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Review Article

Frequency Response Function-based Structural Damage Identification using Artificial Neural Networks-A Review

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Abstract: This study presents and reviews the technical literature and previous studies for the past three decades on structural damage identification using ANNs and measured FRFs as inputs. Much of the previous studies have used modal parameters to ascertain the success of damage identification. However, significant information may not be properly represented through the application of modal parameters. With this in mind, the direct use of frequency domain data in terms of the Frequency Response Functions (FRFs) seems more appropriate. Recent studies indicate that ANNs can be trained on measured FRFs of healthy and damaged models of structure to assess the condition of the structure. According to this review, it is clear that there have been numerous studies which have gone on to apply the ANNs on FRF data of structures in the field of damage identification and it has been shown that ANNs using FRFs can provide several advantages over the modal parameters and damage identification has subsequently become much improved.

Keywords: Artificial Neural Networks (ANNs), Back Propagation Neural Network (BPNN), damage identification, Frequency Response Functions (FRFs), Structural Health Monitoring (SHM)

INTRODUCTION

The existing civil structures are prone to various damages and degrade during their service life. Due to this, the SHM as a process of implementing a damage detection strategy for engineering structures has become a very important subject in relation to the aspects of safety assessment and damage identification of structures.

Damage in structures is defined as any reduction in structural stiffness and mass that negatively affects the functionality of the structures, also their serviceability and safety and finally may lead to failure. There are four levels of damage identification consisting of the determination of the presence of damage in the structure, the determination of damage location and the determination of the severity of damage (Rytter, 1993). Thus, damage assessment is one of the most important factors in maintaining the integrity and safety of structures and has been seen to be very important in monitoring structures for existence, location and severity of damage.

Conventional approaches have been most commonly applied in detecting damage on a structure and they usually rely on visual inspection (Ismail *et al*., 2006). However, these inspection techniques are often inadequate for evaluating the health state of a structure, especially when the damage is invisible to the human eyes. Thus, it is very important to monitor the structural behavior, especially when damage is not observable. Some artificial intelligence approaches such as the Artificial Neural Networks (ANNs), Genetic Algorithm (GA) and fuzzy logic have been used extensively for damage assessment with varying degrees of success.

Among the damage identification methods, the ANNs as a very effective tool used in solving many real life problems and inspired by the human brain, have been applied dramatically to damage identification. ANNs are a very strong method especially when implemented in the field of the structural dynamics. Also, the ANNs under the topic of structural dynamic based-damage assessment can simulate complex relationships and have proven to be robust in the presence of noise.

ANNs are equipped with approximate functions, pattern recognition and classification (Zailah *et al*., 2013; Heidari *et al*., 2011) and can be trained to recognize the characteristics of both undamaged and damaged structures. This trained neural network will then have the ability to identify the presence, location and the extent of damage in structural systems (Lee and Kim, 2007). According to Bakhary (2006) and Bakhary *et al*. (2007), some advantages of ANNs in damage identification as opposed to the traditional damage assessment approaches are as follows:

- Trained ANNs using given data, have the ability to identify damage reliably, even when trained with incomplete data.

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- When ANNs are properly and completely trained, the speed of damage identification is relatively high and numerical simulations do not need to be constructed.
- ANNs are more robust over the noise and uncertainties.
- Any vibration parameters can be selected as inputs of ANNs without increasing the neural network training complexity.

In recent decades there has been an increasing interest in using ANNs to estimate and predict the damage in structures. Based on recent studies, different types of vibration signatures of the structure consisting of time domain data, frequency response functions as frequency domain data and modal parameters as inputs to ANNs have been applied.

A great deal of the preceding works has used modal parameters for damage identification (Abdul-Razak and Choi, 2001). However, significant information such as natural frequencies, mode shapes and damping ratios may not be exactly expressed through the application of the modal parameters. This explains why the direct use of frequency domain data in terms of FRFs appears to be more useful. However, some researchers have directly applied FRFs measurements instead of modal parameter data to prevent loss of information. This review paper summarizes damage identification and structural health monitoring studies based on FRFs which have adopted the ANNs within the last three decades.

STRUCTURAL DAMAGE IDENTIFICATION

Civil engineering structures are susceptible to damage during their service life due to many different factors such as deterioration with age, higher operational loads, fatigue, environmental influences and extreme events such as earthquake. The occurrence of damage can adversely affect the performance of a structure, cause undesirable displacements and stress on the structure and severely reduce the structure's serviceability and safety. When any damage and deterioration that happens in a structure, produces change in the dynamic properties such as stiffness, mass and damping, the consequence is a change in its frequency and modal domains.

The damage if not identified, can result in the failure of the structure components and may contribute to the collapse of the whole structure (Kullaa, 2003; Xu and Humar, 2006). It is therefore, a very important phase of civil engineering structures monitoring to ensure that the structures are safe and can be used properly. Therefore, in SHM it is necessary to detect damage at the earliest possible age of occurrence in structural engineering.

ARTIFICIAL NEURAL NETWORKS

General definition: The human brain consists of about 10^{11} cells called neurons that are interconnected and has the capability to perform certain computations many times faster than the most rapidly working computers (Hagan *et al*., 1996; Haykin, 1999). As depicted in Fig. 1 a basic biological neuron is composed of a cell body, axons, dendrites and synapses. In terms of their functions, the dendrites carry signals as input information into the cell body, axons as outputs for carrying the electrical signals from the neuron to other neurons, whereas the synapse is the point contact between a dendrite of one cell and axon of another cell.

In summary, a neuron receives signals from synapses either located at the cell body or its dendrite, determines its state and finally sends the output down to the axon (Hakim *et al*., 2011; Noorzaei *et al*. 2007; Haykin, 1999). ANNs that are inspired by human biological neurons are computational models which consist of many simple processing elements (neurons) and are highly interconnected with each other. They function to process information and establish complex and non-linear relationships by using certain rules and large sets of data to achieve suitable results (Hakim and Abdul Razak, 2013a, b; Mashrei *et al*., 2010; Demuth *et al*., 2005).

An ANN has the abstraction capabilities, self-adaptiveness and generalization. Therefore, it is very useful to accomplish information processing tasks and pattern recognition and classification. However, ANNs can discover about the relationships between inputs and outputs and generalize the problems even when there is not enough data or when input data contain errors (Kanwar *et al*., 2007).

As shown in Fig. 2, the architecture of ANN consists of an input layer, an output layer and at least one hidden layer (Demuth *et al*., 2005). The appropriate number of neurons in each layer depends on the type of problem that arises.

Each neuron in the input layer represents the value of one independent variable. The neurons in the hidden layer are only for computation purposes. Each of the output neurons computes one dependent variable. Signals are received at the input layer, before passing through the hidden layer and reaching the output layer. Each layer can have a different number of neurons. All

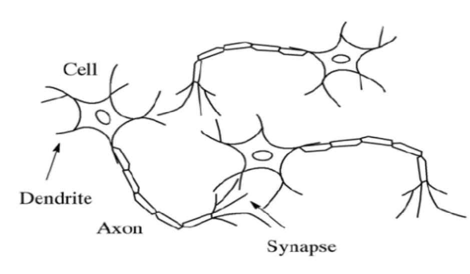


Fig. 1: Biological neuron

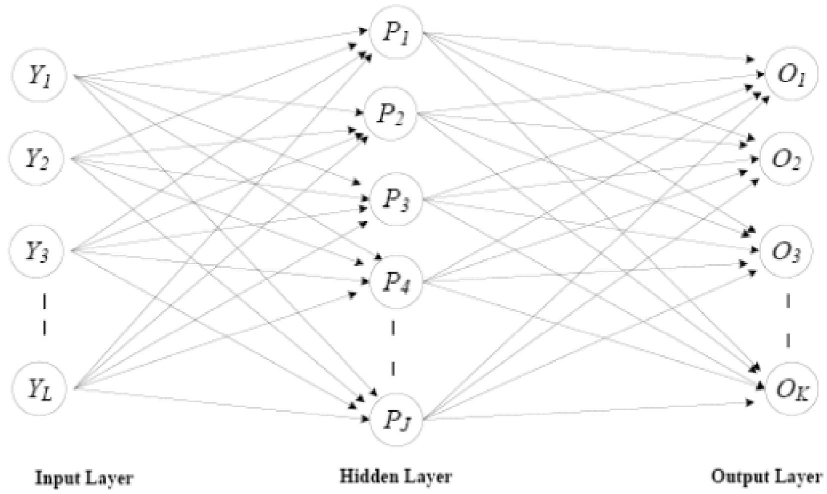


Fig. 2: Architecture of ANN

neurons are interconnected to the neurons in the next layer through their weights.

Learning is the process by which the ANN adjusts itself to a stimulus and eventually produces the desired response. Two types of learning models including supervised and unsupervised learning are used for ANNs. In supervised learning the training samples require an input vector and an output vector. However, in unsupervised learning, the training samples require only an input vector. On the other hand, in supervised learning a network require correct response as output during training, but in unsupervised learning knowing the correct response as output is not necessary.

Among various neural networks, the Multi-Layer Perceptron (MLP) is most commonly used in structural identification problems (Mata, 2011; Karimi *et al*., 2010; Hakim and Abdul Razak, 2011; Obodeh and Ajuwa, 2009; Wu *et al*., 2002). The reason is that MLP networks have been used successfully to address many different problems and can approximate any continuous multivariate function to any degree of accuracy (Li and Fang, 2012; Rumelhart *et al*., 1986). In MLP neurons in each layer, they are connected to all the neurons in both the previous and the subsequent layer. The outputs of the first layer are the inputs for the second layer; the outputs of the second layer are then again the inputs for the third layer and so on (Hagan *et al*., 1996). As the information in a multi-layer perceptron network moves in forward from the input neurons, through the hidden neurons to the output neurons, the type of network is called a feed forward neural network.

The back propagation is one of the best algorithms, as it can train and update the synaptic weights of multilayer perceptron feed forward networks to perform function approximation, pattern association and pattern classification and is considered to be the most applicable due to the mathematical design of the training's complex non-linear relationships (Fonseca and Vellasco, 2003).

The back propagation algorithm has a performance index, which is the least Mean Square Error (MSE) (Folorunsho *et al*., 2012; Efstathiades *et al*., 2007; Lee, 2003). In the MSE algorithm, the error is calculated as the difference between the target output and the network output.

Artificial neural network for structural damage detection: According to Adeli and Hung (1995) computational intelligence approaches such as ANNs, Genetic Algorithms (GA) and fuzzy logics are very attractive processes in the structural damage identification because of their credible performance and robustness in dealing with incomplete and insufficient data, uncertainty and noise.

The detection of damage in a structure based on its response is an inverse process, which indicates that the causes must be recognized from the effects (Zhao *et al*., 1998). ANNs as artificial intelligence systems are becoming very popular in the area of structural damage identification and are suitable for the inverse process. ANNs require specific data from structure responses. For example a number of damage scenarios are applied to the structure model and dynamic responses from these scenarios have been able to be saved in the ANN database. The ANN monitors the dynamic response and attempts to fit any damage-induced shifts to its database. General advantages of applying ANNs lie in their ability to detect the pattern recognition and generalization correctly, even when trained with inaccurate and incomplete data and despite their capability to continue learning and to modify and improve their performance when presented with new data (Yuen and Lam, 2006).

Extensive studies have focused on using the ANNs approach for structural damage identification from dynamic response data. For example, Sohn and Farar (2000), Liu *et al*. (1999) and Loh and Huang (1999), have applied time-domain signals as the inputs of ANNs for structural damage detection.

The use of natural frequencies and mode shapes as modal parameters to detect damage in structures has been addressed by Rosales *et al*. (2009), Pawar *et al*. (2007), Lam and Ng (2008), Sahin and Shenoi (2003) and Salawu (1997). Also, frequency domain data in terms of FRFs have been applied by several researchers to the training of ANNs for the purpose of structural damage detection, which will be explained in the following sections.

FREQUENCY RESPONSE FUNCTIONS (FRFS)

General definition: The measured excitation and response of structure are transformed into the frequency domain using the Fast Fourier Transform (FFT) (Ewins, 2007). The FRF is the ratio of the response to the measured excitation in terms of the frequency domain at each frequency. However, if we were to transform the measured time domain data to the frequency domain data using the FFT, then FRF can be calculated (Cooley and Tukey, 1965). In theory, the measured FRF of the damaged structure, when compared with the response of the undamaged structure, contains information regarding the location and severity of damage (Wu *et al*., 1992). Thus, this vibration signature can be used to identify damage.

Lee and Shin (2002) have stated that there are human extraction errors during the experimental modal analysis that do not exist in the FRF data and therefore, they have proposed that FRF data can provide an abundance of information as the modal domain data are extracted from a limited range around the resonance. Also, when applying direct measure of the FRF data, the experimental modal analysis is not required and modal extraction errors during experiment are avoided.

In summary, FRFs data have the following advantages, which have recently been established for damage identification in structural engineering:

- One measurement of FRF can provide abundance of data
- The experimental modal analysis needs much effort and time. However when using FRFs, the modal analysis is not necessary and human-induced errors, as the modal analysis is performed, can be avoided
- The measured FRFs can be used in structures with modal density and high damping ratios
- The modal domains extracted from the simultaneous domain signals can vary according to different extraction methods used (Bolton *et al*., 2001)

However, according to the above reasons, the FRF is a measurement that isolates the inherent dynamic characteristics of a structure such as natural frequencies and mode shapes. Therefore, changes in the FRFs of structures due to damage can bring about changes of stiffness, mass and damping properties during damage.

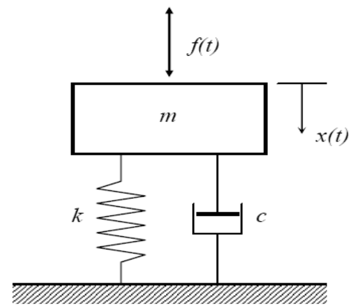


Fig. 3: Basic dynamic equilibrium of a single D.O.F system (Clough and Penzien, 1993)

Finally, the direct use of FRFs in the area of damage identification in the fields of structural engineering seems more appropriate.

Although much of the previous study have examined the modal parameters as the main consideration for damage identification (Kim and Lee, 2000), recently, the FRF that is free from the experimental modal extraction is developed and several researchers have applied the direct use of the FRFs to detect damage apparent in structural engineering. For example, Ambrogio and Zobel (1994) have decided to use the FRFs to detect the existence of damage in a truss structure. Also, Fang *et al*. (2005), Ko *et al*. (2002), Lyon (1995), Imregun *et al*. (1995) and Schultz *et al*. (1996), directly applied the FRFs for structural identification.

FRF formulation: A single Degree of Freedom (D.O.F) of a structure is shown in Fig. 3.

Basic dynamic equilibrium equation of the general mathematical representation of a single Degree of Freedom (D.O.F) is given in Eq. (1) (Clough and Penzien, 1993):

$$m\ddot{x} + c\dot{x} + kx = f(t) \quad (1)$$

where, m, c and k are the mass, damping coefficient and stiffness constant, respectively. In this equation, f (t) is a function that represents the time-dependent excitation force applied to the system and $x, \dot{x}$ and $\ddot{x}$ are the corresponding responses of displacement, velocity and acceleration, respectively.

Equation (1) is the time-domain representation of the structure system. An equivalent equation of motion is determined for the frequency domain. The frequency domain has the advantage of converting a differential equation to an algebraic equation. This is carried out by taking the Fourier transform of Eq. (1). Therefore, Eq. (1) becomes:

$$\left[-m\omega^2 + jc\omega + k\right] X(\omega) = F(\omega) \quad (2)$$

where,

X (ω) = The system response

F (ω) = System forcing function in the Fourier domain

In Eq. (2) when:

$$B(\omega) = -m\omega^2 + jc\omega + k \quad (3)$$

Then Eq. (2) becomes:

$$B(\omega)X(\omega) = F(\omega) \quad (4)$$

If F (ω) and its response X (ω) are known, B (ω) can be calculated by Eq. (5):

$$B(\omega) = \frac{F(\omega)}{X(\omega)} \quad (5)$$

Equation (5) can be rearranged as follows:

$$x(\omega) = \frac{F(\omega)}{B(\omega)} \quad (6)$$

After substituting:

$$H(\omega) = 1/B(\omega) \quad (7)$$

Eq. (6) becomes:

$$X(\omega) = H(\omega)F(\omega) \quad (8)$$

H (ω) is defined as the Frequency Response Function (FRF) of the system. A FRF relates the Fourier transform of the system input to the Fourier transform of the system response. Therefore, the frequency response function is defined as:

$$H(\omega) = \frac{X(\omega)}{F(\omega)} \quad (9)$$

STRUCTURAL DAMAGE IDENTIFICATION USING MEASURED FRFS AND ANNS

As mentioned earlier, a change in FRFs from the undamaged state indicates a possible damage in the structure. Thus, it is necessary to establish a relationship between damage occurring in a structure and its dynamic parameters to determine the health status of the structure. During the last three decades, a lot of studies using various methods in the area of damage assessment have been conducted and reviewed, but to date, there is no review regarding the application of ANNs for structural damage detection using the frequency domain data such as FRFs. The measured FRFs of the damage structure, when compared with the response of undamaged structure contain a large amount of information regarding the existence, location and severity of damage (Wu *et al*., 1992). Thus, this vibration signature can be applied as the appropriate input to an ANN that is being used to identify damage.

The use of FRFs to detect damage in structures has been addressed by some researchers. For example, Wu *et al*. (1992) were the first researchers who had applied ANNs to the structural behavior before and after the damage, where the FRFs are concerned. Damage was simulated by the stiffness reduction of each column member. A two dimension three-storey building was simulated and excited by earthquake-base acceleration. The dynamic responses were obtained on the second and third floors. Two hundred spectral values of FRFs between 0 and 20 Hz, at the interval of 0.1 Hz were used as inputs of the ANNs. The architecture of the ANN and the damage state of structural elements are provided in Fig. 4.

In this study, 0 and 1 as binary numbers are applied as output to represent the damaged and undamaged level of each column member in the building mentioned. According to this research, the ANN trained using FRFs data could predict damage with the accuracy of 25%. A major weakness is that the trained ANN could not identify the column between the first and second floor.

The application of FRFs as inputs of ANNs to damage identification in a 20-bay planar truss consisted of 60 struts is described by Povich and Lim (1994). The damage is modeled by removing struts from the truss structure. In this research, using two accelerometers, 394 FRFs between 0 and 50 Hz are discretized and applied as inputs. Binary numbers 0 and 1 have been used as the output parameters to represent the damaged and undamaged struts. Based on this study, results have demonstrated that, the ANN can detect the damaged member using patterns in FRFs of the truss structure. According to authors the ANN could correctly identify 21 of 60 members as damaged and 38 of 60 constricted to two possible damaged members. A major problem addressed in the method is that the size of the FRF data that is determined by the number of spatial response locations and the number of spectral lines are too large as inputs for ANN applications. The direct use of such large data will consequently lead to neural networks with a very large number of input neurons, which results in a large number of connections. This contributes to an impractical ANN in terms of its training and convergence stability (Zang and Imregun, 2001a, b). Therefore, a Principal Component Analysis (PCA) technique is developed, whereby a linear data compression method achieves dimensionality reduction to the frequency response functions data for feasible application in the ANNs.

The PCA technique is applied by several researchers. For example, Dackermann *et al*. (2010) have presented a damage detection approach to determine the extent of damage in a two-storey framed structure using FRF data as inputs of the ANNs. In this study, the FRF data are compressed to a few components using the PCA approach. The PCA as a powerful tool for filtering noise is a statistical technique and is regarded as suitable for dimensional reduction of data. In this study, the two-storey steel framed structure consisting of two columns, two crossbeams and four joint elements is fabricated and experimentally tested.

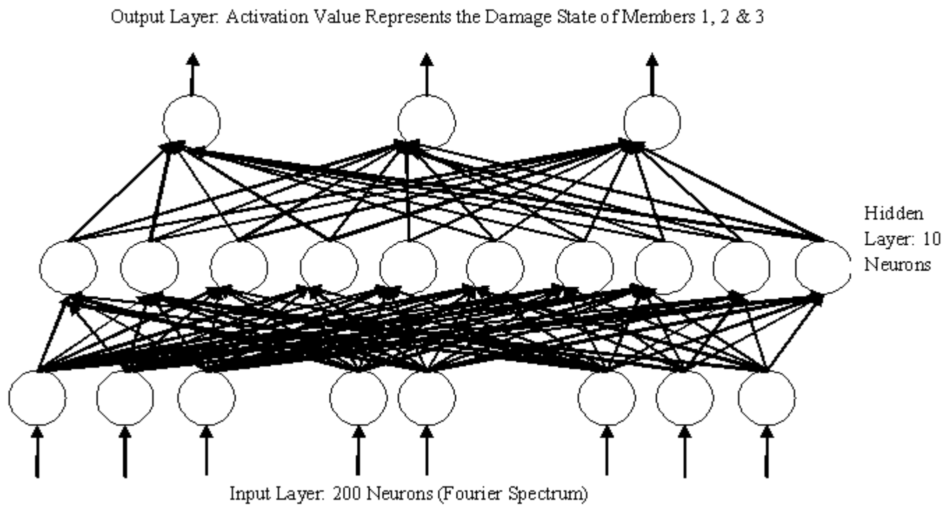
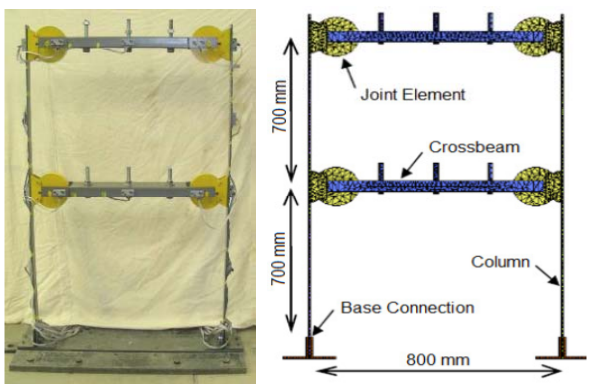


Fig. 4: Architecture of the ANN and the damage state of structural elements (Wu *et al*., 1992)



(a) Experimental structure (b) Numerical structure

Fig. 5: Experimental and numerical structure of two-storey steel framed (Dackermann *et al*., 2010)

This model is then numerically simulated and analyzed using the ANSYS software. The experimental and numerical structure of the two-storey steel framed is depicted in Fig. 5. Three levels of damage severities in two locations of the columns have been considered in this study.

According to authors a neural network ensemble has been created in this research. Utilizing the individual characteristics of data recorded from various sensor locations is the main advantage of neural network ensemble in this study. In this network each network is first trained individually then the outputs of each of the networks are combined to produce the ensemble final output. Based on this study authors have concluded that this approach is adequately robust and accurate in predicting the severity of damage.

Also, combined FRFs and ANNs are applied by Dackermann *et al*. (2011) for damage severity assessment of timber bridge structures. In this study, an experimental four-girder timber bridge that has been fabricated and 12 different damage scenarios containing three damage severities at four different locations are studied. FRFs data extracted from the experimental modal analysis and residual FRFs are derived and applied as the damage indicator. Residual FRFs data are compressed to a few principal components using the PCA method and then applied to ANNs to predict the damage severity. The results from this study have shown the effectiveness and applicability of this algorithm in severity identifications for all damage scenarios.

A FRF-based damage identification method using ANNs is presented by Zang and Imregun (2001a). In this study, authors apply the PCA to reduce the size of FRFs before using them as the input parameters. This method is applied to numerically modeled railway wheels with damage detected, even after a 5% random noise is imposed to the structures. According to this study 4096 FRF data points in three directions have been generated. These data are reduced to 7, 9 and 13 for x, y and z direction and applied as input parameters to three different neural networks, one in each of the *x*, *y* and *z* directions. This procedure is summarized in Fig. 6. Three different ANN models corresponding to their directions are trained and tested using 80 and 20 samples, respectively. The output of the network lies in the condition of the structure, i.e., damaged or undamaged. The results have demonstrated that the ANN is able to classify all damaged and undamaged cases studied. This damage strategy is also applied to a space antenna with different modifications to the neural network for slight damage detection by Zang and Imregun (2001b). It has been found that using too many principal components does not necessarily achieve better results, since there is an increased capability to gain signal noise. Authors using this algorithm have evidently been unable to estimate the severity of damage.

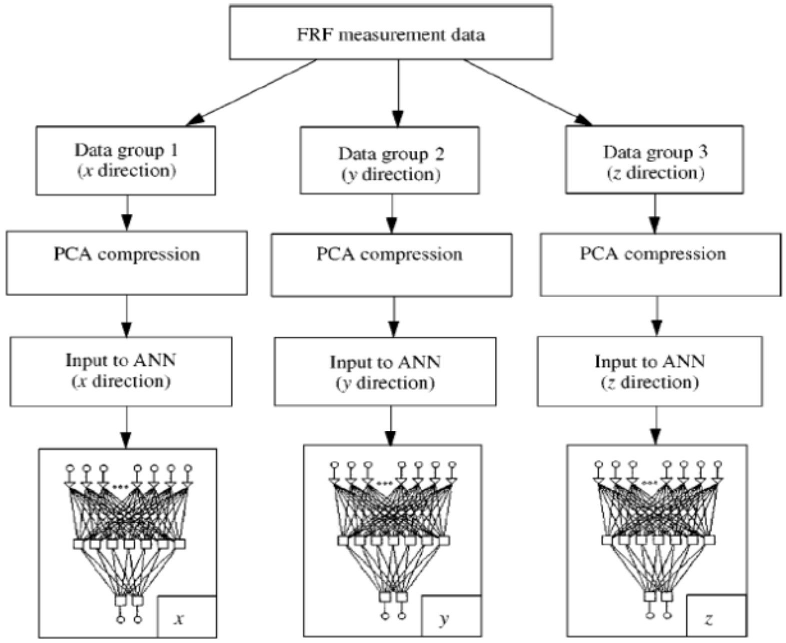


Fig. 6: Preparation of FRF data for ANN (Zang and Imregun, 2001a, b)

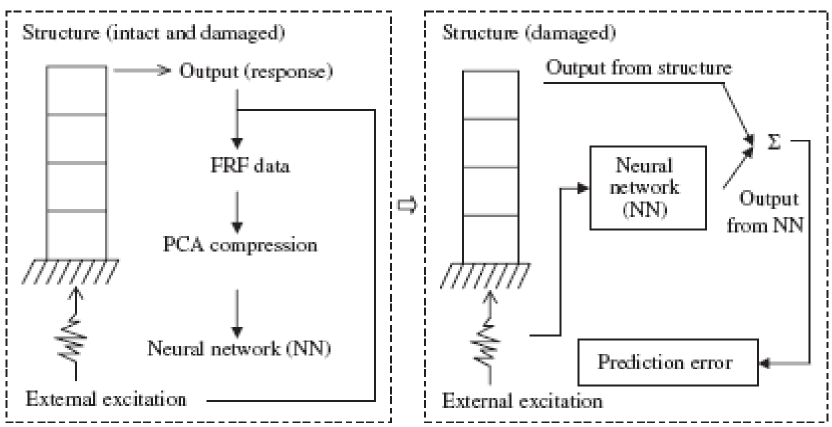


Fig. 7: Damage identification algorithm using ANN (Ni *et al*., 2006)

Next, Ni *et al*. (2006) describe an experimental study of damage identification of a 38-storey reinforced concrete building on a shaking table. In this study, ANNs are trained using measured FRFs. The PCA approach has been applied for the compression of the FRF data. Implementing the ANN in this study for structural damage identification is summarized and shown in Fig. 7.

FRF data that are applied in the neural network are obtained analytically or experimentally in undamaged cases and in different damage scenarios and are also used for training the neural network. This network is tested with a new set of FRF data and is able to predict the damage states. A three-layer feed-forward neural network with the back propagation algorithm is used for damage detection in this research. The network is configured to have 30 principal component projections and 15 neurons in the hidden layer and only one output neuron, indicating overall damage severity. The authors have also successfully shown that the compressed FRF data using the PCA method as inputs for the neural network can predict damage existence and localization much better than the directly measured FRF data.

Experimentally measured FRF data have been applied as inputs of the ANNs for the identification of seismic damage in a 38-storey building model by Ko *et al*. (2002). A 1:20 scale of this tall building model has been tested on a shaking table and diverse damage scenarios which are lightly, moderately, severely and completely damaged are inflicted on this model and FRFs are measured after each damage scenario. For more convenient damage location, this building has been divided into nine regions along the vertical direction as depicted in Fig. 8. Each region consists of

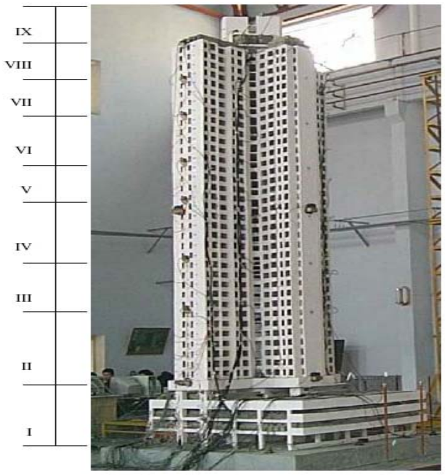


Fig. 8: 38-storey tall building model (Ko *et al*., 2002)

4-5 storeys. The PCA technique is applied to compress the size of FRF data in this research. Using this technique, the most important principal components are applied instead of the raw FRF as input variables of the ANN for damage assessment. Thirteen principal components are applied as inputs of the ANN. The final architecture of the neural network consists of four layers with 13 neurons in input layer corresponding to the 13 principal components, 15 and 18 neurons in the first and second hidden layers, respectively. The output of the ANN is a value between 0 and 1, regarding the damage level and indicates extent of damage of the specified region of model. The authors demonstrate that the effectiveness of the ANNs trained with FRF data in predicting the severity of damage has been accepted.

The measured FRFs are applied as the input to the ANNs for the purpose of damage detection in the steel box girder bridge by Sun (2009). In this study the PCA as a data reduction technique is used for reducing the size of the FRF data. The steel bridge model with multi damage states is presented to show the efficiency of this approach. The self-organizing neural network using FRF data is trained in this work. This type of network is able to analyze high-dimensional data with unsupervised learning algorithm. According to author, network could distinguish the damage states in the steel bridge model with very good accuracy.

Also FRFs reduced as networks input data for the back propagation neural network are applied for structural damage identification by Fang and Jiao (2007). In this study a neural network with 8192 neurons in the input layer and 8 and 4 neurons in hidden and output layers, respectively, could successfully detect damage in different states of the structure with errors under 10%.

A damage identification method using the sub-structuring approach is studied by Qu *et al*. (2004). In this study, the FRF data of two span truss structure with 55 truss elements, from 0 to 200 Hz with an interval of 0.2 Hz per data point are extracted and considered as inputs of the ANN. The Independent Component Analysis (ICA) is applied for compressing the length of input data of the neural network. According to this research, damage scenarios are modeled by means of reducing the stiffness in two truss members and the structure divided into three substructures. However, only the middle substructure has been given due consideration. The results have demonstrated that the sub-structuring method in large structures can improve the ability and computational performance in damage identification

Composite materials have high strength and stiffness. Therefore they have been applied in many applications of structural engineering. Delamination is one of the common damage-types in composite structures. Delamination decreases the frequencies and stiffness in structures and increases modal damping. Some attempts have been made to detect the size and location of delamination using ANNs based on the FRF data. For example, A SHM methodology based on measured FRFs and ANNs for a composite plate is presented by Luo and Hanagud (1997). Based on this study, numerical models are applied to predict the structural dynamic response of the damaged structure. According to this research, two types of damages comprising of stiffness loss caused by transverse and impact cracks and delamination have been considered. Two different neural networks are trained for these types of damages.

The first network concentrates on stiffness loss. In this network FRF data are considered as inputs of network and ratios of the stiffness of damaged structure, to that of healthy structure assume their role as outputs. The architecture of the neural network consists of three layers with 128 neurons in the input layer and 30 and 5 neurons in hidden and output layers, respectively. Sixteen damage scenarios are also considered for the network training. Authors conclude that this network is capable to identify stiffness loss. The second network is trained for FRFs as inputs and delamination information as outputs. This network consists of 128 neurons in the input layer, 30 and 18 neurons in hidden and output layers, respectively. Ten delamination scenarios in lengthy range of 0 to 18 have also been considered. This network could successfully identify delamination damage in the composite plate. Also, the researchers have derived another conclusion that more improvement of the training performance is possible through an automatic optimization of the training control variables.

Also, the delamination of the composite beam structure consists of an induced debonding between a beam and a bonded composite patch is considered as a type of damage by Chaudhry and Ganino (1994). In this study measured FRF data as inputs to the ANN are used to identify the existence and severity of damage in composite debonded beams. According to this work, FRF data obtained from a piezoelectric sensor pair will bond and they will attempt to arrange that delamination site to lie down between the sensor and actuator.

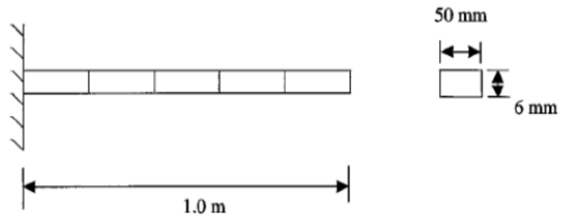


Fig. 9: The cantilevered beam modeled divided into five segments (Marwala and Hunt, 1999)

Seven different beam specimens which consist of two beams with fully bonded composite patches, two beams with a 2" debonded section and another three beams each with a half, one and three inch debonded sections have been used in this study. FRFs are obtained for each of these beams over a frequency range of 10 to 5000 Hz. Finally, the results have demonstrated that the ANN using the BPNN algorithm can identify the presence and severity of delamination with good accuracy. Also, authors found that the performance of ANN is much better when the amount of training samples is high.

A committee of ANNs which applies the information from the FRFs and modal data to predict the damages in structures is presented by Marwala and Hunt (1999). Based on this study, two individual ANNs are trained for structural diagnostics prediction using the modal and FRF data. In the first network, frequency energies calculated from the FRFs are applied as the input parameter and mode shape vectors are used as inputs in the second network. A 1 meter cantilever beam is applied to illustrate the method and it is divided into five segments as shown in Fig. 9. Combined network has been trained to identify the existence of damage in each segment.

In this study, the ANN architecture with 55 inputs neuron, 25 hidden neurons and 5 outputs neuron is employed. Also, the training of ANN is done using 243 data. The results have demonstrated that the combined network is trained with an error of 7.7% for the committee neural network compared to 9.5 and 9.75%, respectively for individual neural networks. This means that the committee of neural networks commits less error than the existing methods. Also, results have demonstrated that the committee network is able to detect multiple damages with high accuracy when compared to individual methods. In this study, the committee network has shown less variance than the FRF and modal methods individually and this is one of the main advantages shown by the committee network. Less variance to decreases the level of uncertainties and can subsequently improve the results. The average variance for individual methods is 33.28 compared to an average variance of 15.1 for the committee network. The committee network requires two trained networks, which means that it would take a long computational time and this can be one of the main shortcomings.

Marwala (2000) has extended the above research study by employing the wavelet transform data together with FRFs and modal parameters that consists of natural frequencies and mode shapes. In this study, an experimental investigation is done on steel cylindrical shells. Data generated from experiments are used for the training of ANNs. However, three individual networks are trained and finally combined in a committee network. The author has concluded that the combined network can identify the damage better than the individual network. According to this study, the performance of the committee method is enhanced when measured data from the experimental study are applied. The authors then made the conclusion that a committee of neural networks which applies both FRFs and modal data gives results that are more accurate and reliable than neural networks which have been using the FRF data or modal data individually.

FRFs as neural network inputs are used to present a damage identification method by Yeung and Smith (2005). Two different types of unsupervised learning neural networks consisting of Probabilistic Resource Allocating Network (PRAN) (Roberts and Tarassenko, 1994) and DIGNET network (Thomopoulos *et al*., 1995) to damage identification are applied. In PRAN, the distribution of the input is modeled by a set of Gaussian probability density functions. The DIGNET is a self-organizing neural network for automatic pattern recognition, classification and data fusion and is designed for clustering noisy input patterns. The self-organizing capability of DIGNET is based on competitive learning where clusters are generated or eliminated during the learning phase. In this study, a finite element model of a suspension bridge is considered to verify the approach and environmental effects in the form of thermal stressing are modeled. For both types, the damage detection outcomes are reasonably good, with the PRAN network generally outperforming the DIGNET network. Based on this work, the ANN could detect damage with 70% accuracy.

ANN-based damage identification using measured FRF data has been used by Zang *et al*. (2003). In this study, two different correlation indices as damage indicators for measured FRF data, comprising of Amplitude Correlation Criteria (ACC) and Global Shape Criteria (GSC) are proposed.

A network with two inputs consisting of the Averaged Integration of Amplitude Correlation Criteria (AIACC) and Average Integration of Global Shape Criteria (AIGSC) is trained. Damage existence, locations and severities are taken considered as outputs of the neural network. These methods are used experimentally on a three-storey bookshelf structure. Authors have concluded that these methods are capable to identify damage for most damage related cases. However, there is little false identification made.

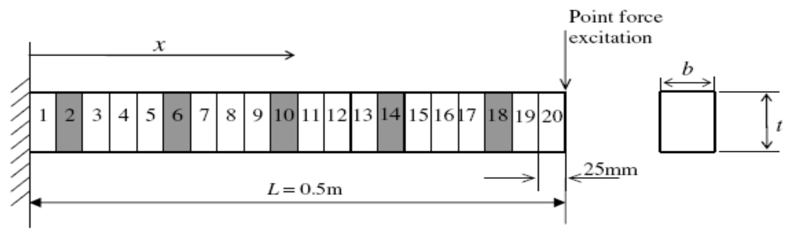


Fig. 10: The division of the cantilevered beam (Fang *et al*., 2005)

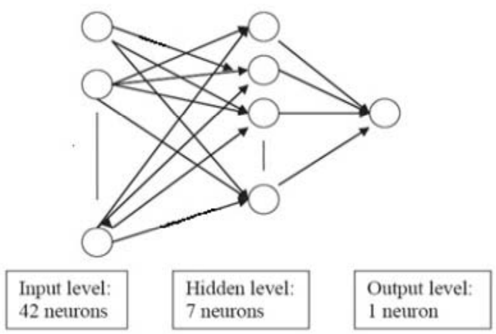


Fig. 11: Artificial neural network configuration (Zang *et al*., 2003)

ANNs have been employed to perform structural damage detection using the FRF data in a benchmark cantilevered beam structure by Fang *et al*. (2005) .Therefore, in the present study, an input-output relation between the FRFs and the damage location and severity using the neural network is established. The cantilevered beam is equally divided into 20 elements as depicted in Fig. 10. Single and multiple damages that cause stiffness loss in one or multiple elements on a cantilevered beam are considered in this work. In this research different training algorithms such as the Dynamic Steepest Descent (DSD) and Fuzzy Steepest Descent (FSD) and Tunable Steepest Descent (TSD) have been considered, while promising specifications such as improved learning speed shown.

Networks trained based damage detection in this study could assess single and multiple cracks in a cantilevered beam by using FRF data with very good accuracy. This new approach demonstrated very high accuracy in predicting damage location and severity. Also, according to this work, the performance of the DSD and FSD algorithms is better than that of the FSD algorithm.

Zapico and Molisani (2009) applied FRFs as input variables in ANNs to detect damage in steel structures. In this work, a feed forward neural network with the back propagation algorithm is used for damage detection in the steel beams. According to this research 42 spectral line values and only one output that indicate the damage in steel beams were considered. Therefore, as shown in Fig. 11, the architecture of the ANN consists of three layers with 42 input neurons, 7 neurons in the hidden layer and 1 neuron in the output layer. Based on this study, authors have concluded that ANN trained using FRF data was able to identify damaged beams with very good accuracy.

A research study on structural damage detection using FRFs and ANNs is done by Lee and Kim (2007) and Kim (2003). In these works the Signal Anomaly Index (SAI) which expresses the changes in the shape of FRFs or Strain Frequency Response Function (SFRF) is suggested. As stated in Eq. (10), the SAI is the difference between two FRFs of intact and damaged states in a Euclidean norm:

$$SAI = \left(\frac{\sum_{fi=f1}^{fn} \left| H^B(f_i) - H^C(f_i)^2 \right|}{\sum_{fi=f1}^{fn} \left| H^B(f) \right|^2} \right)^{\frac{1}{2}} = \frac{\left\| FRF^B - FRF^C \right\|}{\left\| FRF^B \right\|} \quad (10)$$

Superscripts B and C represent the intact and damaged states and functions of H and FRF represent the frequency response function in continuous and discrete forms. Also f_l and f_n in this equation are the lowest and highest frequency ranges. According to this study, several numerical models and experimental tests have been performed in a model bridge as depicted in Fig. 12.

According to authors, an ANN using numerical results is trained and tested using experimental simulated signals. In this network, one hidden layer that consists of 10 neurons and an output layer with 9 neurons is trained using results from modeled damages on nine locations in the FEM. Results demonstrated that ANN trained using the Signal Anomaly Index (SAI) is able to identify damage as a promising tool for SHM. Also, Chang *et al*. (2002) developed a Signal Anomaly Index (SAI) vector in terms of the FRF data before and after damage as input to an ANN for bridge damage identification.

ANNs are applied for the FE model, where they update both structural parameters and damping ratios using the FRF data by Lu and Tu (2004). In this study the two-level neural network approach is considered. In the first level, structural parameters such as stiffness using natural and ant resonance frequencies as the response data are updated, but in the second level only variable damping ratios using integrals of FRFs as response data are updated.

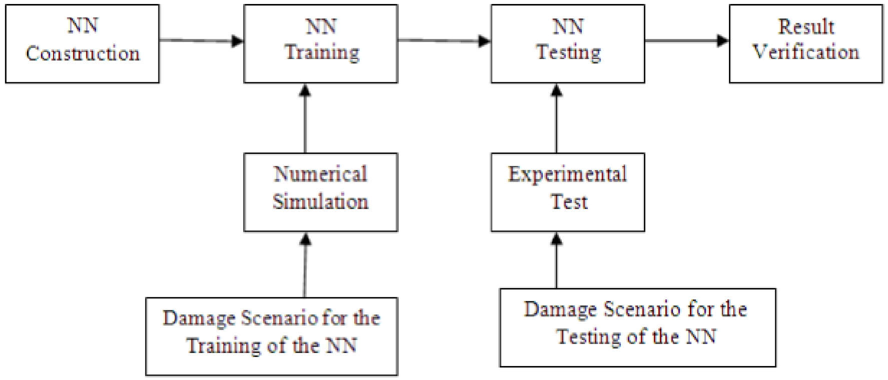


Fig. 12: Damage detection algorithm (Lee and Kim, 2007)

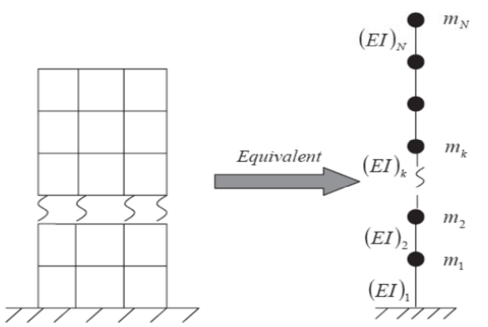


Fig. 13: Multi-storey building frame (Chang *et al*., 2002)

Integrals of FRFs are used for the updating of the damping ratios because of their inherent features with the damping factors. A numerical example of a multi-storey building frame is applied to demonstrate the implementation of the proposed method as depicted in Fig. 13. According to this paper, the neural network trained is able to identify the variable damping ratios and structural parameters within an error of 4%. Results of the numerical example showed that this procedure is efficient and effective.

A Multi Layer Perceptron (MLP) on a 10-bar truss structure and a 25-bar transmission tower has applied by Manning (1994). Author used the FRF data and an estimated measurement of member stifness as the training samples. Damage is simulated by reducing the cross-sectional area of a member. The MLP consists of 40 inputs, two hidden layers with seven and five neurons and four outputs. According to this research, a trained neural network is able to predict the change in the member in the cross-sectional area with 10% error.

Probabilistic ANNs are developed and applied to damage identification in an aerospace housing component structure by Klenke and Paez (1996). The FRF data are used in the training of neural network and the network output determines whether the structure is damaged or not, based on experimental measurements. According to authors, five different types of damage cuts are created in the structure. The results are quite successful and the network is able to identify all damage types with good accuracy. The damage in this structure is detected, even in the most lightly damaged cases. The severity of damage has not been considered in this study.

System identification and ANNs as two different methods have been applied for structural health monitoring in large scale laboratory reinforced concrete bridge models by Owen and Haritos (2003). Simulation data for undamaged and damaged models indicate that comparing the FRF data has provided a more sensitive indicator of system change than simply using the natural frequencies. According to authors, the system identification method provides more information on the location and extent of damage, but it needs more measurement points and requires more prior knowledge. ANNs trained using FRFs provide less information about the location and extent of damage, but they need less input data. Also, ANN is less sensitive to noise. Comparison drawn between the weaknesses and strengths of two aforementioned methods has demonstrated that they should be applied together. However, both system identification and ANNs are successfully applied to reinforced concrete bridges according to their damaged state using the FRFs.

The applicability of ANNs to damage identification using transfer functions instead of the FRF data in composite structures has once been examined by Rhim and Lee (1995). The transfer function is applied because it represents compact and complete information about a dynamic system from given input-output data. Two phases which include training and testing are considered to detect the presence and to identify the damage characteristics. Various damage scenarios are designated and the patterns organized into different pattern classes according to the severity and location of the damage. In this research, system identifications are implemented to extract the FRFs as the features of the structural systems. These features are applied as the inputs for the training of MLP. The ANN as a strong tool can well predict the existence and severity of damage. Numerical verification results show the feasibility of the suggested approach in this study. This approach can be applied with limited number of sensors.

CONCLUSION

Several attempts in using dynamic parameters such as FRFs and modal parameters are reported. Each dynamic parameter carries its own advantages and shortcomings in damage detection. A large part of earlier studies have applied the changes of modal properties involving the mode shapes, natural frequencies and damping ratios as input variables of ANNs for structural damage detection.

As mentioned previously, modal parameters necessitate much effort and time to extract. Also the extraction of modal parameters needs expertise and sometimes user interaction may add to the human extraction errors and uncertainties suffering in the modal parameter results.

It is noteworthy that significant information may not be exactly expressed using modal properties only. However, although much of previous studies have applied the modal domain data as the inputs of ANNs for damage identification, the feasibility and efficiency of training ANNs on FRFs data for structural damage identification are demonstrated instead of modal parameters because of several advantages by some other researchers.

FRFs can provide a lot of data which contribute to the provision of more useful information, also the fact that where FRFs are concerned, the experimental modal analysis is not required and human errors during experimental can be avoided. On the other hand, FRFs are very sensitive to any reduction in structural stiffness and mass and they can be applied as a good damage indicator. Therefore, ANNs have been applied by several researchers to the aspect of damage identification using FRF data as inputs on the network.

One of the most important shortcomings with regards on the use of FRFs with ANNs is the large size of the FRF data. The size of the FRF data that is determined by the number of spatial response locations and number of spectral lines is very large for ANN training. The direct use of such massive FRF data leads to ANNs having a large size of input neurons, which ignites several problems in terms of computational efficiency, convergence stability and training efforts. Also, researchers who have applied completed FRFs with few thousands of data points have discovered that there is too much information for the neural network training purpose and also it results in time-consuming-training.

To overcome these problems and to improve the performance of ANNs, some novel approaches have been employed for data reduction. The approaches have exploited the compressed FRFs as inputs of the ANNs instead of the direct FRFs for damage identification. PCA is one of the more common techniques to condense the FRF data as input variables of ANNs for the determination of damage existence and severity. The implementation of ANNs and PCA technique enable researchers to do accurate and robust damage detection. Robust damage detection indicates its ability to identify whether or not the damage happens at a very early stage, other than demonstrating its ability to locate the damage and provide some estimates of the severity of the damage.

According to this review study, it is clear that over the past three decades there have been numerous studies which initiate the adoption of the ANNs on the FRF data of structures in the field of damage identification. Also, it has been demonstrated that ANNs using FRFs can provide several advantages over the modal parameters and further improving the damage identification. Recent studies indicate that ANNs can be trained on measured FRFs of healthy and damaged models of structures to fulfill the purpose of assessing the condition of the structure.

RECOMMENDATIONS FOR FUTURE WORKS

This review study is a starting point for relevant people or parties who would like to do research in the damage identification area using ANNs. Based on researchers who have already contributed in this review paper, the training of ANNs with a large size of FRFs can aggravate various training problems, with special regards on the convergence and computational time.

Therefore, one of the most important challenges in using FRFs-based damage detection is the development of novel techniques and algorithms for data reduction and the selection of more useful FRFs as inputs of the ANNs. Therefore, the development of such algorithms should be promoted.

Application of ANNs using FRFs in the damage identification of real structures with multiple damages is found to be limited. Thus, more studies in this area need to be carried out. Identification of damage using various types of ANNs with respect to FRFs as the input variable is also restricted. Therefore, the performance of different types of ANNs for damage detection can be further investigated.

ANNs applied in this review usually adopt a supervised learning approach which requires FRF data as inputs and damage detection as the corresponding output data. However, the output data is not always available. Thus, further studies on the ANN implementation under the unsupervised learning method for training and testing patterns are encouraged.

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