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An automatic bridge damage diagnostics method using empirical mode decomposition based health indicators and neuro-fuzzy classification

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Summary

Large amounts of data are generated by structural health monitoring systems continuously. Data-driven methods can transform the available data into valuable information for decision makers. However, these methods for structural health monitoring of bridges are usually developed and tested by analysing a finite element model of the bridge, where the uncertainties affecting an in-field bridge are usually omitted. Modal parameters of the bridge are usually used to monitor the health state of the bridge, but it can be a difficult and time-consuming process to extract these parameters from the bridge vibration data in a reliable manner. Conversely, when the raw vibration behaviour of the bridge is monitored, promising results for bridge condition monitoring and damage diagnostics can be obtained in a fast way. In this paper, we propose a data-driven methodology to assess the health state of bridges, by analysing their vibration behaviour. The aim of the first step of the method is to extract statistical, frequency-based and vibration-based features from the measured bridge vibration. The second step is used to define a set of bridge Health Indicators by assessing the trend of these extracted features over time. The main novelty of this work lies in the use of the empirical mode decomposition method to assess the trend of the extracted features over time, rather than to analyse the dynamic behaviour of the structure directly. Finally, a Neuro-Fuzzy classifier, which is trained using a supervised process, is used to assess the health state of the bridge automatically. The proposed method is validated and tested by monitoring the vibration behaviour of an in-field bridge, which is subjected to a progressive damage process.

KEYWORDS

bridge condition monitoring and damage diagnostics, empirical mode decomposition (EMD), neuro-fuzzy classifier, structural health monitoring (SHM)

1 | INTRODUCTION

Structural health monitoring (SHM) strategies are used to monitor the behaviour of critical infrastructure, such as bridges, tunnels and buildings, with the aim of guaranteeing the safety, reliability and availability of the infrastructure.[1] In fact, the analysis of static and dynamic responses of the infrastructure can provide information about the infrastructure health state to bridge managers. Such information can help in finding an optimal maintenance schedule, which would result in minimizing the whole life cycle cost of the asset.[2] SHM techniques are widely adopted in the transportation framework, composed of highway and railway networks, due to the continuous deterioration process of their assets (e.g., bridges), affected by ageing, traffic loads and environmental effects.[3,4] The SHM of bridges is of particular interest because in Europe there are more than one million of bridges, and this number is expected to increase.[5] Bridges need SHM strategies to (i) identify the ongoing degradation mechanisms of the bridge materials and avoid unexpected and catastrophic failure of the asset[6] and to (ii) ensure the safety of the workforce and understand whether the infrastructure behaviour during the work activities (such as maintenance and renewal activities) is within the predicted safety limits.[7] The behaviour of a bridge is monitored by installing a measurement system (such as GPS receivers, accelerometers, strain gauges and cameras) on the bridge infrastructure.[8–10] A large amount of data is generated by these sensors continuously, and thus, data-driven methods are required to assess the health state of the infrastructure automatically, accurately and rapidly.[11]

Several data-driven SHM methods for condition monitoring and damage detection of bridges are presented in literature, such as clustering techniques, principal component analysis (PCA), support vector machine (SVM) and artificial neural network (ANN) models.[4,9,12] In recent years, several authors proposed supervised and unsupervised clustering techniques by analysing either the bridge raw acceleration data (or slightly processed, such as sorted acceleration or symbolic representation of the acceleration) or the bridge modal parameters.[13–16] These methods showed promising performance in classifying the health state of the bridge correctly, and good performance was achieved when raw bridge acceleration (or slightly processed data) was used to assess the bridge health state. However, misclassifications were obtained due to changes of environmental conditions of the bridge, and the need of supervised classification technique was pointed out.[16] Similarly, PCA and its modification with time varying windows, known as Moving PCA (MPCA), were proposed to monitor and assess the health state of bridges.[17–19] Modal parameters of the bridge are usually used as an input to the PCA. ANN is the most used data-driven method for bridge condition monitoring and damage detection.[20–22] Raw bridge data, such as acceleration and displacement, modal parameters and materials properties of the bridge, are used as inputs to the ANNs, and good performance has been achieved. However, the accuracy of the ANN method strongly depends on the number of hidden layers and nodes, which are selected by using a trial and error procedure, and finite element models (FEMs) are often used to validate these methods.[9]

The health state of bridge is often assessed by monitoring modal parameters of the bridge.[23,24] However, false alarms and misleading results can be achieved due to the fact that lower modal parameters of the bridge, i.e., the first natural frequencies and mode shapes, can be strongly influenced by changes in environmental conditions and they have low sensitivity to bridge infrastructure damage. Higher modal parameters of the bridge are more sensitive to damage, but they are also more difficult to extract from the measured bridge data in a reliable manner.[25,26] At the same time, the data-driven methods proposed in literature are often verified using an FEM, which is unable to reproduce data noise and uncertainties affecting an in-field bridge behaviour.[27]

In this paper, a data-driven methodology is presented to monitor and assess the health state of in-field bridges, by detecting bridge unexpected behaviour and diagnosing its causes. The proposed methodology consists of three main steps: (i) extraction of statistical, frequency-based and vibration-based features from the bridge vibration behaviour (i.e., acceleration), by reducing the dimension of the bridge behaviour data into valuable information, with respect to the bridge health state[28,29]; (ii) assessment of trends of extracted features and of bridge Health Indicators (HIs), by applying the Empirical Mode Decomposition (EMD) method[30] to the extracted features and (iii) automatic classification of the bridge health state by using a Neuro-Fuzzy Classifier (NFC) method.[31] The main novelty of the method lies in the second step of the methodology (ii). Generally, the EMD is adopted in the SHM framework to identify structural changes by analysing the bridge dynamic behaviour directly; i.e., the dynamic behaviour of the bridge is used as an input to the EMD process.[32] Such applications have shown good results when an FEM is analysed[33–35]; conversely, misclassifications of the bridge health state were observed due to a mode-mixing problem when an in-field large structure was monitored.[36,37] Variations of the EMD process, such as Ensemble EMD (EEMD) and Multivariate EMD (MEMD), can be adopted in order to overcome the mode-mixing problem and achieve good assessment of the bridge condition.[38,39] The application of the EEMD and the MEMD to a large bridge structure provides better results than the EMD, by being able to detect changes of the bridge health state (but not to diagnose the nature of the occurred damages) and reducing the mode-mixing problem. However, the EEMD and the MEMD require higher computational time than the EMD, and the mode-mixing problem is not fully addressed.[36,40] For these reasons, we adopt the EMD method to assess the trend of the extracted features of the bridge behaviour. Indeed, several studies showed that the trend of statistical, frequency-based and vibration-based features can provide valuable information with respect to the level of degradation of components of rotary machinery.[41]

Finally, an automatic assessment of the bridge health state is proposed in the method by the means of NFC, which is trained in a supervised manner by using a dataset of bridge behaviour in different health states.[31] The NFC is adopted to automatically assess the health state of the bridge by using an optimal subset of HIs as an input to the NFC. The optimal subset of HIs is retrieved by using an optimization differential evolution algorithm.[42] The NFC is selected among the machine learning classifiers due to the fact that it combines fuzzy classification techniques with learning capabilities of the Neural Networks. As a consequence, the network structure is developed by the means of if-then fuzzy rules, which are initially defined by using a K-means clustering algorithm.[43] Conversely to ANNs, which require the optimization of the number of hidden layers and hidden nodes, the NFC requires only the optimization of the number of clusters of the K-means algorithm, and the performance of the NFC is slightly influenced by the number of the cluster. Moreover, good performance can also be achieved with a small dataset of the system behaviour.[31] NFC has been adopted to diagnose the health state of system components, such as wind turbine blades[44] and rotor bars,[45] but not for bridge damage diagnostics, where ANNs and clustering techniques have been mostly applied. Hence, the NFC can be used to automatically assess the health state of the bridge by providing robust results without requiring a time-consuming trial and error procedure to optimize its parameters, as the step needed in the ANN method. The proposed method of automatic health state identification based on the NFC also contributes to the novelty of this paper.

The proposed method is illustrated by analysing the behaviour of a real highway posttensioned concrete bridge.[46] The bridge is subjected to a progressive damage process; i.e., the infrastructure of the bridge is damaged in order to study the behaviour of the bridge in different health states and to analyse sudden severe degradation (damage) of the bridge materials. The posttensioned concrete bridge is excited only by changing environmental conditions; i.e., no vehicle is running over the bridge. The performance of the proposed methodology in monitoring the bridge behaviour, by detecting damages of the bridge elements and diagnosing their causes, is compared with a study that adopted modal parameters to assess the health state of the bridge, presented in Siringoringo et al.[46]

The remainder of the paper is organized as follows: Section 2 presents the proposed data-driven methodology for bridge condition monitoring and damage diagnostics; Section 3 illustrates the application of the proposed methodology to the in-field bridge; conclusions and future challenges are discussed in Section 4.

2 | THE PROPOSED DATA-DRIVEN METHODOLOGY

SHM methods are developed for monitoring the health state of infrastructure, by pointing out and diagnosing anomalies in infrastructure behaviour. Data-driven SHM methods can be used to monitor the condition of bridges continuously, without requiring the time-consuming development of an FEM of the structure. The feature extraction process is usually adopted for monitoring the health state of industrial system components,[29] such as wind turbine blades[44] and rotary machinery.[41] In bridge monitoring, this process is not commonly adopted due to the use of bridge modal parameters.[33,37,40] However, when the health state of a bridge has been evaluated by monitoring raw behaviour of the bridge, or slightly processed (e.g., transformation of the bridge acceleration to symbolic values based on a frequentist analysis[13]), promising results were obtained in a fast and reliable way.[14,16] For these reasons, in this paper, we propose a data-driven method based on HIs that are defined by assessing the trend of the extracted features, in order to monitor the health state of bridge infrastructure, by detecting unexpected behaviour of the bridge and diagnosing its causes.

In what follows, the proposed methodology is presented, and each step of the methodology is discussed in the following subsections.

2.1 | Overview of the methodology

The proposed methodology for condition monitoring and damage diagnostics is depicted in Figure 1. The vibration behaviour (i.e., acceleration) of the bridge is recorded by a measurement system (accelerometers) that is installed on

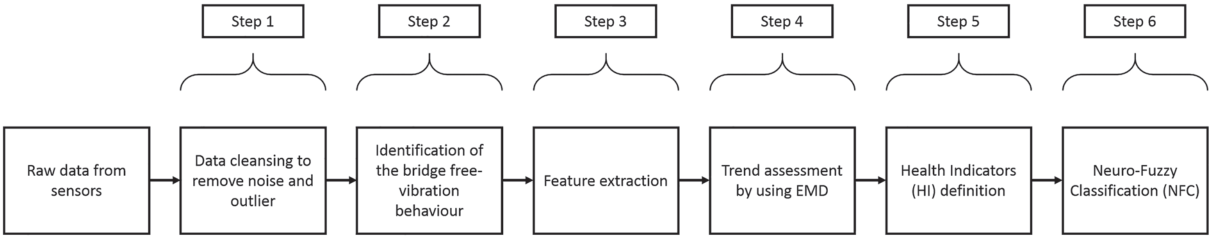

FIGURE 1 Flowchart of the proposed methodology

the bridge infrastructure. Every time when a new set of raw bridge acceleration is provided by the sensors, the raw acceleration is pre-processed with the aim of removing outliers of the data (i.e., the noise) and obtaining the free vibration behaviour of the bridge. The free vibration behaviour of the bridge allows to assess the health state of the bridge by avoiding any potential noise from excitation sources.[47,48] A feature extraction process is then developed, to reduce the dimensionality of the free-vibration bridge behaviour. Indeed, the sensors can provide thousands of values of the bridge acceleration at each time second, whereas features can extract relevant information regarding the bridge health state, by merging the thousands sensor values into a lumped assessment. Statistical features (such as mean value, standard deviation, kurtosis and root mean square), frequency-domain features (such as peaks and amplitudes of the bridge frequencies that are obtained by using the fast Fourier transform [FFT]) and vibration parameters (such as peak ground acceleration, Arias intensity and cumulative absolute velocity) are assessed at each τ time step in order to extract information from the free-vibration behaviour of the bridge.[28,41,49] The assessment of reliable features can be susceptible to the non-stationarity of the bridge vibrations. In fact, the noisy vibrations of the bridge can lead to misleading and noisy features, and thus, a robust and reliable assessment of the bridge health state can be threatened. As a consequence, a further step of data processing is introduced in this paper with the aim of improving the reliability of the health assessment of the bridge, by reducing the noise of the extracted features. Hence, each extracted feature is used as an input to an EMD process with the aim of assessing the trend over time of the feature. Particularly, the residual of the EMD process for each feature is used to evaluate the trend of the feature over time. A set of bridge HIs, which provides information with respect to the level of degradation of the monitored bridge, can be then obtained by calculating statistical parameters (such as standard deviation and skewness) of the trend of extracted features. Before using the data as an input to the NFC, an optimization algorithm is used in order to identify the optimal HIs to monitor and assess the health state of the bridge. In this way, the misleading and noisy features that do not allow to assess the health state of the bridge reliably are not used as an input to the NFC. Finally, the optimal HIs are used as an input to an NFC in order to assess the health state of the bridge automatically.

2.2 | Step 1: Data cleansing

The bridge behaviour is measured by sensors that are installed on the bridge infrastructure. The data provided by the sensors can contain noise due to defective sensors, poor quality of the data transmission from the sensors to the final database, etc.[11] The analysis of such noisy bridge behaviour can lead to false alarms and misleading bridge condition assessment. A data cleansing process (also known as pre-processing) is required to remove noise from the raw bridge behaviour.[4] Several methods are presented in literature to reduce the measurement noise, such as PCA,[50] singular-value decomposition (SVD),[51] wavelet analysis,[52] machine learning method[11] and signal reconstruction process.[53] In this paper, the median filtering statistical process is used to detect and correct outliers, due to its fast and robust analysis in detecting and correcting outliers.[54] Given the data of the raw bridge behaviour X from the sensors and the size of a time interval k, the median filtering process can be defined as follows:

$$\textit{if } |x_i - m_i| > n_{st} \cdot \sigma \;\Rightarrow\; x_i = m_i, \tag{1}$$

where m_i and σ represent the local median and the standard deviation of the data belonging to a time window of size $2\,k+1$, respectively. n_{st} represents the number of standard deviations by which a data x_i of X must differ from the local median to be considered an outlier. The median (m_i) and the standard deviation (σ) are defined as follows:

$$m_i = median(x_{i-k}, x_{i-k+1}, ..., x_i, ..., x_{i+k-1}, x_{i+k}), \tag{2}$$

$$\sigma = \sqrt{\frac{\sum_{j=i-k}^{i+k} \left(x_j - \overline{x}\right)^2}{n-1}}. \tag{3}$$

Equation 1 shows that a value x_i that differs from the median (m_i) by more than n_{st} standard deviations is recognized as an outlier and replaced with the median (m_i) of that time window of size $2k + 1$. The size of the time interval k is defined by the user depending on the nature of the considered case study; e.g., the sampling rate of the sensors influences the definition of k: A higher sampling rate would require a smaller size of k. Indeed, the higher the number of data points provided by the sensors, the higher the number of possible outliers that can influence the assessment of the local median (m_i). The number of standard deviations (n_{st}) that defines the acceptable deviation of a point from the local median is defined by the user, according to the chosen confidence interval.[11]

2.3 | Step 2: Identification of the bridge free-vibration behaviour

The free-vibration behaviour of the bridge is analysed with the aim of assessing the bridge health state. The forced vibration response of the bridge is not considered due to the fact that (i) the robustness of the extracted feature can decrease due to highly non-stationary and usually quite short duration of the forced vibration and (ii) the assessment of the bridge health state can be influenced by the excitation source, which can give a misleading condition assessment.[47,48] The bridge free-vibration, which can be defined as the vibration of the bridge that decays in an approximately exponential form following an external excitation, can be extracted from the vibration data by analysing the available information: (i) If a bridge is excited by a moving vehicle, the free-vibration behaviour can be identified by knowing when the vehicle leaves the bridge,[47] and (ii) if the bridge is excited by changing environmental condition, such as wind, the free-vibration behaviour of the bridge can be identified as the decreasing bridge vibration behaviour that follows a peak value of the bridge vibration behaviour.[55] This second approach can also be used when information about moving vehicles is not available. Finally, it should be noted that free-vibration data can be time consuming to be extracted when a bridge is stressed by heavy traffic. However, in this case two solutions are possible, (i) the free-vibration can be extracted when the traffic on the bridge is light or absent, and (ii) the free-vibration extraction is automated, as shown in Section 3.1.1.

2.4 | Step 3: Feature extraction

Large data storage capacity and high computational power are required to efficiently store and analyse the data provided by the sensors: Each sensor provides N values of the bridge behaviour for each second; i.e., each sensor has a sampling rate of N Hz.[41] Conversely, the dimension of the bridge behaviour data can be reduced into more valuable information, with respect to the bridge health state, by extracting features from the acceleration data. For this reason, 18 features are extracted from the free-vibration behaviour of the bridge every τ seconds, by reducing the dimensionality of the data from $N \bullet \tau$ to 18 for each sensor; i.e., every τ seconds, the 18 features are evaluated for each sensor and stored to monitor the evolution of the bridge condition over time. τ can be defined by optimizing the accuracy of the NFC during the training phase. The features are extracted from both time domain (such as mean value and standard deviation) and the frequency domain by using an FFT approach (such as amplitude and peak of the first harmonic). In this way, statistical, frequency-based and vibration parameters of the bridge are evaluated in order to assess the health state of the bridge. In fact, changes in statistical and vibration features of the bridge behaviour can identify a damage of the bridge structure: An increase of the bridge vibration behaviour can be caused by a reduction of bridge stiffness, which leads to a lower structural ability in resisting to external excitation in a static and stable manner.[28] Similarly, a change in the frequency-based feature, which estimates modal and vibration characteristics of the bridge, can represent changes in bridge physical characteristics, such as stiffness and mass.[33,37,40] Furthermore, the statistical features can be influenced by noisy measurement of the bridge acceleration, and consequently, the robustness of the bridge health state analysis can be improved by introducing a heterogeneous set of features (i.e., statistical, frequency-based and vibration parameters), alongside the data cleansing process. The 18 features are chosen due to their ability in describing the health state of a system during different system health states.[28,41]

The 18 features are defined as follows in Table 1.

2.5 | Step 4: Assessment of the features trend

The extracted features contain information about the health state of the bridge; however, the assessment of the health state of the bridge can be jeopardized by the high level of oscillations in the features. For example, Mosallam et al.[41] and Cannarile et al.[58] have shown that a robust and reliable assessment of the system health state can be threatened if noisy features are evaluated. Similarly, the assessment of the bridge health state can be threatened by evaluating features that show oscillation. Hence, in this paper, a further step of data processing is introduced, which consists of using the extracted features as an input to the EMD process. The EMD is able to provide a smooth monotonic trend of the features, and as a consequence, the health state of the bridge can be identified more clearly. In fact, the extracted features are expected to provide information about the health state of the bridge (e.g., when the stiffness of the bridge decreases, a reduction of the bridge frequency is expected). However, the continuous assessment of the features every time interval τ can be impacted by the noise of the recorded in-field bridge behaviour. A reliable assessment of the bridge health state can be then threatened by relying on the extracted features directly (e.g., when the stiffness of the bridge decreases, the decrease of the bridge frequency might not be pointed out clearly due to noise of the data). Therefore, when the features that are extracted during an interval $[0, \tau^*]$ are used as an input to the EMD process, the feature trend over time is evaluated by relying on the residuals of the EMD: As a consequence, a more reliable assessment of the health state of the bridge can be achieved (e.g., the decreasing trend of the bridge frequency can be pointed out by the EMD residuals, when the bridge stiffness is decreasing). The interval $[0, \tau^*]$ is chosen to monitor the health state of the bridge continuously; i.e., the trend of the features is evaluated and updated every τ^* interval, when new features are extracted from the free vibration of the bridge. The value of τ^* can be identified by maximizing the accuracy of the NFC during the training process.

The EMD is a data-driven decomposition method that is able to decompose the feature pattern (F) in the interval τ^* into multiple simple harmonics of various frequencies, called Intrinsic Mode Functions (IMFs) [30n]. The process to obtain the IMFs is known as shifting process, and it is performed until a monotonic function remains or a stopping criterion is reached. This final time series is known as residuals (r) which represent the trend of the decomposed feature pattern. In this paper, the shifting process of the EMD is stopped when the difference between residuals of successive IMFs is lower than a predetermined threshold, which equal to 0.2.

TABLE 1 Features extracted from the processed acceleration data

Statistical features	Frequency-based features	Vibration-based features
Mean value	Peak of first harmonic	Cumulative velocity of the bridge
Standard deviation	Amplitude of first harmonic	Peak ground acceleration
Skewness	Mean period of the bridge beaviour[22] $T_m = \frac{\sum_i A_i^2 \left(1/f_i \right)}{\sum_i A_i^2} \quad for\, 0.25Hz \leq f_i \leq 20Hz$ (4)	Peak ground displacement
Kurtosis	Mean frequency of the bridge behaviour	ARIAS[56] $I_A = \frac{\pi}{2g} \int_0^t a(t)^2 dt$ (5)
Root mean square (RMS)		Damage Potential Indicator (DPI)[57] $D_{pi} = \frac{\frac{\pi}{2g} \int_0^t a(t)^2 dt}{v_0^2}$ (6)
Median		Cumulative Absolute Velocity (CAV) $CAV = \int_0^t \lvert a(t) \rvert^2 dt$ (7)
Coefficient of variation		
Euclidean norm		

The EMD decomposition can be represented as shown in Equation 8: The feature pattern, denoted as F, in the interval τ^* is decomposed into multiple IMFs (h_i) and a residual curve (r).

$$F = \sum_{i=1}^{M} h_i + r, \tag{8}$$

where M is the number of IMFs.

2.6 | Step 5: Definition of health indicators

The trend of the proposed feature over time provides information about the health state of the bridge by pointing out such information from the noisy extracted features. The residual of the EMD can be lumped into a set of HIs, which represent the health state of the bridge by merging a number of parameters.[41] The HIs are defined by evaluating two statistical parameters of each feature trend: (a) the standard deviation of the trend (HI_1), in order to take account of the variability of the feature trend, and (b) the normalized cumulative sum of the feature trend (HI_2), to take account of the positive/negative monotonicity of the feature trend. A set of 36 HIs (18 feature trends and 2 statistical parameters for each trend) is computed each time τ^* when a new assessment of the feature trend is carried out.

2.7 | Step 6: The NFC

The NFC is adopted due to its stable performance when the parameters (e.g., the number of cluster of the K-means clustering algorithm) are modified, and due to its ability of merging fuzzy classification techniques with the learning capabilities of a neural network. The NFC requires a database of historical behaviour of the bridge in different health states, in order to perform the training process. The NFC is trained by using a supervised process; that is, the health state of the bridge is known when the database of bridge behaviour is analysed. The NFC is trained with the HIs values that represent each health state experienced by the bridge. In this way, when a new set of unknown HIs is available, it is used as an input to the NFC, which is able to assess the health state of the bridge automatically. Not all the HIs contain valuable information about the health state of the bridge. An HIs selection process is necessary to find, among the HIs, a subset of optimal HIs that are informative with respect to the health state of the bridge.[44] In what follows, the main steps of the NFC are presented in Section 2.7.1, whereas the HIs selection process is presented in Section 2.7.2.

2.7.1 | The main steps of the NFC

The detail description of the NFC is out of the scope of this paper, and an interested reader can find more information in Cetişli and Barkana.[31,43] An example of the NFC structure is depicted in Figure 2, for an NFC with 3 fuzzy rules (clusters of the K-means algorithm) and two classes. In what follows, the main steps of the NFC (Figure 2) are presented:

1. A database of set of HIs is used as an input to the NFC. A supervised training process is carried out in this paper.
2. A K-means clustering method is applied to the HI data of each class with the aim of defining fuzzy if-then rules.
3. The weight of each cluster of each class is assessed by evaluating the ratio between the size of each cluster with respect to the size of that class.
4. A Gaussian probability density membership function is defined for each cluster, by using the centre of each cluster as the mean value of the Gaussian distribution, whereas the standard deviation of the membership function is equal to the standard deviation of the HIs that belong to that cluster.
5. A fuzzification process is developed by assessing the membership value of each HI to each Gaussian probability distribution.
6. A defuzzification and normalization process is finally carried out in order to assign each HI to a class; i.e., each HI is assigned to the class with the higher membership value.

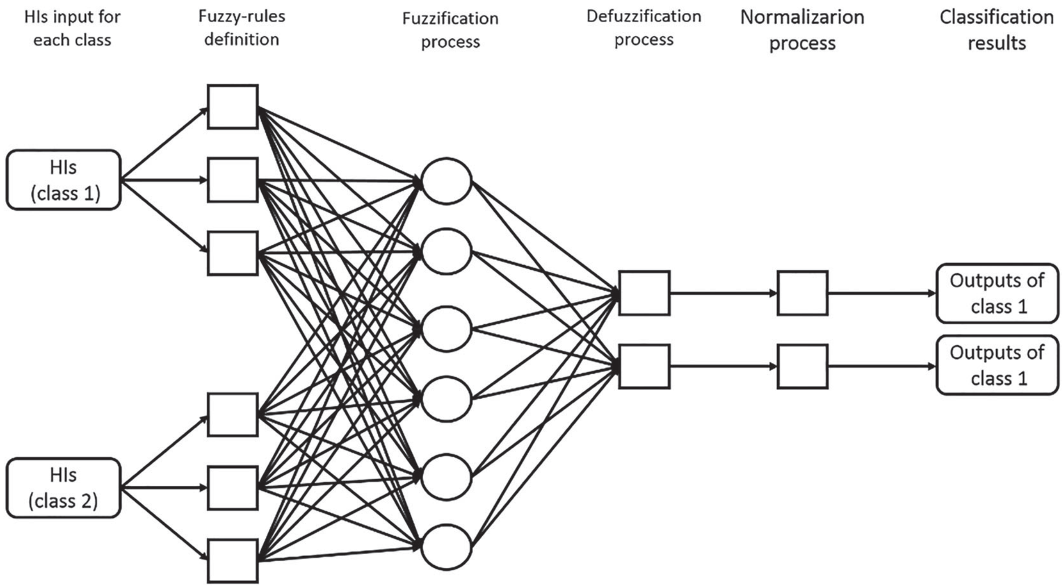

FIGURE 2 Example of NFC algorithm

7. The accuracy of the process is assessed, by counting the number of correct classifications, i.e., the number of HI values that have been assigned to the correct class.
8. The performance of the NFC is assessed by computing an objective function, which represents the inverse of the accuracy of the NFC. Steps 4 to 7 are repeated iteratively with the aim of minimizing the objective function, maximizing the accuracy of the NFC and identifying the optimal value of the mean and standard deviation of the membership functions.

When the training process of the Neuro-Fuzzy classifier is complete, the NFC can be tested on a new and unknown set of bridge behaviour data. The testing process is also used to select the optimal subset of HIs that allows to maximize the accuracy of the NFC.

2.7.2 | The HI selection process using an optimization algorithm

The accuracy of the NFC is influenced by the quality of the HIs, because some of the 36 HIs can be redundant or non-informative in respect to the health state of the bridge.[44] An HI selection process is carried out to find a subset of HIs that guarantee high accuracy of the NFC, by minimizing false alarms and the degree of misclassification. An optimization algorithm is adopted by using a Modified Binary Differential Evolution (MBDE) algorithm.[42] The optimization algorithm allows to select a subset of HIs iteratively and assess the accuracy of the NFC by using only the selected subset of HIs as an input to the NFC both during the training and testing phase, as shown in Figure 3. A multi-objective optimization process is performed to minimize the fitness function, which is defined as follows:

$$fit = \left\{ \left(\frac{\sum_{i=1}^{T_{Train}} \left(L_{Real}^{Train} - L_{NFC}^{Train} \right) \times 100}{T_{Train}} \right)^{-1}, \left(\frac{\sum_{i=1}^{T_{Test}} \left(L_{Real}^{Test} - L_{NFC}^{Test} \right) \times 100}{T_{Test}} \right)^{-1} \right\}, \tag{9}$$

where T_{Train} and T_{Test} represent the size of the target vectors for the training and test processes, respectively and L_{Real}^{Train} and L_{Real}^{Test} represent the real health state of the bridge for each bridge behaviour belonging to the training and testing target vectors, respectively. L_{NFC}^{Train} and L_{NFC}^{Test} represent the health state assigned to each bridge behaviour by the NFC during the training and testing process, respectively. Equation 9 shows that the fitness function is minimized when the

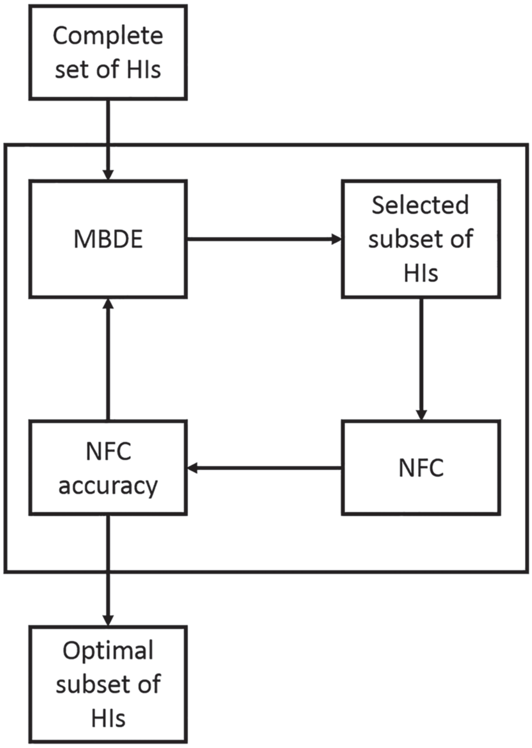

FIGURE 3 Optimization algorithm to select the optimal HIs

performance of the NFC is maximized; i.e., the higher the number of correct classification of the NFC, the lower the value of the fitness function. The training process is carried out in a supervised manner, whereas the test process is carried out by analysing a new and unknown set of bridge data. The optimization algorithm proceeds iteratively until a maximum number of iterations are reached, the accuracy of the NFC is maximized and the optimal subset of HIs is fixed. The optimal set of HIs can then be used to validate the proposed NFC, by monitoring the health state of the bridge when new and unknown behaviour of the bridge is provided by the sensors.

It is worth noting that if the data for different health states are not available at the beginning of the analysis, the proposed NFC method can be still adopted by relying on (i) the HIs for identifying different classes of the bridge health state and train the NFC accordingly; (ii) an FEM model to simulate the bridge behaviour in different health states and (iii) an initial training of the NFC that relies mainly on the healthy behaviour of the bridge, and subsequent retraining of the NFC every time when a new health state of the bridge is identified by the NFC via outliers. In this case, however, the NFC training can be imbalanced due to a large number of healthy measurement data, in comparison to those in other states. Therefore, the performance of the NFC algorithm can be evaluated considering multiple parameters, such as its accuracy, precision and recall.

In the next sections, the proposed methodology is tested in monitoring and assessing the health state of an in-field bridge.

3 | APPLICATION OF THE PROPOSED METHODOLOGY

The performance of the proposed data-driven methodology is verified by monitoring and assessing the health state of a posttensioned concrete bridge.[46] The bridge is subjected to a damage test; i.e., the infrastructure of the bridge is intentionally damaged in order to study how the bridge behaves in different health states. The posttensioned concrete bridge is excited by changing environmental conditions. The aim of the proposed methodology is to monitor the behaviour of the bridge and detect and diagnose its damage.

The results of the proposed methodology are presented and discussed in the subsection of Section 3.1.

3.1 | Analysis of the posttensioned concrete bridge

The posttensioned concrete bridge has the main span of 32 m, side spans of 12 m, and its width is 6.6 m (Figure 4a). The bridge was subject to a vibration measurement test before being demolished in order to obtain the bridge behaviour in different health states. The acceleration of the bridge was monitored by a measurement system made of two reference sensors and four sensors that were moved periodically along the bridge length to obtain a complete modal description of the bridge. In this paper, we consider the acceleration provided by the two reference sensors, which were kept fixed throughout the duration of the test. The sampling rate of the sensors was 100 Hz, and they were installed at location shown by circles in Figure 4b. The main excitation source of the bridge was due to changing environmental conditions, such as wind and the traffic passing on the highway underneath the bridge. A progressive damage test was performed by cutting a pier of the bridge, as shown in Figure 4c. A detailed description of the damage test can be found in Siringoringo et al.[46] The bridge acceleration of six different classes of the bridge health state were monitored (Figure 4c):

- Class 1: The undamaged (healthy) condition of the bridge was monitored for 50 min.
- Class 2: The pier was cut by 5 cm, and a steel column was installed to have a temporary support of the bridge, while studying different damage scenarios. This state was monitored for 5 min.
- Class 3: The pier was cut by five additional centimetres, and the bridge health state during this scenario was monitored for 20 min.
- Class 4: The steel column was lowered by 1 cm, and the bridge deck was settled at 1 cm lower of its starting position. This scenario was monitored for 20 min.
- Class 5: The steel column was further lowered by 1 cm, and the bridge deck was settled at 2 cm lower of its starting position. The acceleration of the bridge during this scenario was recorded for 50 min.
- Class 6: The steel column was lowered by 3 cm, and the bridge deck was settled at 2.7 cm lower of its starting position. The bridge acceleration was monitored during this scenario was recorded for 20 min.

The behaviour of the bridge in the different scenarios was recorded for different time intervals. For this reason, Class 2 is not considered in this paper due to the low amount of data available, which does not allow to adequately

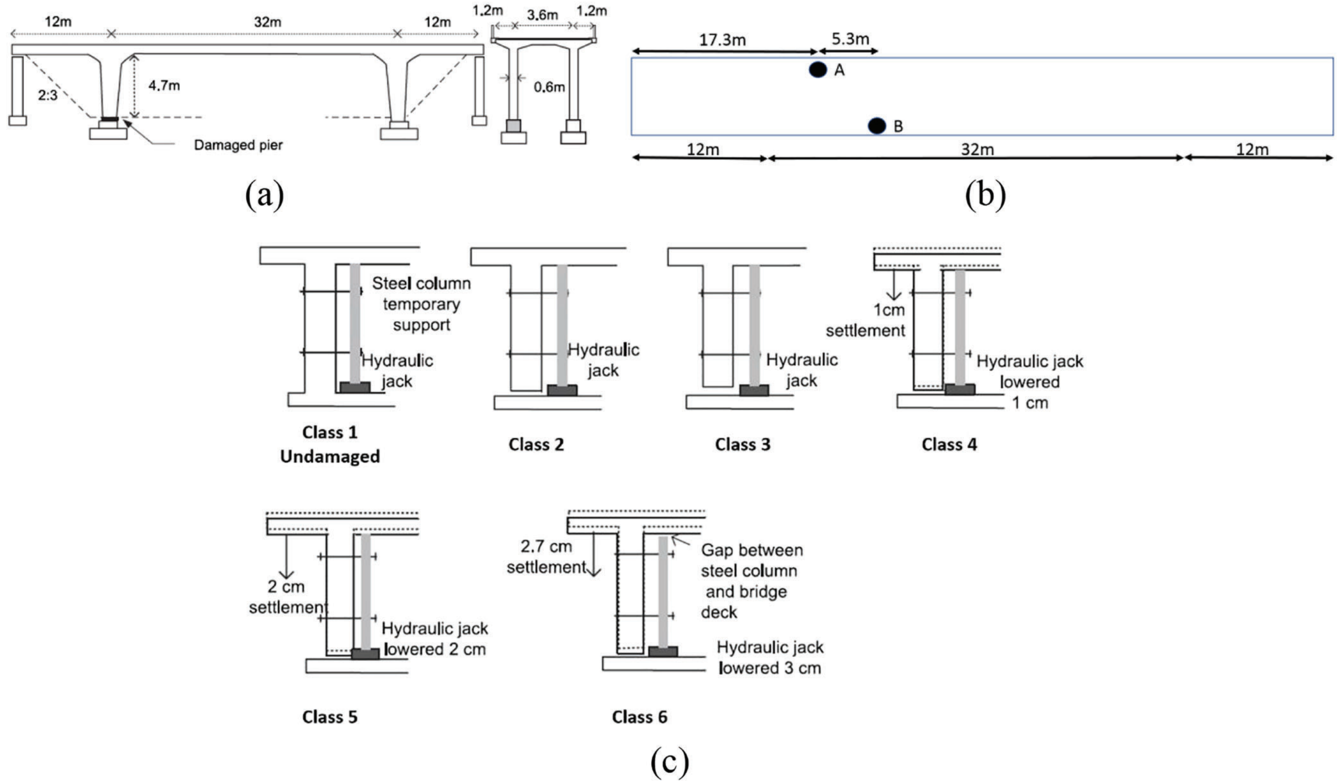

FIGURE 4 The posttensioned concrete bridge[46]

train, test and validate the NFC. Furthermore, 20 min of acceleration data is considered for each remaining class, in order to analyse scenarios that have the same amount of data and to verify the ability of the proposed method in identifying different health states of the bridge. The retrieved database of bridge behaviour is divided in three smaller groups of data: (a) the first group (group 1) contains 10 min of data and is used to train the NFC; (b) the second group (group 2) is made of 3 min of data, and it is used to test the NFC and select the optimal set of HIs in order to monitor the health state of the bridge; (c) the third set of data (group 3) made of 7 min of data, which are used to verify the proposed methodology. This third group of data is not labelled; i.e., the class of the data is not known a priori, and thus, the ability of the proposed NFC in assessing the health state of the bridge automatically is verified.

Finally, all groups of data are used as an input to the proposed methodology, in order to remove the data noise (step 1), extract the features (step 2), define the features (step 3) and their trend (step 4) and compute the bridge HIs set (step 5). Then, the HIs are used as an input to the NFC that assesses the health state of the bridge (step 6).

3.1.1 | Steps 1 and 2: Data cleansing and free-vibration bridge behaviour identification

The bridge is excited randomly by unknown changes in wind and traffic, which is passing on the road under the bridge. As a result, the bridge acceleration can show sudden spikes due to external unknown sources of excitation. For example, Figure 5 (top) shows the raw data of the bridge acceleration provided by a sensor during a time interval of 300 s. The raw acceleration shows high level of noise, such as sudden increases and spikes, e.g., the spike at time 240 s, where the acceleration of the bridge reaches 10 cm/s^2 for few measurements before returning to an equilibrium position. The noise of the acceleration is reduced by applying the median filtering statistical process, presented in Section 2.2. Figure 5 (bottom) shows the processed acceleration of the bridge, i.e., after the outlier removal process. The response of the bridge to external excitations is not changed; i.e., the induced acceleration of the bridge is not changed in terms of time position, but rather, the noise of such induced acceleration is reduced.

The next step (step 2) of the methodology aims to identify the free vibration of the bridge, with the aim of analysing the bridge behaviour without considering the potential influence in the external excitation source. The free vibration of the bridge is identified by looking for peaks in the acceleration. In fact, when an external force excites the bridge, the bridge usually shows its maximum vibration when the external force is acting (or just acted) on the bridge, whereas the bridge behaviour decays by following an exponential function when the action of the external force is ended. Figure 6 shows the typical behaviour of the bridge when an external force acts on the bridge structure: The bridge is in an equilibrium position up to 2 s, then an external force excites the bridge and the acceleration of the bridge increases. When the influence on the bridge is over, the acceleration decreases towards the equilibrium point. The dots in Figure 6 represent the extreme values of the bridge acceleration, which are removed from the acceleration data; i.e., the acceleration

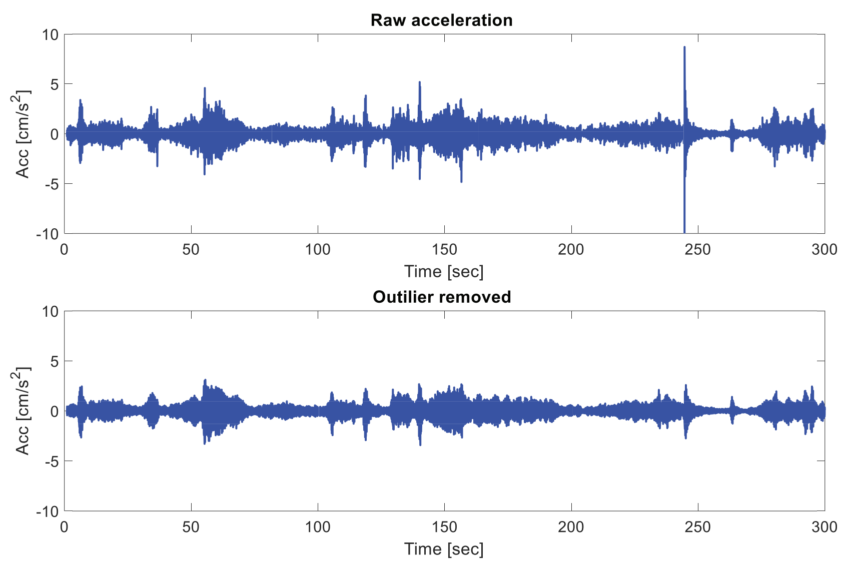

FIGURE 5 Raw and processed acceleration of the bridge

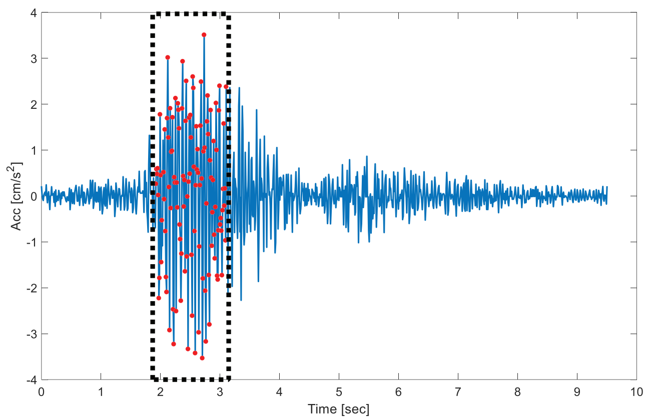

FIGURE 6 Identification of the bridge free-vibration behaviour

data within the dotted-box are removed. In this way, any potential effect from the external source of vibration is not considered in the assessment of the bridge health state.

3.1.2 | Step 3: Feature extraction

The feature extraction process allows to extract the valuable information about the health state of the bridge from its free-vibration behaviour. Therefore, the 18 features are extracted from the free-vibration behaviour of the bridge every τ seconds. For example, Figure 7 shows the evolution over time of three (out of 18) features, when τ is equal to 3 s, and 10 min of data for each class is considered. The value of τ is optimized during the NFC training process, as shown in Section 3.1.4. The three features in Figure 7 represent a statistical feature (kurtosis), a frequency-based feature (frequency of the first harmonic) and a vibration feature (Arias intensity). Each class of the bridge health state is depicted in Figure 7, by the means of (i) a cross-marked line to represent class 1 (healthy state of the bridge); (ii) a circle-marked line to represent class 3; (iii) a dot-marked line to represent class 4; (iv) a diamond-marked line to depict class 5 and (v) a square-based line to show class 6. Although the features show some outliers when the bridge is damaged, on average, the three features of the different classes are overlapping and noisy, and they have a high level of oscillations. A robust and reliable assessment of the bridge is not possible by analysing such features directly. For this reason, a further step of data processing is introduced by using the EMD, in order to retrieve the HIs of the bridge.

3.1.3 | Steps 4 and 5: Feature trend and HI definition

The trend of the features during an interval $[0, \tau^*]$ is assessed by using the features as an input to the EMD process. The trend of the features is then lumped into the two HIs of the bridge health state, presented in Section 2.6. Figure 8 shows the evolution of the two HIs of the three features depicted in Figure 7, when τ^* is equal to 20 τ. Particularly, Figure 8a shows the HIs that are extracted by using the kurtosis of the vibration of the bridge as an input to the EMD; Figure 8b shows the HIs that are retrieved from the trend of the first harmonic of the bridge; Figure 8c shows the HIs that are defined by using the Arias intensity of the bridge as an input to the EMD. It worth noting that the HIs allow to identify the different classes of the bridge health state clearly, particularly the HIs of the kurtosis in Figure 8a allow to point out the different health states of the bridge. Therefore, the use of the EMD to extract the trend of the statistical, frequency-domain and vibration-based features, which is the main novel aspect of the proposed methodology, is able to point out the different health states of the bridge in a clear and well-separated manner. At the same time, however, some HIs are not able to identify the different bridge health states (e.g., HIs of Arias intensity Figure 8c shows almost a constant value throughout the monitored interval). Therefore, an accurate assessment of the bridge health state might not be achieved by monitoring the evolution of such an HI. This latter result explains the reason why an HI selection process in needed during the testing step of the NFC. Indeed, the HI selection process allows to identify a subset of HI that

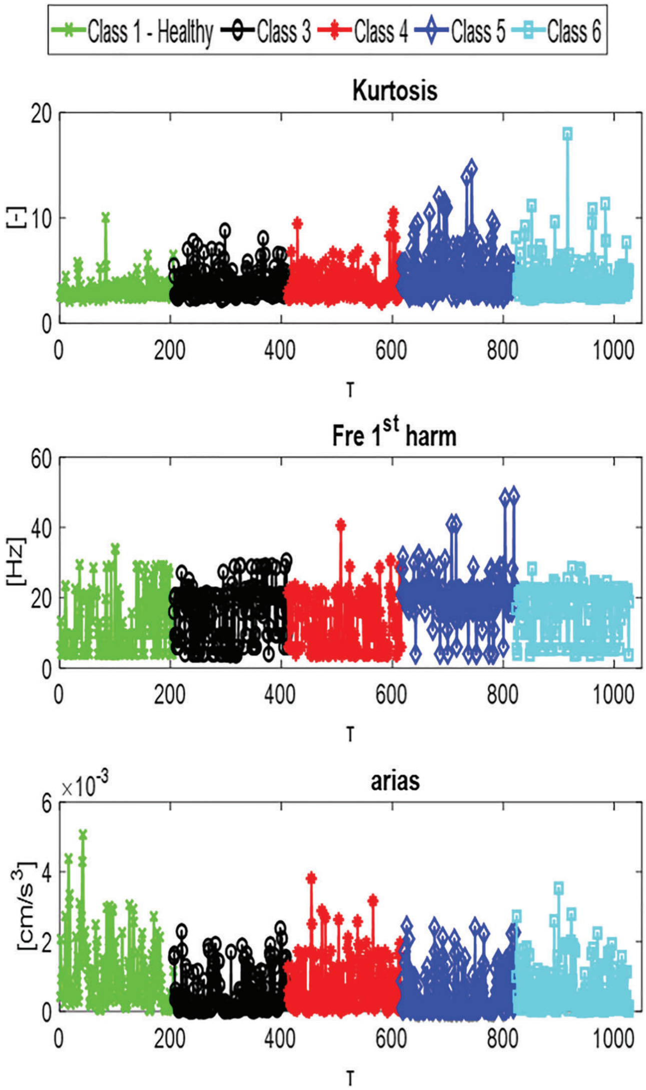

FIGURE 7 Example of feature extracted from the free-vibration behaviour of the bridge

optimize the accuracy of the NFC in evaluating and monitoring the health state of the bridge. In this way, non-informative HIs that lead to misclassifications of the bridge health state are not considered.

3.1.4 | Step 6: NFC for automatic assessment of bridge health state

NFC training

The NFC is adopted in order to automatically assess the health state of the bridge, by analysing the extracted HIs. The data of group 1 are used to train the NFC in a supervised manner; i.e., the health state of the bridge during the training process is known, and it is used as target results for the NFC. The training process aims to set the NFC parameters (number of clusters, mean and standard deviation of the Gaussian membership functions) to optimize the accuracy of the classification process. The number of clusters is assumed to be equal to the number of classes (5) in this case, and it is kept constant during the analysis. At the same time, the parameters τ and τ^* are optimized during the training process: the HIs of the data in group 1 are used as an input to the NFC by modifying either τ or τ^*, as shown in Figure 9. For example, when τ^* is equal to 30 τ, the NFC shows higher accuracy. The highest accuracy is achieved when τ is equal to 2 s, which is chosen as the optimal τ. The optimal values of τ^* and τ are then used for the HIs selection process, to train the NFC with a dataset of 100 values of each HIs and to monitor the health state of the bridge.

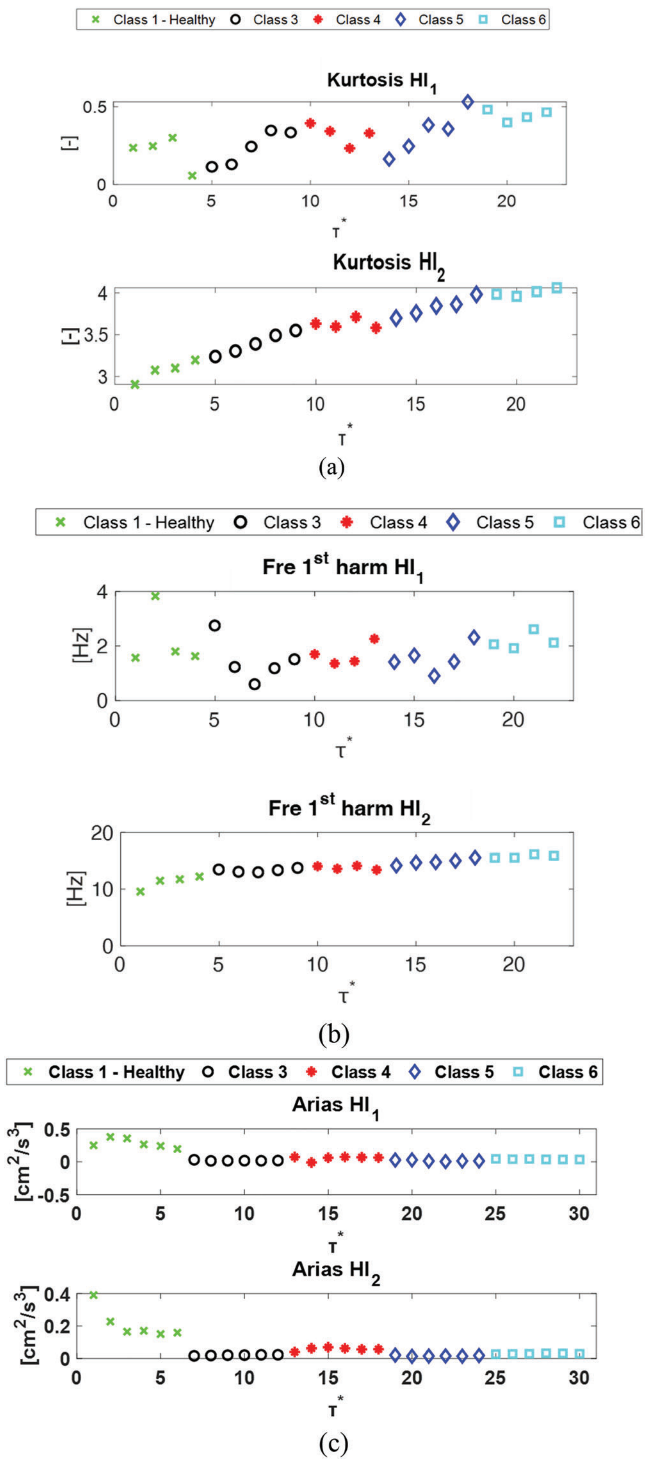

FIGURE 8 HIs evolution of the features showed in Figure 7

HI selection process

The selection process of the HIs is carried out by adopting the MBDE optimization algorithm, presented in Section 2.7.2. The MBDE performs an iterative optimization by selecting a subset of HIs and evaluating the NFC performance by using the selected subset of HIs as an input to the NFC during both training and testing phases. The testing process is performed by using unlabelled data of group 2, which are used as an input of the proposed method in order to assess the HIs values during these time intervals. The iterative process of the MBDE terminates when a maximum number of 2,500 iterations is reached. The MBDE parameters (weighting factor, control parameter and size of the population[42])

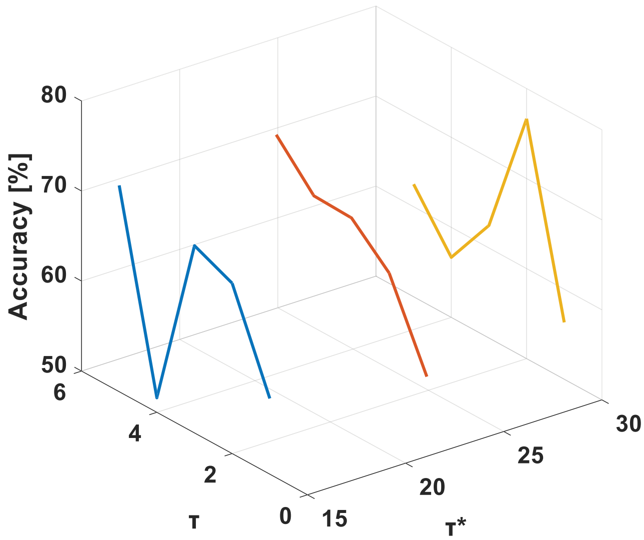

FIGURE 9 τ and τ* optimization process.

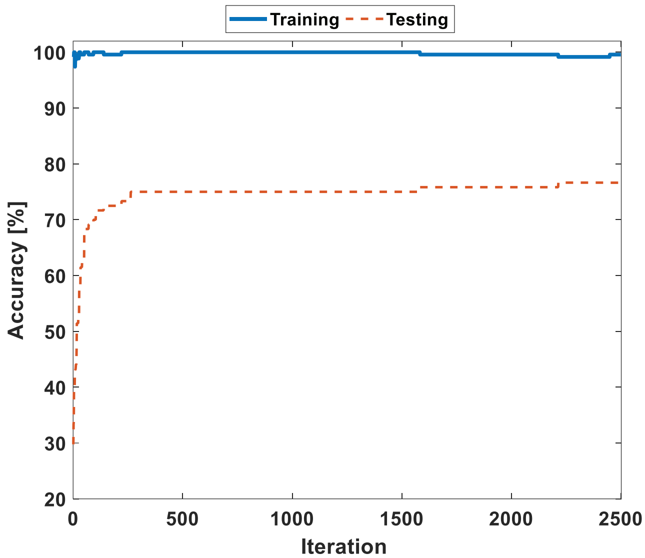

FIGURE 10 Evolution of the fitness function during the HIs selection process

are chosen by performing a trial and error procedure and are equal to 0.8, 0.3 and 20, respectively, whereas 2,500 iterations are chosen as trade-off between the high computational-time required by the MBDE and the number of iteration performed.

The evolution of the inverse of the fitness function of Equation 9 is depicted in Figure 10: The higher the number of iterations, the higher the accuracy of the NFC (the lower the fitness function of the MBDE). Therefore, the MBDE is able to select subsets of HIs that lead to an improvement of the NFC accuracy. The dotted line in Figure 10 shows the improvement in the performance of the NFC during the testing phase: The accuracy of the NFC during the first iteration of the MBDE, when the subset of HIs is randomly selected by the MBDE, is 27%, whereas at generation 2,500, it is 77%, due to the MBDE search that is able to select the possible optimal HIs. Furthermore, the dotted line in Figure 10 shows a rapid increase of the NFC accuracy during the first 400 iterations, which is followed by a ca. 1,000 iterations that do not improve the accuracy of the NFC. This result can be due to the definition of the MBDE parameters that lead the optimization research into a local minimum of the fitness function. The local minimum is erroneously identified as a global minimum of the MBDE fitness function, and the population of the selected HIs is slightly modified during these iterations. However, at iteration 1,500, the MBDE is able to leave the local minimum, and the NFC accuracy increases accordingly. Finally, at iteration 2,300, a new subset of HIs that allows to increase the accuracy of the NFC is found.

The accuracy of the NFC during the supervised training phase is always close to 98%. This latter performance of the NFC can be explained by considering the fact that, for each subset of HIs chosen by the MBDE, the NFC is able to set the value of its parameters in order to optimize the classification of the data during the training phase. The optimal subset of HIs is identified during the testing phase, as shown in Figure 11. The optimization algorithm, which is implemented in Matlab, requires 1 h and 10 min to be completed by using an Intel core i3–4130 with CPU @ 3.4 Hz.

Figure 11 shows the subset of selected optimal HIs (shadowed areas in Figure 11). HI_1 is the most selected HI by being selected for 6 features (out of 18), and HI_2 is selected for 5 features. This result of two HIs is expected due to the fact that both HIs show good performance in identifying the different health states of the bridge, as shown in Figure 8. Particularly, Figure 11 shows that the optimal HIs are related to those extracted features that are able to capture the effect of the reduction of stiffness caused by the inflicted damages: increase of the bridge vibration and reduction of the bridge frequency. For example, the HIs of the kurtosis (4) and those of the amplitude of the first harmonic (11) are selected among the best HIs for assessing the health state of the bridge. The kurtosis HIs represent an increase of the outliers of the bridge acceleration, which can be expected due to the cut of the pier of the bridge. Similarly, the HIs of the amplitude of the first harmonic represent a change in bridge frequency, which can be caused by the reduced stiffness of the bridge.

It should be noted that the set of the 36 HIs is comprehensively represented by 2^{36}–1 possible combinations, and the MBDE might not have reached the best subset of HIs due to the large number of possible combinations of the HIs. However, the optimal subset of HIs in Figure 11 is identified by reaching a balance between computational time and accuracy of the NFC. This subset of HIs of Figure 11 is used to verify the proposed methodology in analysing unknown and unlabelled data of the bridge behaviour.

3.1.5 | Results of the proposed methodology for bridge condition monitoring and damage diagnostics

The unlabelled data of group 3 are used to verify the accuracy of the proposed methodology. The acceleration of the bridge of group 3 is used in the methodology in the chronological order, i.e., the 7 min of acceleration of the healthy bridge (class 1), followed by the 7 min of acceleration of class 3. In this way, the real-time monitoring of the bridge is

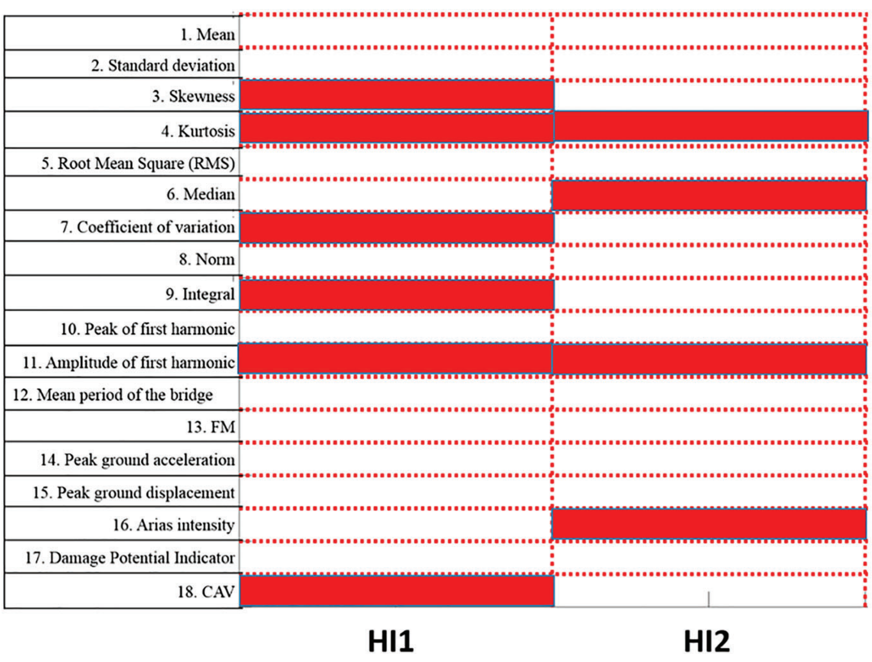

FIGURE 11 Selected HIs by using the optimization algorithm for bridge condition monitoring and damage diagnostics

simulated. A dataset of 70 values for each optimal HI is used to assess the performance of the NFC. The accuracy of the methodology is assessed by comparing the health state of the bridge assigned by the NFC with the real bridge health state.

Table 2 shows the results of the accuracy of the NFC as a condition monitoring and diagnostic tool. The overall accuracy of the NFC is 78.3%; i.e., 78.3% of the considered scenarios of group 3 are correctly identified by the proposed NFC. The lowest accuracy of the NFC is obtained for classes 3 and 5, i.e., the fully cut of the pier and when the pier is fully cut and the deck is settled 2 cm lower of its starting position, respectively. The fully cut of the bridge pier (class 3) is correctly recognized with 66.67% accuracy, and as a result, 37.4% of class 3 scenarios are misclassified as class 4 scenarios. Class 5 is misclassified 41.6% of times to be either class 3 or 6. Therefore, the NFC is able to identify the damage of the bridge structure; however, some misclassifications of the nature of the damage are shown due to small changes of the bridge structural behaviour during these scenarios, i.e., a small loss of stiffness of the bridge, as pointed out by the modal analysis of the bridge by Siringoringo et al.[46]

Table 2 suggests that the proposed NFC can be used as both bridge condition monitoring and damage diagnostic tool, in order to identify anomalies in bridge behaviour and point out their causes. In fact, the accuracy of identifying the presence of the damage is higher than 90% (class 1), whereas the nature of the bridge damage is correctly identified 75% of times (average of results for classes 3 and higher).

3.1.6 | Discussion of the results

The proposed data-driven methodology allows to monitor the health state of the posttensioned concrete bridge by relying on the data analysis of its vibration behaviour. Statistical, frequency-based and vibration-based features are extracted from the data, and the trend of these features is assessed by the means of the EMD approach. HIs of the bridge are evaluated by computing four statistical parameters of the features trend. Different health states of the bridge are identified by the proposed HIs, and therefore, the NFC method is developed to automatically assess the health state of the bridge by relying on the assessment of an optimal subset of HIs. The NFC for bridge condition monitoring and damage diagnostics, i.e., where both the healthy and damaged states of the bridge are monitored, showed a good accuracy in identifying and diagnosing the damages of the bridge structure automatically. It should be noted that an overall accuracy of 78.3% is a good result in monitoring the health state of an in-field bridge due to the unknown source of uncertainty and changing environmental conditions. Indeed, similar machine learning methods, which are based on ANNs and verified on FEMs by adding white Gaussian noise to the simulated bridge behaviour, have shown an average accuracy of 65%,[21,22,59] whereas clustering techniques, which were verified on in-field bridges, have shown an average accuracy of 68%, with a maximum accuracy of 75%.[14] At the same time, Siringoringo et al.[46] performed a modal analysis of the bridge during each health state of the bridge and showed that the modal parameters of the bridge are slightly modified by the first inflicted damages (classes 2 to 5), whereas the most severe damage (class 6) modify the modal parameters of the bridge significantly, and as a consequence, it is possible to identify such damage clearly and the accuracy for class 6 is high.

The performance of the NFC strongly depends on the quality and amount of data available for the training process, which is limited in this case study. As a consequence, the performance of the proposed NFC is expected to improve by increasing the size and quality (in terms of different behaviour of the bridge) of the training set (group 1). Similarly, the performance of the proposed methodology is expected to increase if the number of both extracted features and HIs is reduced, by considering only the most informative features. In this way, the number of possible combinations of HIs is reduced, and the MBDE can identify the best subset of HIs in a shorter time period.

Finally, it is worth mentioning that the main novelty of the proposed methodology, i.e., the use of the EMD to assess the trend of the extracted features, is the ability to identify and diagnose different health states of the bridge by providing the NFC method with HIs that separate well the behaviour between the different states of the bridge.

TABLE 2 Performance of the NFC for bridge condition monitoring and damage diagnostics

Case study	Overall accuracy	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Condition monitoring and diagnostics	78.3%	91.67%	n/a	66.67%	83.33%	58.34%	91.67%

4 | CONCLUSION

Large amounts of data are generated by SHM techniques that are adopted to monitor the behaviour of bridges. Therefore, data-driven methods can allow to assess the health state of the bridge automatically, accurately and rapidly. Although data-driven methods have been presented in the literature, these methods are often verified on an FEM, which usually do not consider all the data noise and uncertainties affecting an in-field bridge. In this paper, a data-driven methodology has been presented by analysing an in-field posttensioned concrete bridge, which is subjected to a progressive damage test. First, the proposed methodology is used to remove outliers from the raw vibration behaviour of the bridge and to identify the free-vibration behaviour of the bridge. Then, HIs of the bridge can be assessed by computing the trend over time of statistical, frequency-based and vibration-based features, which have been extracted from the free-vibration behaviour of the bridge. The trend of the extracted features is assessed by adopting the EMD method. The proposed HIs extraction method has shown the ability to identify different health states of the bridge. Finally, the NFC method has been introduced to automatically assess the health state of the bridge by relying on the analysis of an optimal subset of HIs, which has been identified by using a MBDE optimization algorithm. The NFC has shown good performance in bridge condition monitoring and damage diagnostics. It must be noted, however, that bridge behaviour data in known healthy and degraded states are needed in order to train the NFC method with a supervised approach. This source of bridge behaviour data might not be easily accessible for in-field monitoring of a new bridge. In this case, the NFC method can be adopted by following one of the two approaches: (i) The NFC can be trained by using an unsupervised approach; i.e., the behaviour of the bridge in different health states of the bridge is not known, and the proposed method is adopted to automatically point out the different health states; (ii) an FEM of the bridge can be developed to simulate the expected behaviour of the bridge in healthy and degraded bridge states, and thus, the NFC can be trained accordingly. It is expected that in the unsupervised approach, (i) the NFC method would still have the damage detection ability (i.e., does the damage exist or not), as the proposed data pre-processing could be carried out before data were used within the NFC method. The damage diagnostics ability (i.e., identification of damage location and magnitude), however, would decrease, since the method would not be trained to distinguish between the different states of degradation.

Future work should consider two aspects: (i) the direct usage of HIs in a bridge damage detection method, alternative to the NFC approach, and (ii) further analysis of the performance of the NFC method by using a large dataset of (simulated) bridge data in different health states of the bridge. In this way, the damage detection and diagnostics ability of the NFC method applied to the in-field bridge, which has been demonstrated to be suitable, could be further tested in different scenarios.

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AUTHOR CONTRIBUTIONS

Dr M. Vagnoli: methodology conception and design, data collection, analysis,interpretation of results, draft manuscript preparation. Dr R. Remenyte-Prescott R: methodology conception and design, interpretation of results, manuscript revision.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author, and further necessary agreement would need to be sought from Prof. D. Siringoringo, relating to the in-field data.

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