referred to as DMSE) indicate the optimal neuron sizes for the mapping layer, de-mapping layer, and bottleneck layer, respectively. It's important to note that since the mapping and de-mapping layers have the same number of neurons, the rows of the MSE matrices refer to the neurons in these layers. Additionally, to prevent overfitting, the neuron sizes of the mapping and de-mapping layers should be larger than the bottleneck layer [46].

3. K-means clustering

Clustering is a widely used unsupervised learning technique that divides sample data into clusters or groups. Different clustering methods exist, including connectivity-based, hierarchical, centroids-based, partitioning, distribution-based, density-based, fuzzy, and constraint-based or supervised clustering. In essence, a cluster comprises samples with significant similarities, and various distance measures are employed to gauge the similarity among these samples [49].

The KMC is the simplest and most popular partition-based clustering method, for which the given data is clustered by a pre-defined number of clusters (k). The main idea behind the KMC is to define k centroids (i.e. the means or averages) of all 48 clusters. Given the given data $x_1,\ldots,x_n$, the KMC aims to cluster these samples into k clusters via the following objective function:

$$J=\sum_{i=1}^{k}\sum_{j=1}^{n}\left\|x_j-c_i\right\|_2 \tag{1}$$

where c_i is the mean of the i^{th} cluster and $\|.\|_2$ refers to the Euclidean norm. The KMC is generally an optimization problem, aiming at minimizing the objection function J. In this regard, this function decreases monotonically at each iteration so that this decreasing in a monotonic manner will finally converge to a local minimum.

4. Proposed hybrid method

The proposed hybrid damage detection method consists of two main components: data normalization and feature classification. This method is employed during both the training and monitoring stages. In the initial stage, two models (TLANN and KMC) are trained for these components using training samples, which include certain features extracted from vibration data recorded under the structure's normal condition. The second stage involves utilizing test samples, which consist of the remaining features from the normal condition and all features from the current/unknown state of the structure. These test samples are input into the trained models from the training stage to produce respective outputs.

4.1. Data normalization by TLANN

Due to the importance of the negative influences of the operational and environmental variability condition, it is necessary to remove them from the extracted features. This article proposes the TLANN method that consists of two multilayer feedforward neural networks. The process of data normalization is performed in both the training and monitoring phases. Assume that $\mathbf{X}\in\mathbb{R}^{p\times m}$ is the matrix of the training data including p variables and m observations. The initial step is to train a multilayer feedforward neural network based on the training data $\mathbf{X}$ with the aid of the selected neuron sizes of the hidden layers obtained from the grid search technique so as to determine the network output matrix $\widehat{\mathbf{X}}\in\mathbb{R}^{p\times m}$. It is important to mention that the numbers of neurons in the hidden layers are determined before training the neural network. The main goal is to calculate the residual matrix $\mathbf{H}_\mathbf{x}=\mathbf{X}-\widehat{\mathbf{X}}$. This matrix is then incorporated as the new input data and it is fed into a new multilayer feedforward neural network so as to extract the new output of the network $\widetilde{\mathbf{X}}\in\mathbb{R}^{p\times m}$. The main goal in the second level of the data normalization method proposed in this study is to calculate the new residual matrix $\mathbf{R_x}$= $\mathbf{H_x}$-$\widetilde{\mathbf{X}}$ as the main normalized features of the training stage.

During the monitoring period, one supposes that $\mathbf{Y}\in\mathbb{R}^{p\times n}$ is the matrix of the test samples including p variables and n observations. For the process of data normalization, this matrix is considered as the input data in order to feed into the first neural network, which was trained in the training stage. In similar, one attempts to extract the network output matrix $\widehat{\mathbf{Y}}\in\mathbb{R}^{p\times n}$ and compute the residual matrix $\mathbf{H_y}$=$\mathbf{Y}$-$\widehat{\mathbf{Y}}$. Subsequently, this matrix is applied to the second trained neural network to determine the new output matrix $\widetilde{\mathbf{Y}}\in\mathbb{R}^{p\times n}$. Finally, the residual matrix

$\mathbf{R_y}$= $\mathbf{H_y}$ -$\widetilde{\mathbf{Y}}$ is calculated as the main normalized features of the monitoring phase. For the sake of simplicity, Fig. 2 illustrates the flowchart of the first algorithm of the proposed hybrid method related to the TLANN.

4.2. Feature classification by KMC

After removing the operational and environmental variations from the extracted features, the matrices $\mathbf{R_x}\in\mathbb{R}^{p\times m}$ and $\mathbf{R_y}\in\mathbb{R}^{p\times n}$ are applied to the KMC to detect damage. In this case, the latter serves as the training data, while the former is the test set. Although the KMC is still one of the most popular clustering algorithms, it is sensitive to outliers, noise, and uncertainties such as environmental and operational variations. However, the proposed TLANN method before utilizing the KMC addresses this issue and makes it effective for feature classification. The direct use of the KMC or other kinds of clustering algorithms may not be sufficiently effective for damage detection. Accordingly, it is necessary to define a damage index (DI). Using this criterion, one initially attempts to determine the cluster numbers k cluster. It should be pointed out that the cluster selection procedure is only carried out by the training data or the extracted features related to the normal condition of the structure. In this article, the well-known Silhouette value technique [49] is applied to determine the cluster numbers. In the following, the KMC algorithm is used to cluster the feature samples of $\mathbf{R_x}$ into k clusters $\mathbf{c}_1,\ldots,\mathbf{c}_k$. For each feature vector (sample) regarding the test data $\mathbf{r_y}$, the divergence of this vector from each of the clusters is calculated by the following DI:

$$\mathrm{DI} = \min\left\{\left\|\mathbf{r_y} - \mathbf{c}_1\right\|_2, \left\|\mathbf{r_y} - \mathbf{c}_2\right\|_2, \ldots, \left\|\mathbf{r_y} - \mathbf{c}_k\right\|_2\right\} \tag{2}$$

From Eq. (2), the output is a scalar value. Hence, for all *m* feature samples of the test data, one can determine *m* DI values. The same procedure is carried out using the feature vectors obtained from training data $\mathbf{R}_\mathbf{x}$. Therefore, it is possible to determine n DI values regarding the normal condition. For this case, each of the feature vector ($\mathbf{r}_\mathbf{x}$) obtained from the training data is substituted by the vector $\mathbf{r}_\mathbf{y}$ in Eq. (2). The decision-making for damage detection procedure is on the basis of comparing all DI values with a threshold level [50]. Because threshold level determination plays a crucial role in obtaining precise damage detection results, this study utilizes a methodology on the basis of the extreme value theory proposed by Sarmadi and Karamodin [29]. It is important to mention that the threshold level is obtained from the DI value of the only normal condition or the training data. Thus, if the DI value exceeds the threshold level, this is indicative of damage occurrence; otherwise, the structure is undamaged. On the other hand, it is expected that the DI values of the normal condition of the structure, either the training or validation data, are under the threshold level. The flowchart of the second algorithm of the proposed hybrid method regarding the KMC is shown in Fig. 3.

5. Case study: The Z24 bridge

The Z24 bridge is a well-known post-tensioned concrete box girder bridge within the Structural Health Monitoring (SHM) community. This bridge features a main span of 30 meters and two side spans of 14 meters, as depicted in Fig. 4. It was located in Canton Bern, Switzerland, connecting Koppigen and Utzenstorf, serving as a highway overpass for the A1 route connecting Bern and Zurich. The bridge was supported by two rows of three pinned concrete columns at the endpoints, and two concrete piers were clamped into the girders at the main span's endpoints. Unfortunately, the Z24 bridge was demolished in late 1998 to make way for a new bridge with larger side spans. Between November 11th, 1997, and September 11th, 1998, an extensive and continuous monitoring test was conducted, gathering environmental data, including air temperature, wind characteristics, humidity, and more, using 49 sensors. Additionally, dynamic responses, such as acceleration time histories, were recorded using 8 accelerometers. In the month leading up to its demolition, the Z24 bridge was deliberately subjected to gradual and controlled damage. For further information regarding the SHM project and progressive damage scenarios, please refer to [51].

Peeters and De Roeck [51] conducted a stochastic subspace identification-based operational modal analysis on the Z24 bridge to extract its modal parameters. In this study, we focus on the bridge's natural frequencies (f) from the four vibration modes. These natural frequencies are the primary damage-related features for our damage detection process. The dataset consists of a total of 5652 frequency samples, some of which have missing data. To clean the data, we utilized a data cleaning algorithm proposed by Entezami et al. [51], resulting in a feature dataset containing 3932 modal frequencies, given in Table 1. Among these, the first 3476 samples represent the bridge in its normal condition, while the remaining 456 samples correspond to the damaged state [27, 31]. Figure 5 illustrates the natural frequencies of the four identified vibration modes. Notably, there are abrupt jumps between measurements 1-1738, indicating the influence of environmental variability in the bridge's normal condition. Modal frequencies in measurements 3477-3932 gradually decrease, aligning with the concept of reduced modal frequencies due to stiffness reduction caused by damage. However, it's essential to acknowledge that environmental variations, particularly in normal conditions, can significantly impact modal frequencies. These variations may lead to false alarms and incorrect detection results in vibration-based techniques.

In order to detect damage by the proposed hybrid TLANN-KMC technique, it is necessary to divide the dataset into training and test parts. On this basis, 75% of the natural frequencies of the normal condition of the structure are selected to make the training matrix as $\mathbf{X}\in\mathbb{R}^{4\times2607}$, where p=4 and m=2607. Moreover, the remaining natural frequencies of the normal condition of the structure related to the measurements 2608-3476 as well as all the natural frequencies of the damaged state of the structure regarding the measurements 3477-3932 are considered the test matrix $\mathbf{Y}\in\mathbb{R}^{4\times1325}$, where p=4 and n=1325. It is worth remarking that the same percentages of the training and validation datasets (i.e. 75% and 25%) are used to generate $\mathbf{R}_\mathbf{x}$ and $\mathbf{R}_\mathbf{y}$.

5.1. Damage detection

As the first step of the proposed hybrid technique relates to the process of data normalization, one initially requires determining the neuron numbers of the hidden layers, for two levels of the proposed TLANN approach. Using the direct MSE between the training and validation data, Fig. 6 shows the amounts of n_m, n_b, and n_d related to the mapping layer, bottleneck layer, and de-mapping layer of the first and second levels. For better observations, the inverses of the DMSE matrices are used to find the number of neurons. Accordingly, the maximum values are considered to choose these numbers. From Fig. 6(a) concerning the first level, it is seen that the mapping layer as well as de-mapping layer need 12 neurons (i.e. n_m=n_d=12) and the bottleneck layer requires 4 neurons (i.e. n_b=4). In Fig. 6(b), the neurons of these layers in the second level are identical to 9, 2, and 9, respectively.

According to these numbers, the final feature matrices $\mathbf{R_x}$ and $\mathbf{R_y}$, as shown in Fig. 2, are extracted to use in the KMC for feature classification and damage detection. Considering the flowchart in **Fig. 3**, the first step is to determine the cluster numbers on the basis of the only training data $\mathbf{R_x}$ as illustrated in Fig. 7. As can be seen in in Fig. 7, the fifth sample cluster presents the maximum Silhouette value among all ten sample numbers. Therefore, the KMC needs five clusters to divide all the training samples and obtain the vectors $\mathbf{c}_1,\ldots,\mathbf{c}_5$. In the following, the values of DI regarding the training data are calculated in order to apply the obtained values for the threshold level estimation by modeling the generalized extreme value distribution based on the block maxima method [29]. Finally, the same clusters obtained from the training phase are incorporated to compute the values of DI regarding the test samples in the monitoring stage. On this basis, Fig. 8 illustrates the damage detection result in the Z24 bridge by the proposed hybrid method.

Observing the results, it's evident that all DI values for training samples 1-2607 remain below the threshold level, indicating no false alarms. Moreover, the majority of validation samples 2608-3476, representing the normal condition of the structure, fall below the threshold, with only a few exceptions. Concerning the damaged state (samples 3477-3932), most DI values exceed the threshold, indicating precise damage detection. Only one point has a DI value under the threshold. Regardless of the threshold level, it's notable that DI values related to the damaged state are consistently higher than those for the normal condition. This finding underscores the high damage detectability achieved by the proposed hybrid method. In conclusion, this technique is well-equipped to handle the effects of environmental variability and accurately detect damage.

5.2. Comparisons

While the hybrid method proposed in this study demonstrates its capability to accurately detect damage and handle environmental variability, it's crucial to compare it with established methods and their counterparts. For data normalization, this article introduces the TLANN approach. Therefore, it's fitting to assess the method's performance when only the first level of data normalization is employed. In this context, the article extracts residual matrices Hx and Hy, which are then used as primary features for the one-level ANN (OLANN) approach. Consequently, the first comparison evaluates the proposed TLANN-KMC method against the

OLANN-KMC approach. The direct use of ANN or the OLANN method is another technique for damage detection. Hence, the second comparison involves evaluating the proposed hybrid technique against the traditional OLANN method. Additionally, KMC is a popular unsupervised machine learning technique for damage detection process [52]. Therefore, the final comparison involves assessing the proposed hybrid method against KMC. In Fig. 9, you can observe the cluster numbers required for the OLANN-KMC and KMC methods. The maximum Silhouette values correspond to the eighth and second sample clusters. Furthermore, Fig. 10 displays the damage detection results for the OLANN-KMC, OLANN, and KMC methods. The same threshold estimation methodology is applied to compare their DI values with the threshold levels. Table 2 provides numerical analyses, including Type I and Type II errors, as well as the total error for the proposed hybrid method and the mentioned classical techniques.

In Fig. 10, noticeable variations in DI values can be observed, particularly for the training samples, especially around samples 869-1738, which align with the sudden jumps in modal frequencies shown in Fig. 5. The KMC method exhibits the poorest performance, mainly due to the influence of environmental variability in the modal frequencies, leading to significant variations in DI values as seen in Fig. 10(c). Consequently, a high threshold level has been estimated, resulting in serious false detections. For samples 3477-3932, the majority of DI values fall below the threshold, making it challenging to differentiate between normal and damaged structural conditions, indicating low damage detectability. Although both OLANN-KMC and OLANN methods outperform the classical KMC method, some erroneous results still persist. To provide a more comprehensive evaluation, the study employs triple error metrics, including Type I, Type II, and total errors, to compare the proposed technique with other methods. With the exception of the classical KMC, it's evident that the TLANN-KMC method outperforms both OLANN-KMC and OLANN techniques, boasting the smallest numbers and the lowest percentages of triple errors. Furthermore, the OLANN approach performs better than the OLANN-KMC method. In summary, the comparisons in this section highlight that the hybrid method proposed in this study surpasses other techniques in terms of damage detection under varying environmental conditions.

All the previous results have been obtained by applying a large set of normal and damaged features. In order to evaluate the proposed method under small data, the daily measurements of the Z24 bridge are considered here as shown in Fig. 11. These measurements include 235 samples of modal frequencies, where the samples 1-198 relate to the normal condition and the samples 199-235 are concerned with the damaged state [26]. Accordingly, one can determine a new training matrix by taking 90% of the modal frequencies of the normal condition and making the new matrix $\mathbf{X}\in\mathbb{R}^{4\times178}$, where m=178. Moreover, the remaining 10% of the daily modal frequencies concerning the undamaged condition as well as daily data of the damaged state are inserted into a new testing matrix $\mathbf{Y}\in\mathbb{R}^{4\times57}$.

Using the grid search algorithm, the neuron numbers for the first ANN are determined as 7, 3, and 7 for the mapping, bottleneck, and de-mapping layers, respectively. For the second ANN, the neuron numbers are 4, 2, and 4 for the same respective layers. Figure 12 illustrates the results of damage detection in the Z24 bridge using a limited set of modal frequencies. It's evident that all DI values for the normal condition (samples 1-198) fall below the threshold line, indicating the method's ability to accurately recognize the undamaged state of the bridge. With the exception of three points, the majority of DI values for the damaged state surpass the threshold. Therefore, it can be concluded that the proposed method is also successful in detecting damage using a reduced set of modal frequencies.

6. Conclusions

This study introduced a hybrid unsupervised learning method combining ANN and KMC to address two key challenges: data normalization and feature classification. The goal of data normalization was to mitigate environmental variations in features extracted from measured vibration data, while feature classification aimed at detecting damage. For data normalization, the TLANN approach, consisting of two ANNs, was proposed. The residual matrices, obtained as the difference between the input and output of the second ANN, were used as the primary features. Hyperparameter estimation determined the neuron numbers in the hidden layers of each ANN using the direct MSE. For damage detection, classical KMC clustered the extracted features and calculated DI values, with Silhouette values determining cluster numbers. The Z24 bridge's natural frequencies, a benchmark in the SHM community, were used to validate the method's performance and reliability. Comparisons with classical methods demonstrated the superiority of the proposed technique. The results revealed that the TLANN-KMC method effectively detected damage even in the presence of strong environmental variability. The TLANN algorithm for data normalization significantly reduced the impact of environmental variability, as evidenced by damage detection results and error rates compared to the OLANN-KMC method. The proposed method also outperformed the classical OLANN approach. However, it's worth noting that direct use of KMC for feature classification and damage detection is not recommended when environmental variability strongly affects extracted features. Despite its effectiveness in detecting damage occurrence, the proposed method has room for improvement in recognizing the type and severity of damage. As reported in table 1, The Z24 bridge had various damage patterns with differing levels of severity, suggesting potential enhancements for damage type recognition. Another limitation is the computational time of the proposed method, particularly in the hyperparameter selection process. The TLANN, consisting of two ANNs, requires determining two sets of hyperparameters in different search domains, making it more complex and time-consuming than OLANN-KMC, OLANN, and KMC methods.

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Table 1. Progressive damage tests and their simulation patterns [51]

No.	Damage level	Simulation of real damage patterns
1	First reference measurement	Undamaged condition
2	Second reference measurement	After installing the lowering system
3	Lowering of pier, 20 mm	Settlement of the subsoil, erosion
4	Lowering of pier, 40 mm	
5	Lowering of pier, 80 mm	
6	Lowering of pier, 95 mm	
7	Tilt of foundation	Settlement of the subsoil, erosion
8	Third reference measurement	After lifting of the bridge to its first position
9	Spalling of concrete, 24 m^2	Vehicle impact, carbonization, and subsequent corrosion of reinforcement
10	Spalling of concrete, 12 m^2	
11	Landslide at abutment	Heavy rainfall, erosion
12	Failure of concrete hinge	Chloride attack, corrosion
13	Failure of anchor heads #1	Corrosion, overstress
14	Failure of anchor heads #2	
15	Rupture of tendons #1	Erroneous or forgotten injection of tendon tubes, chloride influence
16	Rupture of tendons #2	
17	Rupture of tendons #3	

Table 2. Comparison of the damage detection methods based on feature classification errors

Method	Classification errors					
	Type I		Type II		Total	
	No.	%	No.	%	No.	%
TLANN-KMC	17	0.48	1	0.21	18	0.45
OLANN-KMC	60	1.72	7	1.53	67	1.70
OLANN	36	1.03	10	2.19	46	1.17
KMC	0	0	407	89.25	407	10.35

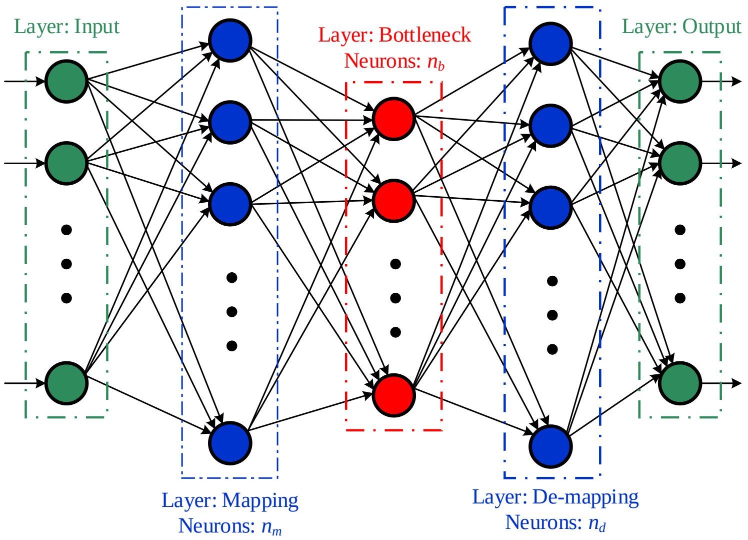

Fig. 1. The multilayer feedforward neural network for data normalization

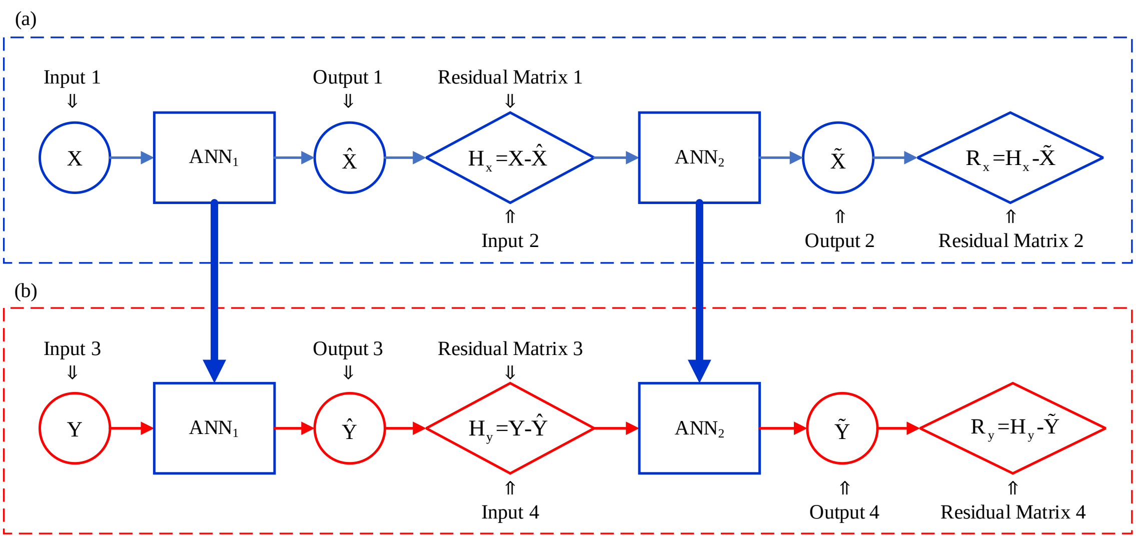

Fig. 2. Flowchart of the first algorithm of the proposed hybrid technique regarding the TLANN: (a) the training stage, (b) the monitoring stage

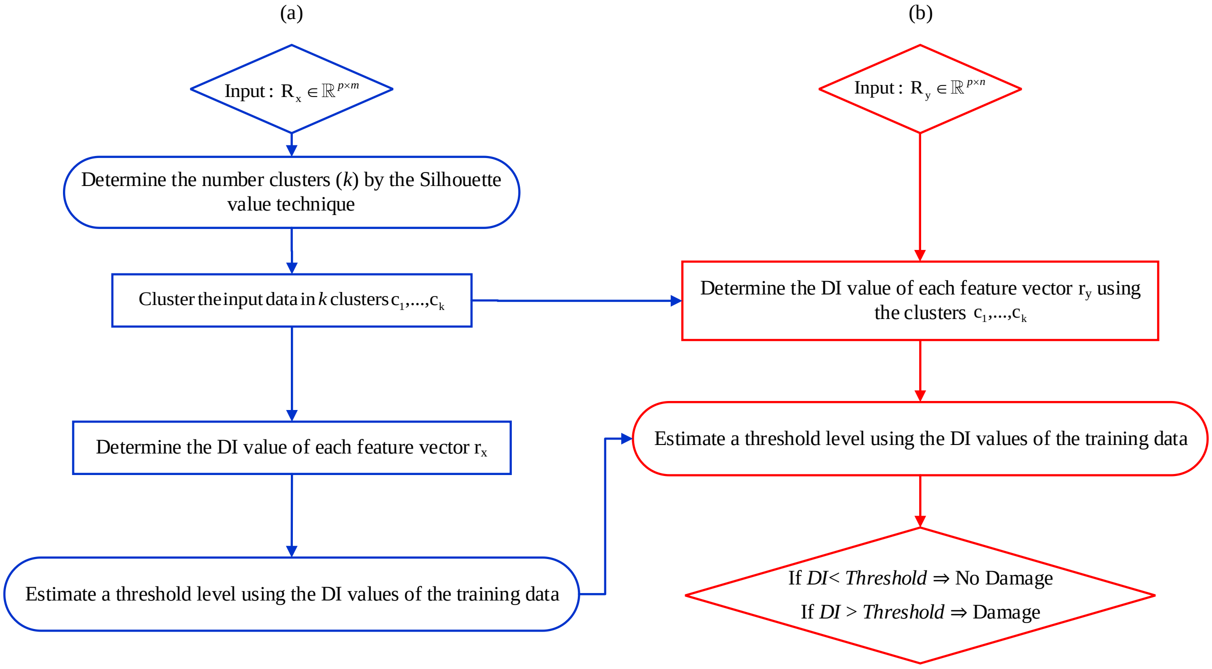

Fig. 3. Flowchart of the second algorithm of the proposed hybrid method regarding the KMC: (a) the training phase, (b) the monitoring phase

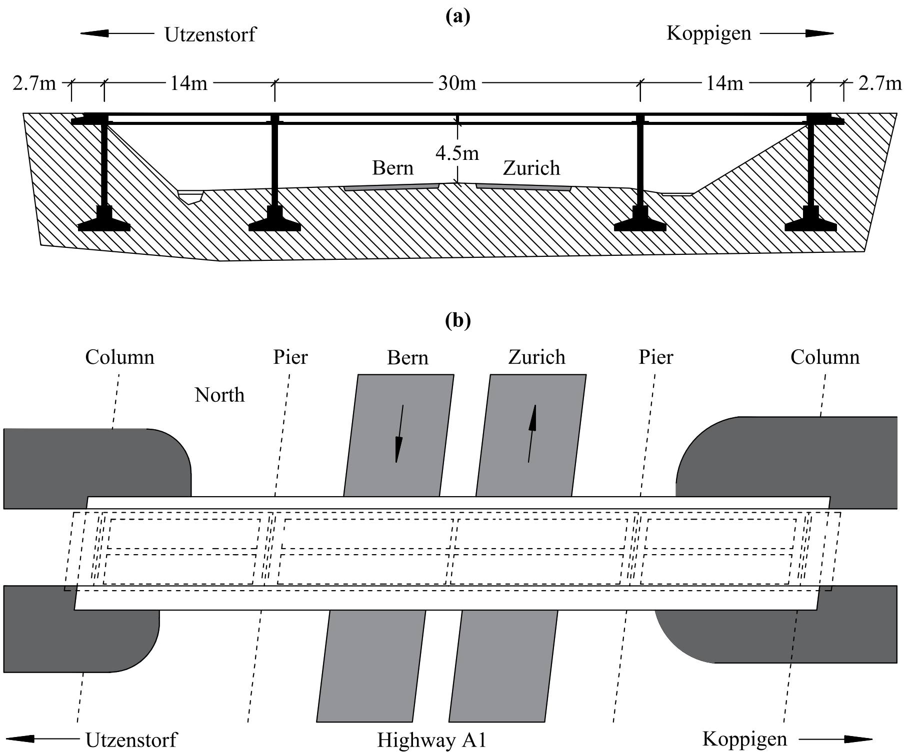

Fig. 4. The Z24 bridge [48]

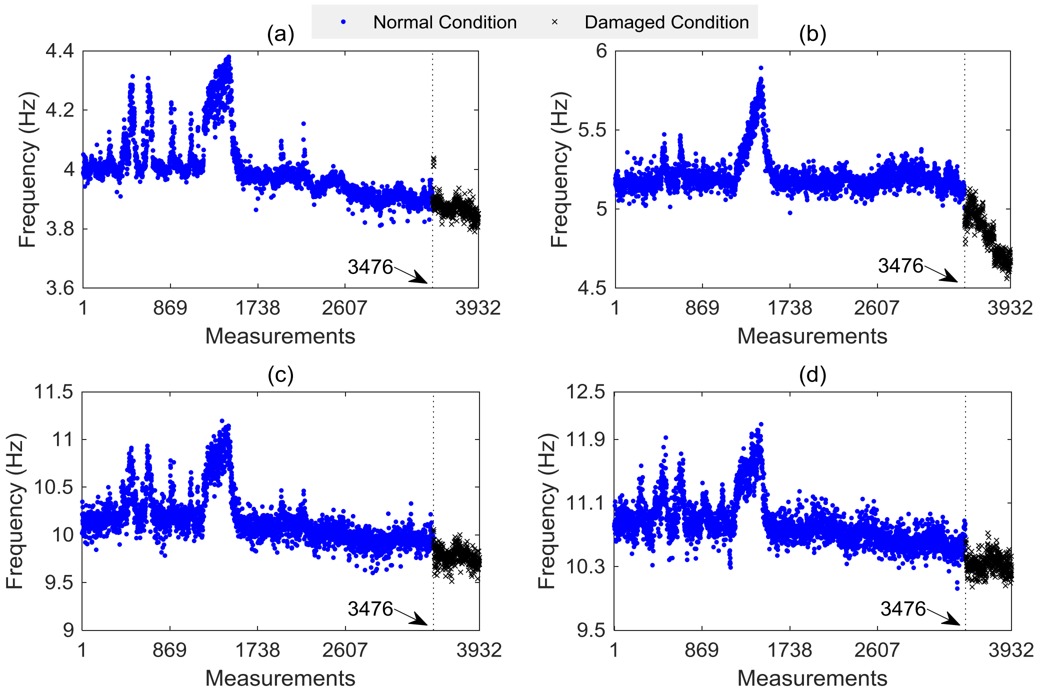

Fig. 5. The natural frequencies in Hz regarding the Z24 bridge: (a) the first vibration mode, (b) the second vibration mode, (c) the third vibration mode, (d) the fourth vibration mode

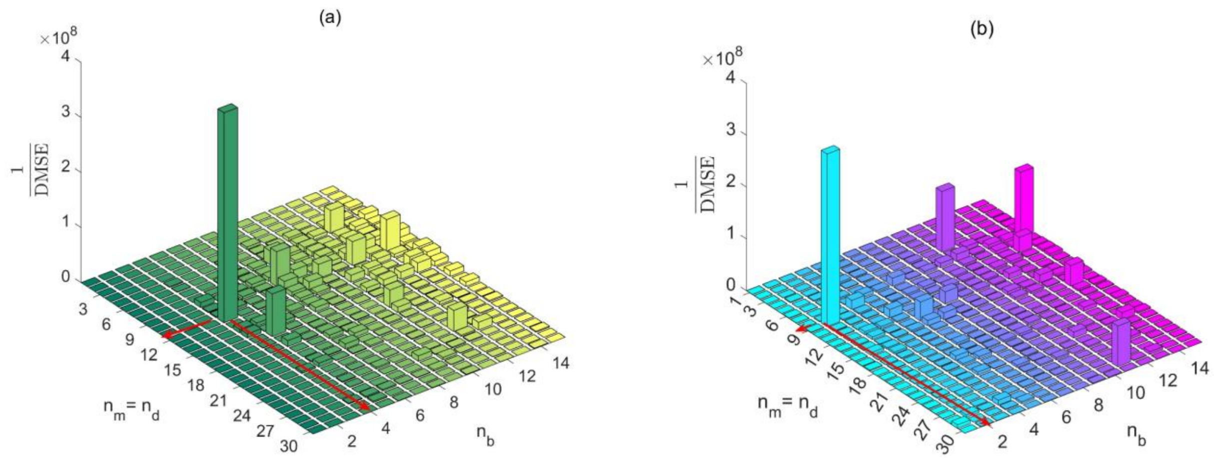

Fig. 6. Hyperparameter estimation for the TLANN: (a) the first level, (b) the second level

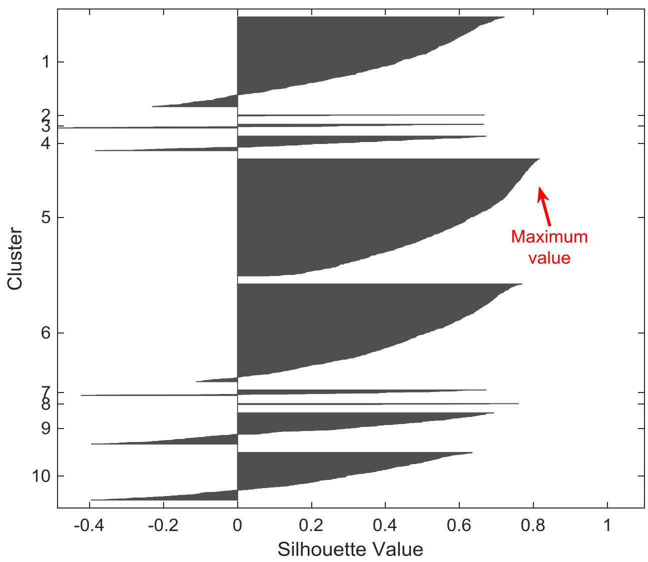

Fig. 7. Selection of the cluster number using the Silhouette value technique

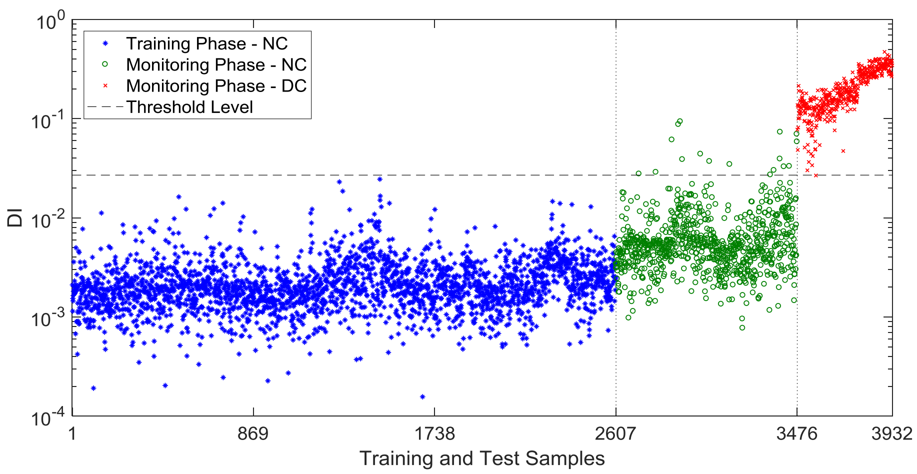

Fig. 8. Damage detection in the Z24 bridge by the proposed hybrid technique

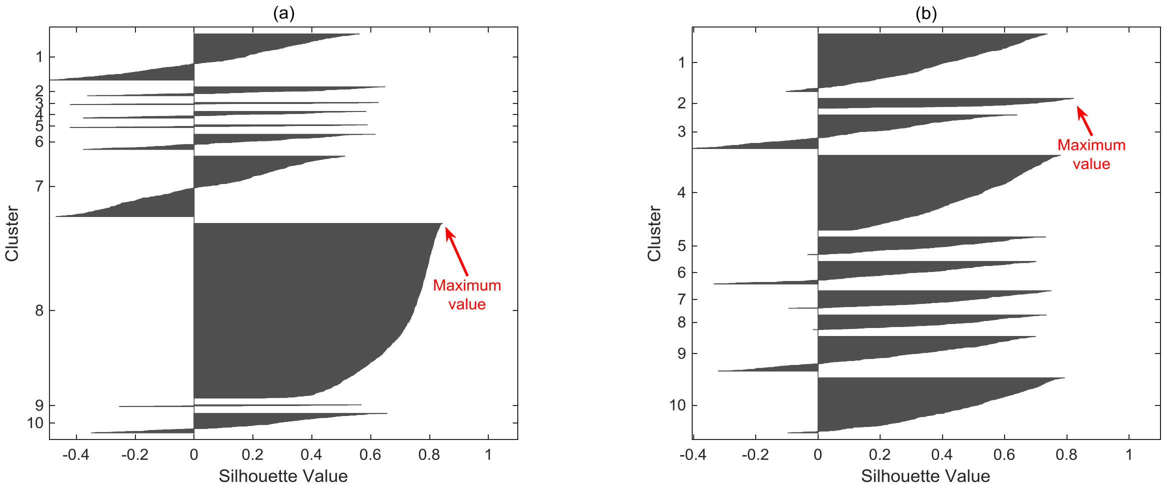

Fig. 9. Selection of the cluster number using the Silhouette value method: (a) the OLANN-KMC, (b) KMC

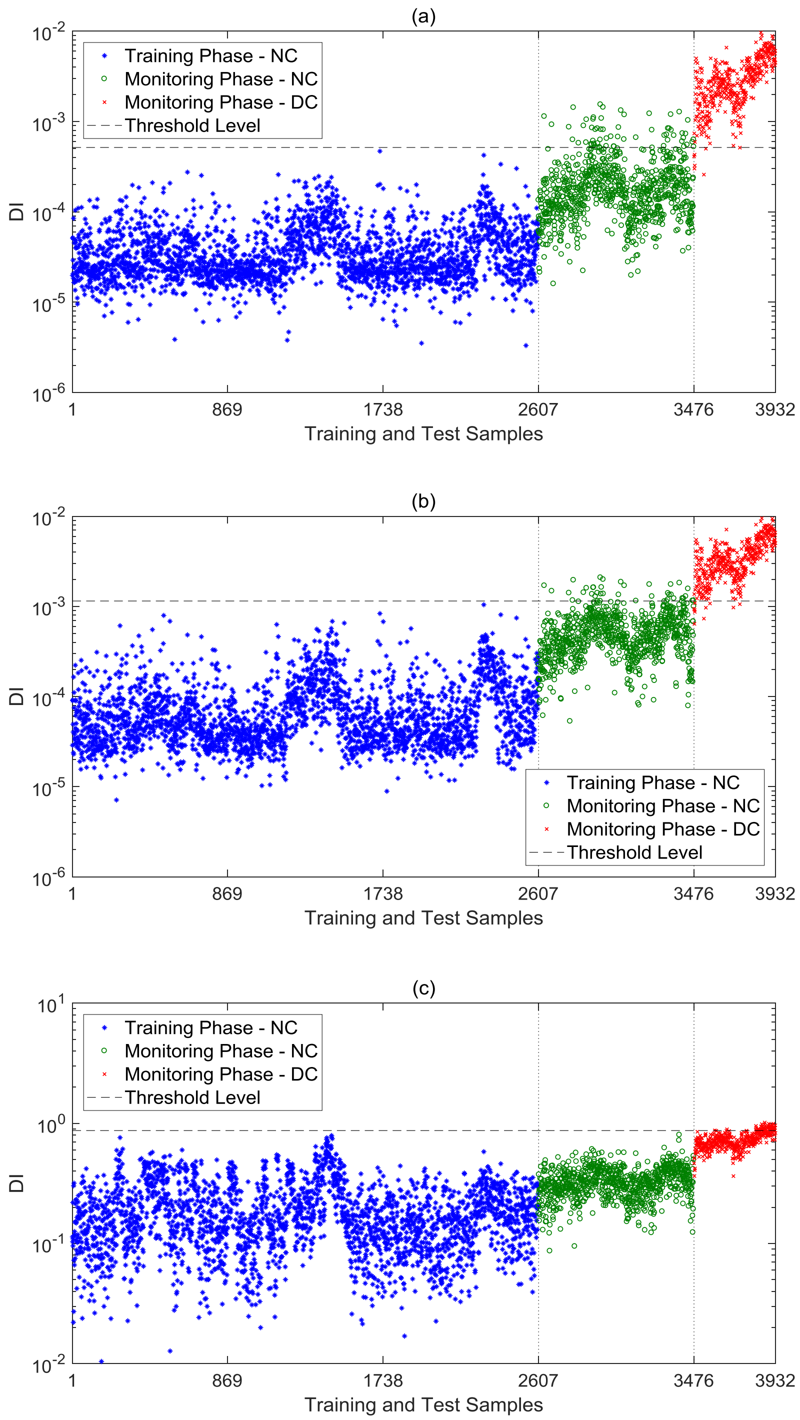

Fig. 10. Damage detection results of the Z24 bridge: (a) OLANN-KMC, (b) OLANN, (c) KMC

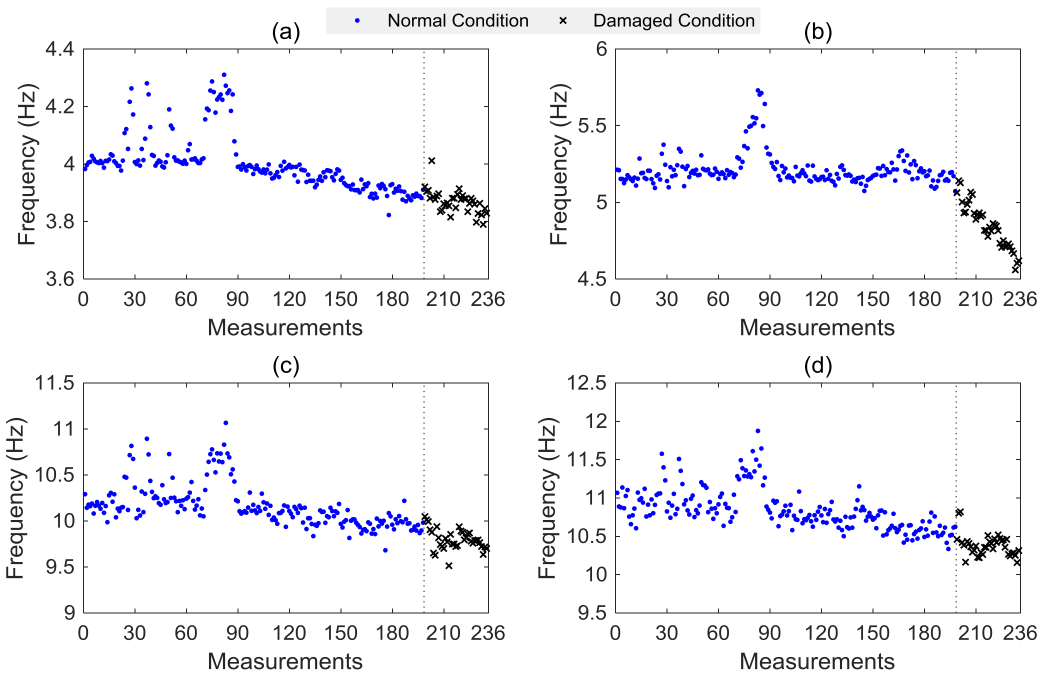

Fig. 11. The small set of natural frequencies in Hz regarding the Z24 bridge: (a) the first vibration mode, (b) the second vibration mode, (c) the third vibration mode, (d) the fourth vibration mode

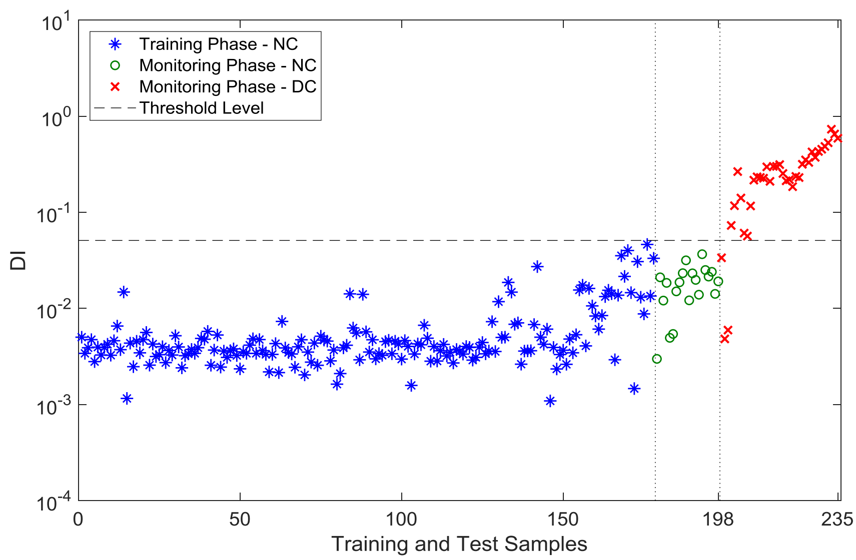

Fig. 12. Damage detection in the Z24 bridge by the proposed hybrid technique and the small set of the modal frequencies (i.e., daily measurement)

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