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Modal parameters based structural damage detection using artificial neural networks - a review

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Abstract. One of the most important requirements in the evaluation of existing structural systems and ensuring a safe performance during their service life is damage assessment. Damage can be defined as a weakening of the structure that adversely affects its current or future performance which may cause undesirable displacements, stresses or vibrations to the structure. The mass and stiffness of a structure will change due to the damage, which in turn changes the measured dynamic response of the system. Damage detection can increase safety, reduce maintenance costs and increase serviceability of the structures. Artificial Neural Networks (ANNs) are simplified models of the human brain and evolved as one of the most useful mathematical concepts used in almost all branches of science and engineering. ANNs have been applied increasingly due to its powerful computational and excellent pattern recognition ability for detecting damage in structural engineering. This paper presents and reviews the technical literature for past two decades on structural damage detection using ANNs with modal parameters such as natural frequencies and mode shapes as inputs.

Keywords: Artificial Neural Networks (ANNs); Finite Element Analysis (FEA); Back Propagation Neural Network (BPNN); Multi-Layer Perceptron (MLP)

1. Introduction

Structural systems in civil engineering are exposed to deterioration and damage during their service life. Damage is defined as a weakening of the structure which may cause undesirable displacements, stresses or vibrations to the structure leading to sudden and catastrophic consequences. Damage can severely affect safety and functionality of the structure and detection of it at early stage can increase safety and extend its serviceability. Thus detection of damage is one of the most important factors in maintaining the integrity and safety of structures.

Visual inspections have always been the most common approaches used in detecting damage on a structure. However these inspection techniques are often inadequate for assessing the health state of a structure especially when the damage is invisible to the human eyes. Thus, in many situations to ensure structural integrity, it is desirable to monitor the structural behavior when damage is not observable. Some numerical techniques such as the finite element method, artificial neural networks, genetic algorithm and fuzzy logic have been applied increasingly for damage

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detection with varied success (Abella *et al*. 2012, Chandrashekhar and Ganguli 2011, Ghodrati Amiri *et al*. 2011, Li *et al*. 2010, Mahzan *et al*. 2010, Lakshmanan *et al*. 2008 and Kim *et al*. 2007). In recent decades there has been an increasing interest in using neural networks to predict and estimate the damage in structures.

ANNs can be considered as an Artificial Intelligence (AI) technique and the structure of an ANN bears a very approximate similarity to the human brain. ANNs are employed when the relationship between the input and output is complicated or when the application of another available technique requires long computational time and the effort is very expensive (Hakim 2006). ANNs are a powerful tool used to solve many real life problems. They have the capability to learn from their experience in order to improve their performance and to adjust themselves to changes in the environment.

Damage detection as an inverse problem can be identified using ANNs from the measured responses under excitation of the structure. The inverse problem is defined as the determination of the internal structure of a physical system from the system's measured behavior or identification of the unknown input that gives rise to a measured output signal. The neural network can be trained to recognize the characteristics of an undamaged structure as well as those of the structure with elements of varying degrees of damage. The trained neural network will then have the ability of identifying the location and the extent of damage of individual elements (Li and Yang 2008).

There are four levels of damage identification consisting of determination of the presence of damage in the structure, determination of damage location and determination of the severity of damage (Rytter 1993). The fourth level that is prediction of the remaining service life of the structure is associated with fatigue life and fracture mechanics and will not be addressed in this review. In this paper a review of the literature for damage identification and structural health monitoring based on measured dynamic properties by using ANNs during the last two decades is presented.

2. Artificial neural networks

2.1 General definition

The brain is a highly complex, nonlinear and parallel computer that has the capability to perform certain computations many times faster than the fastest digital computer and consists of a large number of highly connected elements called neurons. These neurons have three principal components consisting of dendrites that carry electrical signals into the cell body, the cell body itself that effectively sums and thresholds these incoming signals and the axon for carrying the signal from the cell body out to other neurons (Haykin 1999).

The point of contact between a dendrite of one cell and axon of another cell is called a synapse. Fig. 1 is a simplified diagram of two biological neurons (Hagan *et al*. 1996). In summary, a neuron receives signals from synapses either located at the cell body or its dendrite, determines its state, and sends the output down to the axon (Hakim 2006).

ANNs are inspired by human biological neural networks, whereby they capture the brainy function manipulation to approach a specific problem by using certain rules to achieve suitable results (Jadid and Fairbairn 1996). ANN is composed of several processing elements namely neurons that are interconnected with each other. The network structure consists of an input layer, an output layer, and at least one hidden layer (Saldarriaga *et al*. 2009, Lakshmanan *et al*. 2008, Demuth *et al*. 2005). The appropriate number of neurons in each layer depends on the type of problem.

Fig. 2 shows the model of an artificial neuron which consists of a neuron that receives N weighted inputs that are summed and passed through an activation function to produce a single output. The output of this kind of neuron can be expressed in Eq. (1) (Sakla 2003 and Yeh 1998). In this equation, y_j, Op, w and θ are input, output, weight and bias of neuron, respectively.

$$O_p = f\left(\sum_{j=1}^{N} w_i y_j + \theta\right) \tag{1}$$

The activation functions usually have a sigmoid shape, but they may also take the form of other non-linear functions. Learning is the process by which the ANN adjusts itself to a stimulus and eventually produces the desired response. The network learning model can be divided into two categories, including supervised and unsupervised learning.

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. Table 1 indicates the comparison between the biological model and the artificial neural network.

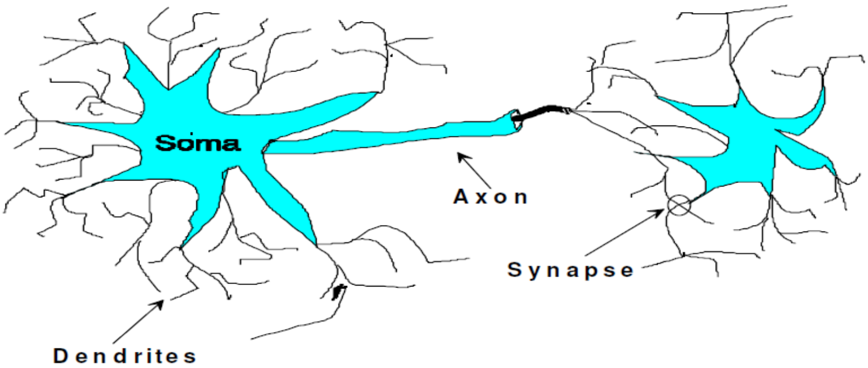


Fig. 1 Schematic biological neurons connected by synapses (Hagan *et al*. 1996)

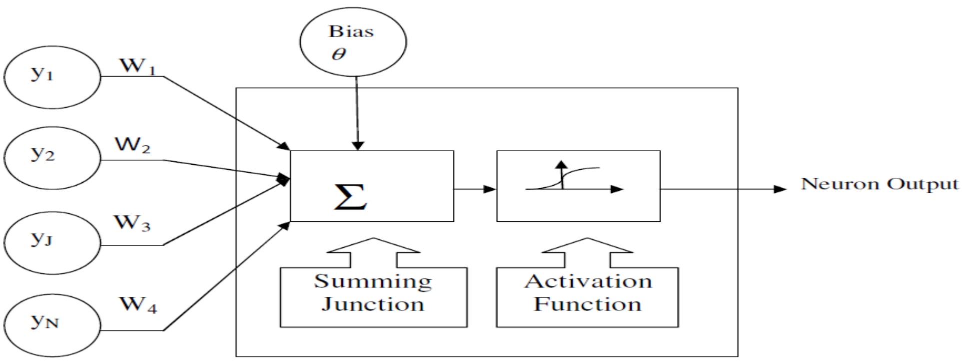


Fig. 2 Artificial neuron

Table 1 Comparison between artificial neural network and biological model

Biological Model	Artificial Neural Network
Neuron	Node
Axon	Connection
Synapse	Weight
Speed 10^{-3} s	Speed 10^{-9} s
Size 10^{11} neurons	Size 10^{3} nodes

2.2 Artificial neural networks architecture

A group of neurons can be collected and commonly referred to as an ANN. As shown in Fig. 3, a typical neural network has three layers namely the input layer, the hidden layer and the output layer. 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, pass through the hidden layer, and reach the output layer. Each layer can have a different number of neurons and activation functions such as sigmoid and linear functions. All neurons are interconnected to the neurons in the next layer through their weights. The structure of an ANN is often determined by the characteristic of the input data and behavior that needs to be approximated. In general, a single-layered ANN has been found suitable for simple patterns or behaviors, while multi-layered ANNs are used to approximate more complex nonlinear behaviors (Wasserman 1989).

Back Propagation Neural Network (BPNN) defines a systematic way to update the synaptic weights of multi-layer feed-forward supervised networks and is considered to be the most applicable due to the mathematical design of the learning complex nonlinear relationships (Fonseca and Vellasco 2003). Back propagation algorithm has a performance index, which is the least Mean Square Error (MSE) (Noorzaei *et al*. 2007, Ince 2004, Lee 2003). In MSE algorithm, the error is calculated as the difference between the target output and the network output. Among various neural networks, Multi-Layer Perceptron (MLP) is most commonly used in structural identification problems. Their applications to engineering problems have been summarized and reported in literature (Hakim *et al*. 2011, Noorzaei *et al*. 2008, Wu *et al*. 2002, Xu *et al*. 2002).

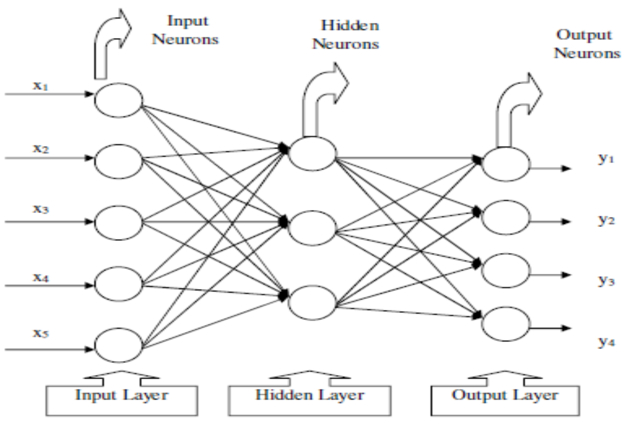


Fig. 3 Artificial neural network architecture (Pawar *et al*. 2007)

3. Structural damage detection

Civil engineering structures are subjected to deterioration and they may be damaged during their life time. The occurrence of damage in entire structures affects their functionality and leads to a decrease in the load carrying capacity of the structure thereby making it an unsafe structure. Therefore for the purpose of assuring safety and to prevent the reduction in the useful life due to the existence of cracking or deformation, it is necessary to monitor the occurrence, location, and extent of damage. Undetected damage may potentially lead to more damage due to further deterioration and finally to catastrophic failure.

In many situations, such damage is not visually observable, and to ensure structural integrity it is desirable to monitor the occurrence, location, and extent of such damage. Detection of damage before any event or immediately after an extreme event can help engineers assess the condition of a structure and make a sensible decision regarding the retrofit or replacement of the damaged structure thereby preventing expensive repairs resulting from the absence of structural assessment (Parloo *et al*. 2003, Pandey and Barai 1995). Any deterioration has a cause, and it should be the purpose of the engineer to find the cause, otherwise if the cause is ignored, the deterioration will be repeated. So, it is very important to detect damage at the earliest possible age of occurrence in structural engineering.

4. Structural damage detection using ANNs

Any reduction in stiffness of a structure can lead to a change in the dynamic parameters such as natural frequencies, mode shapes and damping ratio. A change in these parameters from the datum state indicates a possible defect 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 two decades a lot of research work has been conducted and reported pertaining to damage assessment. Two comprehensive review of available literature on structural health monitoring have been carried out by Doebling *et al*. (1996) and Sohn *et al*. (2004).

Current methods and different damage detection techniques consisting of changes in measured mode shapes and their derivatives, changes in modal parameters and changes in flexibility coefficients are summarized in these reviews. Various approaches in the area of damage detection area have been proposed, reported and reviewed, but up to date there is no review regarding the application of ANNs for structural damage detection using modal parameters such as natural frequencies and mode shapes. The purpose of this paper is to present a summary on the application of ANNs to develop damage identification algorithms using dynamic parameters such as natural frequencies, mode shapes and combination of both, during the last 20 years.

4.1 Frequency shifts

Natural frequencies can be easily obtained from a dynamic measurement anywhere on the system and is very common and popular damage indicator. The fact that changes in structural properties cause shifts in natural frequencies, warrant the use for structural health monitoring and damage detection. It is worth mentioning that frequency changes have limitation for applications to different types of structures and require high resolution and accurate measurements.

The feasibility of using an ANN trained with only natural frequency data to recognize the severity of damage in steel bridge girder is presented by Hakim and Abdul Razak (2013a, 2011a, b). The required data for the ANNs consists of natural frequencies of the first five modes of the undamaged and damaged bridge model are obtained from experimental modal analysis and have been successfully applied as the training patterns for the ANN. Based on this work ,the dynamic tests carried out on the damaged and undamaged test structure demonstrated that the reduction in stiffness during the damage lead to a reduction in natural frequencies for different modes. According to results in this study, ANN could predict the damage severity with an error of 5.6, 6. 25 and 7.79% for training, testing and validation, respectively and seems to be quite promising in terms of accuracy. This research was extended by the same authors (2013b) to consider adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) techniques to identify damage using natural frequency data obtained from experimental modal analysis. According to this research, ANN can be utilized as an early evaluation and other artificial intelligence technique such as ANFIS can be subsequently implemented to identify the severity of damage in a girder bridge with higher accuracy.

Kazemi *et al*. (2011) applied a procedure based on ANN and Particle Swarm Optimization (PSO) to determine the location and depth of cracks in cantilever beams. The first three natural frequencies of beams were obtained from the finite element analysis and applied as inputs of ANN. Particle Swarm Optimization (PSO) approach was applied to train the neural networks. Four trained ANNs were then applied to predict the location and depth of cracks. Results were in good agreement with actual data. However, a disadvantage of ANNs is their need for a huge number of training datasets to provide reliable predictions.

The natural frequencies and frequency response functions (FRFs) were applied as the inputs of the ANN and adaptive neuro fuzzy interface system (ANFIS) in order to predict the location and size of cracks in curvilinear beam elements by Saeed *et al*. (2012) and Saeed and George (2011). In these researches, changes in natural frequencies and amplitudes of FRFs of the beams for cracks of different sizes at various locations were determined from the finite element method and applied as input data for ANN and ANFIS. According to these studies, cracks longer than 5 mm can be located with acceptable accuracy, even if there are different levels of noise in the input data. Also the authors showed that this approach was less accurate for small cracks and sensitivity analysis showed that ANN is more sensitive to the noise than ANFIS approach.

Guo and Wei (2010) proposed a method to detect damages of different locations and severity on a simply supported rectangular beam using ANN based on the frequency change parameters. The simulation was performed with a simply supported beam in the laboratory. The process was divided into damage detection, location, degree of injury identified and combined the modal analysis with neural network technology to achieve damage assessment. This method also had strong robustness that was not impacted by small model errors and the detection accuracy was not influenced by incomplete measurement information.

The use of natural frequencies to detect damage in structures has been addressed by some researchers. In this section an attempt has been made to include earlier work during the two last decades. For example, Rosales *et al*. (2009) presented two methods consisting of the Power Series Technique (PST) and ANNs for detecting cracks in beam elements using the analysis of shifts in the frequencies as a dynamic parameter. Bernoulli Euler cantilever beam and a spinning beam as two structural elements were checked with PST and cracks were defined by introducing springs to represent the stiffness reduction. The aim was the detection of the existence and location of damage and the depth of crack. For this purpose, the natural frequencies measured in the damaged beam were selected as the input and the location and value of the spring constant were the output. Two dimensional FEA of a cracked beam was applied for obtaining data for training of ANN. Four hundred scenarios of damage were considered in this study. Then, frequencies measured in a physical experiment were introduced in the trained ANN and applied as input in the ANNs algorithm to detect the damage. Finally the ANN approach was applied to the case of the damaged cantilever beam.

The authors highlighted that the PST technique is very easy and can detect the crack with small errors and low cost but this method could only detect the crack at the first stage. On the other hand ANN produced larger errors but could handle and solve more complex problems such as nonlinearities due to large deformations or cracks. This study showed that a combination of the PST and ANN methods can detect existence, location and depth of the crack better than each method separately using natural frequencies.

Ramadas *et al*. (2008) presented a method to combine damage detection features of ultrasonic Lamb wave with first and second natural frequencies for detection of transverse cracks in a composite beam. In this investigation, first and second natural frequencies, amplitude ratio and Time of Flight (TOF) were considered as inputs to ANN and crack location and depth were the outputs of ANN, as depicted in Fig. 4. The training data sets for ANN were generated using FEA.

It was reported that if Lamb wave technique and vibration are applied individually for sizing of transverse cracks, Lamb wave technique fails when the damage zone is close to the fixed boundary and vibration technique fails when the damage zone is close to the free edge. Thus it was apparent that when damage features of more than one technique were combined, the domain of damage detection increased and damage could be recognized more accurately than using damage features of each technique individually. In this work the ANN was an efficient tool and could predict the damage location and depth with an accuracy of 95.8% and 89%, respectively.

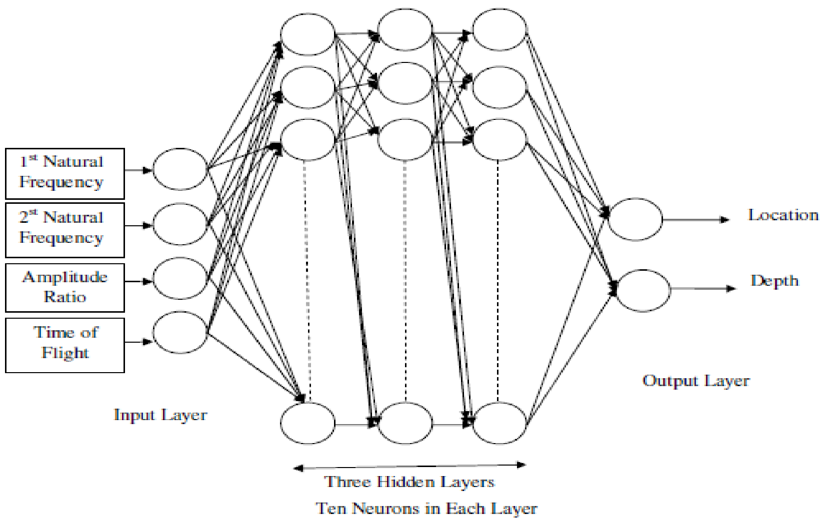
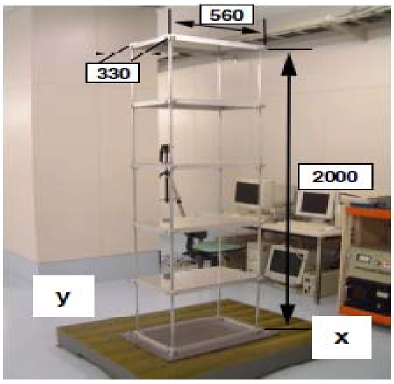


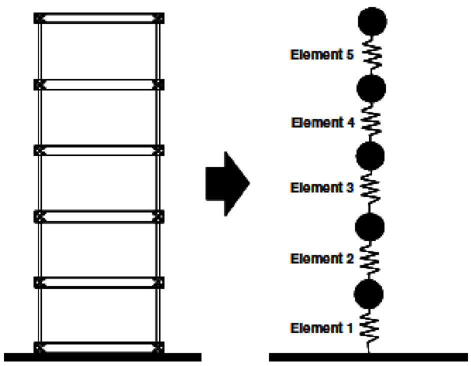
Fig. 4 ANN architecture used for damage detection (Ramadas *et al*. 2008)

Damage assessment of prestressed concrete beams using ANN approach incorporating natural frequency measurements was investigated by Jeyasehar and Sumangala (2006). Based on experimental results in this work, there is a strong relationship between natural frequency, ultimate load, crack load, crack width and deflection on damage identification of prestressed concrete beams and there is no mathematical model to show the behavior of beams on damage. ANNs do not need a mathematical model and in this study were used to estimate the damage in prestressed concrete beams. Aforementioned parameters used as inputs to train and test of the neural network from both damaged and undamaged beams. Two hidden layers with 7 and 5 neurons were considered in this work. The predicted extent of damage in the beam was the output of network. Static and dynamic data of the datum and damaged beams were obtained experimentally. Based on this work, the ANN trained with natural frequencies, using only dynamic data obtained for different applied loads on a prestressed concrete beam; the damage level could be assessed on error of less than 10%. It is shown that ANN trained with post-crack stiffness and natural frequency is adequate to predict the damage with reasonable accuracy. This research was extended by Sumangala and Jeyasehar (2011) to formulate a method using the results obtained from an experimental study carried out in the laboratory. Prestressed concrete (PSC) beams were cast, and pitting corrosion was introduced in the prestressing wires and allowed to be snapped using accelerated corrosion process. Both dynamic and static tests were carried out to study the behavior of undamaged and damaged beams. The network was trained only with natural frequency and stiffness of damaged and undamaged beams. Also, good results obtained with the use of natural frequencies at different loads of a prestressed concrete beam.

A damage detection system to assess structural integrity using natural frequencies was proposed by Tsuchimoto *et al*. (2004). In this system, the damage sites were first detected globally by using ANN method, and then the damage was identified locally by determining the changes in the structure's eccentricity between centers of rigidity and weight due to the damage in order to narrow down the damage sites. This strategy was applied to a scaled 5-story structure in which the beams were fixed at both ends. The experimental structure is shown in Fig. 5(a). This structure was modeled as a 5-mass shear system as shown in Fig. 5(b). It can be seen in Fig. 5(b), that each element represents a single story.



(a) 5-story experimental structure



(b) Multi-mass shear system

Fig. 5 Experimental and modeled structure (Tsuchimoto *et al*. 2004)

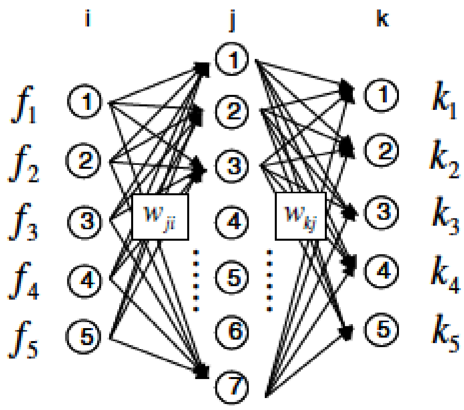


Fig. 6 Feed-forward neural networks (Tsuchimoto *et al*. 2004)

In this study, a neural network used in the global damage detection strategy included 5 inputs and 5 output neurons, respectively. The first five natural frequencies were selected as the input, and the reduction rate of the stiffness of each element or story were selected as the output. This network is shown in Fig. 6. According to the results, ANN showed very good accuracy in identifying the extent of damage, and then by detecting change in eccentricity, the damage locations could be narrowed down.

Suresh *et al*. (2004) applied a modular ANN architecture to identify the location and height of cracks in cantilever beams. In this research the first three natural frequencies were analytically computed for diverse crack locations and heights and were considered as inputs of ANN. Depth and location of cracks were appointed as outputs of ANN. According to the authors, measured natural frequencies as inputs of modular ANN can be applied to detect damage in structures with a high level of accuracy. Also, the results of a comparative study showed that the radial basis function (RBF) network performed better than the multilayer perceptron (MLP) network.

Natural frequencies were used to detect the location and depth of cracks in a clamped-free beam and a clamped-clamped plane frame by Suh *et al*. (2000), who presented a technique by combining neural network with genetic algorithm for damage assessment. The location and depth of a crack were inputs for neural network and the structural eigenfrequencies were the outputs. Finite element model of aforementioned structures were used to confirm the effectiveness of this approach. After training of neural network, genetic algorithm (GA) was employed to detect the location and depth of crack from measured natural frequencies. This was extended by Sahoo and Maity (2007) to consider the problem in selection of suitable values of neural network such as learning rate, and momentum, type of activation function, convergence criteria and training algorithm.

Neuron-genetic algorithm based on modal parameter and strain values were applied to determine the severity and location of defect. Genetic algorithm was applied to select reasonable and good values of the network parameters by treating them as variables and back propagation ANN for damage detection. The capability of this method was verified using a beam and a plane frame structure.

ANNs have been applied to detect the extent, location and magnitude of the damage by Kim and Kapania (2002). The natural frequencies of a damaged beam were used as inputs for ANNs and the outputs were the location, extent, and the magnitude of the damage. Differences in natural frequencies of intact beam and damaged beam were employed for damage identification in this study. To increase the sensitivity of the natural frequencies to detect small magnitude of damage, high frequency modes may be used. However high frequency modes are more sensitive to environmental conditions than low frequency modes and this is one of its major drawbacks.

ANNs have been utilized by many researchers to identify damage location and severity in bridges using natural frequencies. The first twelve natural frequencies measured from the Tsing Ma suspension cable tension bridge in the Hong Kong were used as the inputs and outputs of the autoassociative neural network to detect damage by Chan *et al*. (1999). This network is called autoassociative because the samples at the input layer were reproduced at the output layer. In this work an index is defined as the difference between the target outputs and the outputs estimated from the autoassociative network and are able to detect the anomaly caused by a 5% reduction in cable tension. From this study, it can be concluded that the suggested combination of the autoassociative network using the index has the ability to differentiate the changes caused by damage and changes due natural variations of the system.

Also, damage was detected in a steel bridge element using ANN by Spillman *et al*. (1993). A 4.5 m steel bridge element was considered as an example in this research and damage was simulated by cutting the element and bolting plate reinforcement over the top of the cut. Thus, by removing the plate, loosening and tightening bolts of the plate, full, partial and undamaged states of the elements, respectively could be considered.

Based on this work, when the plate attached, the element was mentioned as undamaged. Three sensors consisting of two accelerometers and a fiber optic modal sensor was installed on the element. The FFT of the time history signal from each sensor was computed and recorded. The amplitudes and frequencies of the first two modal peaks of Fourier transformed acceleration time history signal were used as inputs. The impact intensity and location were also provided as inputs to the neural network while each of the possible damage states were the outputs. In this study, ANN architecture with 14 inputs neuron, 20 hidden neuron and 3 outputs neuron was employed for each of the possible damage. Using these three sensors, the results demonstrated that accurate diagnosis was achieved in 58% of the cases considered.

Ceravolo and De Stefano (1995) employed natural frequencies as the input parameters to ANN to predict the two dimensional coordinates representing the damage location in a truss structure. In this study, the damage was modeled by removing the truss elements. A Back Propagation Neural Network (BPNN) model with ten input neurons representing to ten natural frequencies and two output neurons corresponding to the x and y directions was applied. One hidden layer consisting of ten hidden neurons was chosen based on trial and error method. In this work only single damage was considered and truss structure was modeled by FEA. Eighteen patterns consisting of various single damage cases were considered for neural network training. Results showed good agreement between natural frequencies and location of damage.

The analysis of relative sensitivities of structural dynamic parameters using ANN based on combined parameters was reported by Hesheng *et al*. (2005). The combined parameters calculated with the three different parameters as follows:

i) Change in rates of the natural frequencies
ii) The change in ratios of the frequencies
iii) The assurance criteria of flexibilities

These parameters were introduced as the input of the neural network. Based on analytical results such as cantilever and truss with different damage scenarios, it was concluded that the combined parameters were more compatible for the input samples of ANNs than the other parameters, individually.

ANNs were developed to detect the damage in cantilever beams using natural frequencies by some researchers. For example, the assessment of damage in numerically simulated cantilever beam using natural frequencies was conducted by Ferregut *et al*. (1995). The architecture of neural network consisted of three layers with six neurons in the input layer corresponding to the first six natural frequencies, 17 and 11 neurons in hidden and output layers respectively. In output layer the first neuron was allocated for damage magnitude and the other 10 neurons were for damage location. In this research study, the damages were modeled by reducing the depth and width of the corresponding element from 1% to 30% and the network was trained using 240 data samples. The researchers found that only severe damages were recognized. According to the authors, the reason for this is that natural frequencies are insensitive to low level of damage.

In addition, an ANN was developed to identify damage in a four-element cantilevered beam by Leath and Zimmerman (1993). In this research, the damage in the beam was modeled by reducing Young's modulus by up to 95%. ANN was applied to identify the map from the first two bending frequencies to the level of damage in each member. In this study, up to 35% damage could be detected using ANN.

Composite materials have high strength and stiffness. Therefore they have been used in many application of structural engineering. One of the common damage in composite structures is delamination. Delamination decreases the frequencies and stiffness in structures and increase modal damping. Some attempts have been made to detect the size and location of delamination using ANNs based on shifts in natural frequencies. Chakraborty (2005) suggested an ANN delamination model for predicting the shape, size, and location of delaminations in laminated samples with an elliptical embedded delamination. In this investigation, ten natural frequencies of the specimen were the input variables of ANN, while the outputs were size, shape and location of delamination. One hidden layer with 9 neurons was considered in this study based on the trial and error. The author compared ANN results with the finite element results and obtained good agreement for them.

Also, good results have been obtained with the use of natural frequencies of damaged composite beams generated from finite element simulations by Okafor *et al*. (1996) using ANNs. In this study, the existence and location of delamination were identified by comparing experimental and theoretical results. The size of delamination was estimated by ANN. It was demonstrated that the third and fourth natural frequencies were better indicators for delamination detection. The efficiency and application of this method was verified experimentally.

In addition, Islam and Craig (1994) reported the effectiveness of using natural frequencies as the inputs for neural networks in determining the size and location of delamination in a cantilever beam. The first five natural frequencies were selected as input parameters of neural network. Two neurons corresponding to delamination location and size were selected as outputs. The neural network was trained with 14000 training samples. This work was verified using both numerical and experimental examples and results demonstrated that ANN is capable to identify the location and size of delamination in cantilever delaminated beam.

Damage detection of a cracked column using ANN was studied by Yau (2005). In this study, the first natural frequency of the cracked column under different compression load by an analytical method were calculated and applied as inputs and the crack size, crack location and the compression load of the column were chosen as outputs of the ANN. The authors according to the results of testing patterns on numerical example by a trained ANN found that BPNN is a useful tool for predicting the applied compressive force to the column, and the crack size-location on the cracked column.

Also in this study, the high precision of predictions for the cracks of a damaged column was demonstrated when analysis was done using a larger number of vibration frequencies computed to give the inputs of the BPNN. Finally the authors compared the results for detecting the crack location on the column from that analytically solved from the characteristic equation with back propagation neural networks and concluded that ANN can predict the cracks and compression force on a cracked column with good accuracy and results demonstrated that increasing the number of inputs will improve the accuracy of the predictions.

Identification of damage in a steel lattice mast subject to wind excitation using ANNs was done by Kirkegaard and Rytter (1994). The steel lattice mast considered in this research was 20 meters high. An ANNs was trained using patterns of the relative changes of the first five natural frequencies. Training sets were generated from a FEA and using data with 0% to 100% reduction in area of selected diagonals. Four outputs corresponding to four of the diagonals were chosen. In the architecture of ANN two hidden layers of five neurons each, were chosen in this work. ANN could reproduce the training data, but it had less success on the test data. The authors examined the effects of the location and quantification of the damage and concluded that at 100% damage, ANN could locate and quantify the damage but at 50% it could only predict the existence of damage. In this investigation damage less than 50% could not be detected.

4.2 Mode shapes

As mentioned in the previous section, one approach to structural damage assessment is to use natural frequency. However, the natural frequencies are not sensitive to damage, thus limiting their application. A mode shape that is an indication of the shape of vibrational deformation of the system can give more information than natural frequencies and are much more sensitive to system damage. For this reason mode shape is more useful in damage location techniques. Available literature on the application of the ANNs for damage detection using mode shapes is limited. However some researchers have employed mode shapes instead of natural frequencies for detection of damage in structures using ANNs.

Application of the ANNs for damage identification using mode shapes in beam structures were investigated by Park *et al*. (2009) and Pawar *et al*. (2007). Park *et al*. (2009) proposed a sequential methodology for damage detection in beams using time-modal features and ANNs. These approaches include acceleration-based damage alarming for real time damage incidence and modal feature-based damage estimation for offline damage assessment. In the time domain damage assessment, an acceleration-based neural network is designed to assess the occurrence of damage in a structure by using cross-covariance functions of acceleration signals measured from two different sensors.

By using the acceleration feature, the network was trained for potential damage scenarios and loading patterns which were unknown. In the modal-domain damage assessment, a modal feature-based neural network was designed to estimate the location and severity of damage in the structure by using mode shapes and modal strain energies. By using the modal feature, the neural network was trained for potential damage scenarios. The authors proposed a damage detection procedure as summarized in Fig. 7.

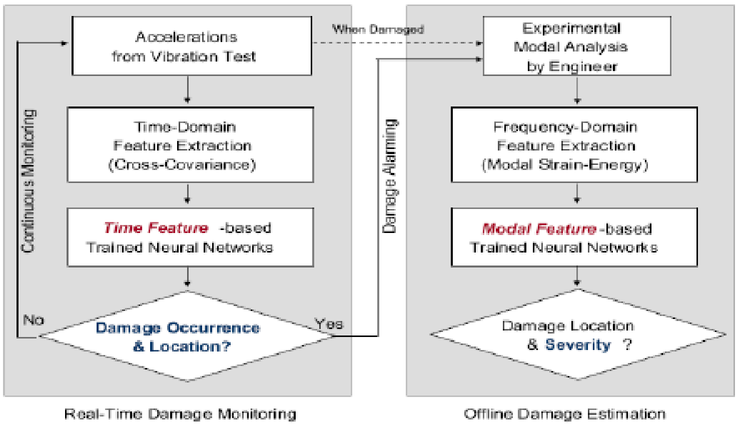


Fig. 7 Sequential damage detection approaches using ANNs (Park *et al*. 2009)

In addition, Pawar *et al*. (2007) presented a numerical evaluation of a new damage index method and formulated it in the form of a vector of Fourier coefficients acquired by spatial Fourier analysis of mode shapes in the spatial domain of damaged beams using ANNs. Fourier coefficients are sensitive to both damage size and location. In this method a FEA of a damaged beam with fixed boundary conditions was applied to obtain the mode shapes and results were compared with different types of time domain application of Fourier analysis for vibration difficulties.

An ANN was employed to assess the damage location and size using Fourier coefficients of the first three mode shapes of aforementioned beam as input parameters. The number of input parameters for the ANN was the number of modes selected multiplied by the number of Fourier coefficients selected for damage identification. Analytical works showed the performance of this approach and demonstrated that damage assessment using Fourier coefficients and ANNs has the ability to identify the location and damage size with very good accuracy. The authors showed that damage caused changes in the Fourier coefficients of the mode shapes, which were found to be sensitive to both damage size and location. Therefore, a damage index in the form of a vector of Fourier coefficients was formulated in this study.

ANNs have been applied by some researchers to identify damage in bridges using mode shape. The differences or the ratios of the mode shape components before and after damage and also direct mode shapes were used as the input to the neural networks for damage detection of multiple-girders simply supported bridges by Lee *et al*. (2005). This model was verified by using two numerical models, i.e., laboratory and field test data. It was noted by the authors and demonstrated through the modeling errors of up to 20% in the baseline finite element simulations that, when using direct mode shape as network inputs, the method generated relatively high errors indicated low accuracy of damage assessment. However, in this research it was found that the mode shape differences or the ratios of mode shapes before and after damage were less sensitive to modeling error and this method was capable of detecting damage with good accuracy. As shown in Fig. 8, the architecture of neural network consists of an input layer, two hidden layers, and an output layer.

In this Figure, i denote the element number and subscripts o and d denote datum and damaged cases. Also, Φ , $\Delta\Phi$ and Φ_d / Φ_o are the mode shape, the mode shape differences and the mode shape ratios before and after damages, respectively. The output layer contains the element stiffness indices as Eq. (2), where k is the stiffness matrix.

$$S_i = \frac{k_{i,d}}{k_{i,o}} \tag{2}$$

Also the proposed method was verified on the laboratory bridge model and similar results were obtained. For more confidence, this method also verified on Hannam Grand Bridge in Korea and ANN trained using mode shape differences and mode shape ratios could recognize the location of damages with good accuracy. Small errors were encountered for severity of damage.

A two step algorithm to detect simulated damage in a finite element model of a girder beam of the Crowchild Bridge located in Canada was presented by Xu and Humar (2006). Two single and one double damage cases was studied in this study. The 2D finite element model of the girder beam with 20 elements and the Crowchild Bridge with 15 beam elements are shown in the Figs. 9 and 10, respectively.

As shown in Fig. 8, each intermediate node has three degrees of freedom i.e., horizontal and vertical translation and rotation. Abutments have two degrees of freedom comprising of horizontal translation and rotation. Only the rotational degree of freedom for pier nodes was considered. In the first step a damage index using modal strain energy was employed to locate of damage and in the second step, an ANN for estimating of damage magnitude was proposed. Measurement errors were simulated by inputting 5% noise to the mode shapes. Good results were obtained in predicting the damage location in the girder model from the first step. However when the damage indices were obtained from translational modes, some errors in location of damage occurred. For the second step, the authors demonstrated the effectiveness of ANN in predicting the damage severity where there was very good agreement.

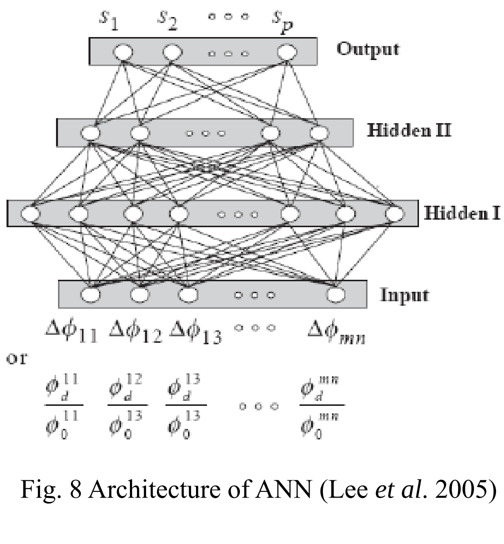


Fig. 8 Architecture of ANN (Lee *et al*. 2005)

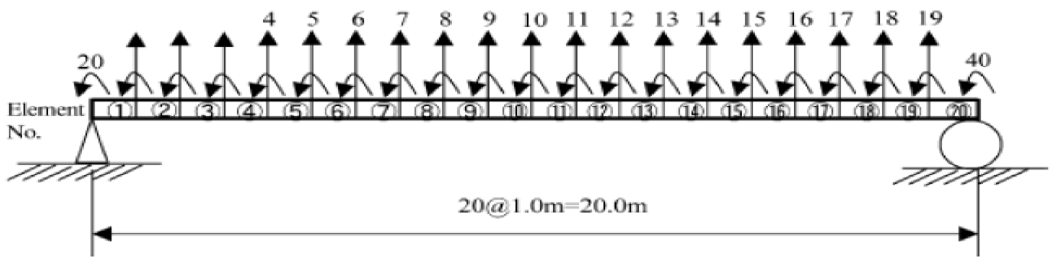


Fig. 9 Finite element model of a beam (Xu and Humar 2006)

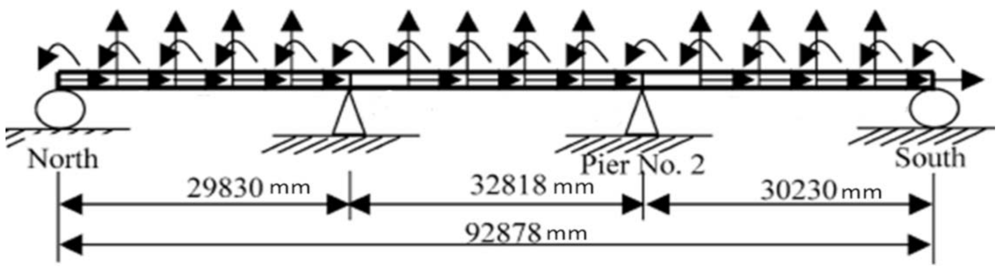


Fig. 10 Girder model of the Crowchild Bridge (Xu and Humar 2006)

Just-Agosto *et al*. (2008) applied the neural network method with a combination of mode shapes and thermal damage detection signatures to develop a damage detection tool. They applied the developed technique on sandwich composite beams for the purpose of crack detection. Results showed that the network can successfully detect damage.

Toro *et al*. (2003) employed the fundamental displacement mode shape curvature of a sandwich composite structure to detect localized damage corresponding to a reduction in stiffness. Three dimensional finite element simulations of sandwich composite structures were done and artificial neural networks were conducted based on training performed with the FEA. Based on this study, mode shape curvature of a sandwich structure could identify the damage.

Frame structures are considered as important applications of vibration-based structural health monitoring. Elkordy *et al*. (1993, 1994) applied Back Propagation Neural Network (BPNN) to identify damage in three different models of a five-storey steel frame structure. These models include two finite element models and one experimental structure. The first finite element model was a two-dimensional frame with beam elements while in the second finite element model, truss, beam and plate elements had been used. The authors used mode shapes and the percentage change in member stiffness as inputs and outputs of the neural networks, respectively and were identified the map between them. In this study damage was introduced to the model by reducing the member stiffness in the bottom two stories from 10% to 70%.

Two ANNs were trained on mathematical models and verified with experimental data. It was seen that the network trained with data generated of the first finite element model was not able to produce correct damage estimation. However the network trained with data generated of second finite element model using truss, beam and plate elements gave good damage predictions with less than 10% error for damage severities. According to ANN trained with experimental data ,it was further found that the model was more accurate in predicting damage to the first and second stories as well as estimating the extent of the defect.

Also ANNs have been trained to identify damage in truss structures using mode shapes. Three lowest modes of the two-dimensional truss structure with nine bays have been considered to train the ANNs for detecting and locating damage by Faravelli and Pisano (1997). In this study, the authors assumed that damage happens in only one element at a time. The suggested neural network consists of two sub neural networks. The first sub neural network determines if any of the truss members is damaged. Classification of damage element into three groups consisting of diagonal, vertical and horizontal element groups was determined by the second sub neural network. The efficiency of the network varies depending on which element group imposes the damage.

4.3 Combined modal parameters

According to a review by Salawu (1997), although shifts of natural frequencies are a useful parameter to recognize the existence of damage in a structure, it is not sufficient to locate the damage. Therefore, more information such as mode shape is needed to overcome this weakness. Additionally, multiple modes are often needed to provide better prediction of damage severities and locations.

A combination of natural frequencies and mode shapes for detecting damage using ANNs has been used by many researchers. The applications of combined modal parameters on specific structures such as beams, frames, bridges, buildings and other structures have been investigated which are explained as follows:

4.3.1 Beams

Aydin and Kisi (2012) employed the first four natural frequencies and mode shape rotation deviation data as input to the neural network models to estimate the location and extent of cracks in Timoshenko beam structures. In this paper, multilayer perceptron (MLP) and a radial basis function neural network (RBNN) were applied to training of the data sets. According to the results, ANN models can be applied in diagnosing the multiple cracks on beam structures. Also, comparison of the error results of MLP and RBNN showed that the RBNN model performed better than the optimal MLP model.

Combination of natural frequency and mode shape for prediction of crack severity and its location in a cantilever beam using ANN technique is applied by Das and Parhi (2009). In this study the inputs to the ANN were relative deviation of first three natural frequencies and first three mode shapes and the outputs of ANN were relative crack depth and relative crack location. A set of training samples are used to train the ANN for prediction of crack location and crack depth. Experimental test has been done to verify the robustness of the developed ANN and the comparison showed this approach can be applied as a useful and effective tool for damage identification.

Li *et al*. (2005) applied an algorithm for location and severity prediction of crack damage in beam like structures using a combination of global and local vibration-based analysis data as input in Radial Basis Function (RBF) ANNs. A FEA was done to obtain the dynamic characteristics of undamaged and damaged cantilever steel beams for the first three natural modes. In this study, an experimental validation was considered and modal parameters such as resonant frequencies and strain mode shapes were obtained using several steel beams with six distributed surface bonded electrical strain gauges and an accelerometer mounted at the tip. In this work, it was seen that trained ANN using the data obtained from the numerical damage case can predict the severity and localization of the crack damage successfully.

Sahin and Shenoi (2003a, b) presented a damage assessment algorithm using a combination of changes in natural frequencies and curvature mode shapes as input in ANNs for the location and severity prediction of damage in numerical models of composite beam structures. In this study, three different networks were trained and dynamic characteristics of intact and damaged cantilever steel beams were obtained from the FEA. The first three natural frequencies, the absolute differences in mode shape curvatures and finally, the maximum absolute differences in curvature of the mode shapes and their corresponding locations along the beam were chosen as input parameters for first, second and third network, respectively. In addition, more neural networks were trained using combinations of all the above parameters.

Different damage scenarios were modeled by reducing the local thickness of the elements at different locations along the finite element model of the beam structure. An experimental analysis was done to obtain modal parameters such as the resonant frequencies and strain mode shapes and the data obtained from the experimental analysis was used for the quantification and localization of the damage in ANN. A schematic picture of damage identification method is shown in Fig. 11.

According to the results of this study, the performance of each network was more efficient compared to the trained network that applies all the combined input parameters. Based on this study, maximum absolute differences in mode shape curvatures and their corresponding locations along the beam produced fairly accurate damage location, while natural frequencies did not produce useful information about location or magnitude of the damages.

To illustrate the effects of uncertainties, noise was injected to frequencies and the maximum differences in mode shape curvature data. It was demonstrated that when noise data was added to the networks, more accurate estimations were obtained for damage location in comparison to severity of damage.

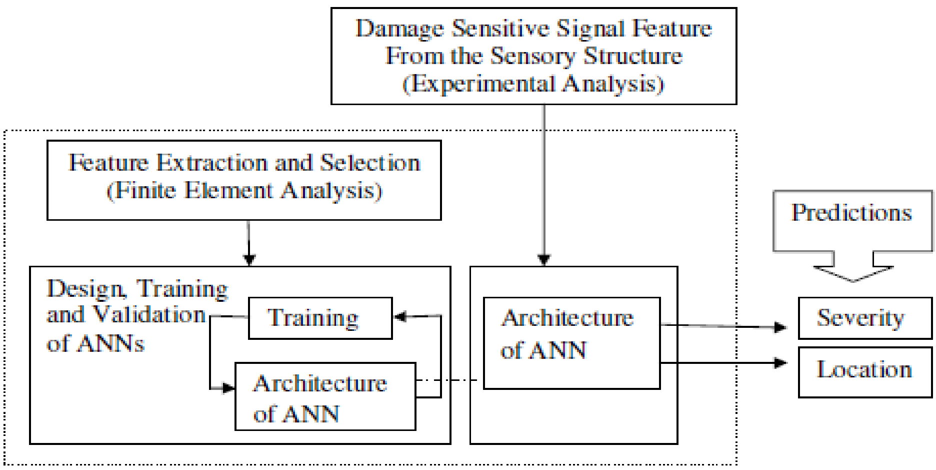


Fig. 11 A schematic picture of damage assessment method (Sahin and Shenoi 2003)

Zhao *et al*. (1998) employed the dynamic properties of structures for detecting and locating damage and support movement in a three-span continuous beam using a Counter Propagation Neural Network (CPN). The architecture of CPN is composed of an input layer, only one hidden layer and an output layer. The type of learning in CPN is unsupervised and it can work with incomplete data. In the CPN algorithm all weighting arrays are not updated simultaneously, therefore it uses less computation time than a BPNN. In this study, four different inputs including natural frequencies, mode shapes, slope array and state arrays were considered. Dynamic properties of the structures in continuous beams and static displacements on plane frames were applied as diagnostic parameters for the network and damages were simulated by reducing the values of Young's modulus of members and the required data was obtained via FEA. The authors concluded that natural frequencies and slope arrays gave better results compared to mode shapes and state arrays. The authors also showed that the dynamics parameters were good diagnostic parameters for damage assessment, while static displacement was not suitable to detect multiple damages as similar displacements can be obtained with different combination of damage and loading. Finally, this study deduced that ANNs have the ability to detect damage in structures and are promising tools in damage detection.

To predict the location of damage in a structure, the mode shape curvatures changes are more sensitive than mode shapes themselves and can be obtained from the measured displacement components of the mode shape. Therefore a better localization of damage could be done by considering curvature of the mode shapes (Hamey *et al*. 2004, Kolakowski *et al*. 2004, Koh *et al*. 2003). The mode shape curvature approach cannot provide the prediction of the severity of the damage. Also, the application of the mode shape curvature approach is limited to structures that can be simulated as a set of girders. The usefulness of mode shape curvature as a good indicator for damage identification of beam structures was shown by Pandey *et al*. (1991).

Chang *et al*. (2000) also proposed a structural damage detection method based on natural frequencies and first mode shape curvature using an iterative neural network technique. This technique was verified from experimental and numerical studies of a RC beam. In this study the network was first updated using initial training data sets consisting of assumed structural parameters as target outputs and their corresponding dynamic characteristics which included natural frequencies and first mode shape curvature, calculated from the FE model as inputs. Then, the structural parameters predicted from the trained ANN were used in the FEA to reproduce the measured dynamic characteristics. The network model would go through the second training phase if the simulated dynamic parameters deviate from the measured ones. After the training process, the structural parameters identified from the measured vibration signals were applied to infer the location and extent of damage. In this study, four damage cases were simulated and the results demonstrated that all damage cases were successfully detected, but some small errors were seen when experimental data was applied. According to the authors, this may be due to uncertainties related to material properties or material in homogeneity.

The prediction of hole defect sizes and locations in glass fiber reinforced plastic (GFRP) composite laminated beams using ANN was applied by Jenq and Lee (1997). Inputs of the network consists of the frequency shifts of the first four modes and two output nodes corresponding to the hole size and location. The finite element model was calibrated by using measurement data to enhance the accuracy of the analytical model. After that, five hundred sets of simulations were performed to generate training data sets with various sizes of holes at different locations. The authors were then able to predict the hole size and location with average errors of 7% and 6%, respectively using an ANN including one hidden layer consisting of 15 neurons.

The application of ANNs for damage assessment in a fiber reinforced plastic (FRP) beam was reported by Byon and Nishi (1998). The first three natural frequencies and/or the third mode shape of the beam were selected as inputs of neural network and damage was modeled by cutting the unidirectional composite fibres and replacing with teflon film. Artificial neural network could predict the location and amount of damage successfully.

Natural frequency and mode shape as the input parameters to a radial basis neural network to update the finite element model based on experiment modal data was applied by Levin and Lieven (1998). A ten-element cantilever beam was used as an example and showed the capability of ANNs for verifying modal updating parameters for the numerical model using experimental modal data.

4.3.2 Frames

Kanwar *et al*. (2007) developed a correlation between the damage in the 2D rigid frame of the RC three-storey building with dynamic parameters using an ANN model. In this study, the dynamic characteristics were obtained analytically under different levels of damage using modal analysis of the frame by changing the rigidity of the structure. In this study the results from modal analysis consists of storey height, mode shape coefficient and fundamental frequency ,were mentioned as inputs and the damage index (DI) was selected as the output and ANN trained for estimating of damage in the structure. The authors defined the damage in four stages consisting of minor, moderate, severe and collapse depending on the value of damage index between 0 and 1. In this work, authors showed that an increasing of the damage index in each storey with reducing in the frequency during the damage. It was noted by the authors that the trained neural network could predict the damage index values in the RC frame building based on their approach with maximum error of 6% which indicates high accuracy for the prediction of damage.

Bakhary *et al*. (2007) described the application of ANN with the consideration of uncertainties. In this research, random errors were considered and a numerical single span steel portal frame is modeled to show the proposed method. The steel frame is divided to six sub-structures as depicted in Fig. 12. Each sub-structure contains of five elements. In this study, the damage severity for each sub-structure is denoted by a Stiffness Reduction Ratio (SRF). SRF is defined as Eq. (3).

$$\mathrm{SRF} = 1 - \frac{E'}{E} \tag{3}$$

In Eq. (3) E is the Young's modulus in the undamaged state and E' is Young's modulus at the desired damage level. For the damage assessment in this study, the training data was obtained from the FEA, which involved generating large numbers of damage case studies based on an initial baseline finite element model. The input data consisted of natural frequencies and mode shapes, and the output layers consisted of Young's modulus i.e., E values, to represent the stiffness parameter. After training of the ANN model, the testing data was then applied to the ANN model to obtain the locations and severities of damages.

Bakhary (2010) extended this research to consider a statistical vibration based damage identification that includes the effect of uncertainties in the measured data and finite element model of the steel frame. In this research nine mode shape points and frequencies for the first three modes of a structure were used as the input parameters. The output parameters were Young's modulus (E) of every section. Rossenblueth's points estimation method was used to determine the statistics of the identified parameters. Results demonstrated that a probabilistic method using ANN is capable of detecting the damaged members with a higher confidence level and good accuracy.

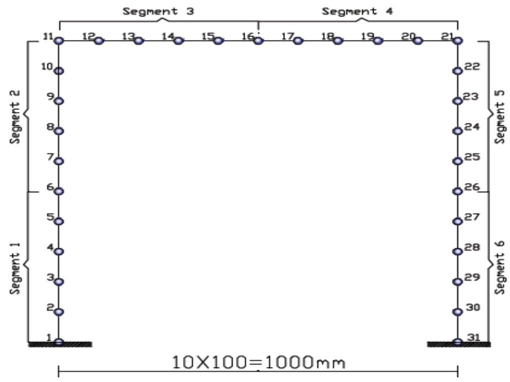


Fig. 12 Finite element model of the steel frame (Bakhary *et al*. 2007)

Lam and Ng (2008) applied separately damage-induced changes in modal characteristics such as natural frequencies, mode shapes and Ritz vectors as pattern features for training two ANNs. In this study, the calculation of Ritz vectors was done based on a set of measured natural frequencies and mode shapes. A benchmark structure that is a four storey, two-bay by two-bay steel frame with six damage patterns is considered in this research. Based on this work, the authors found that the efficiency of the ANNs trained using natural frequencies and mode shapes for structural health monitoring was better than that of ANNs trained via measured Ritz vectors. There is no detail about the calculation of the Ritz vectors in this paper. Lam *et al*. (2006) also employed the use of damage-induced Ritz vector changes as ANN inputs to recognize damage location and severity.

Zapico *et al*. (2001, 2003) described a procedure for damage detection in a two storey steel frame structure and a composite floor based on ANNs. In this investigation, three different ANNs were considered. In the first network, the first natural frequency and in the second network, the first mode shape were used as input parameters while for the third network, the first two longitudinal bending frequencies were chosen as inputs. The reliability of each neural network was verified using numerical and laboratory data of the structures. The first network was not well against new data and could not generalize from the first natural frequency as the selected input and failed. According to the second network good generalization occurred for the numerical data. However for laboratory data in second network due to the low accuracy of the extracted mode shapes, generalization could not be achieved and failed. Finally the third network which trained the first two longitudinal bending frequencies was capable of providing correct damage identification, especially when the structural damage and the associated changes in vibration properties were simulated analytically.

Yun and Bahng (2000) reported a method for estimating the sub-structural stiffness parameters of a complex structural system by using an ANN with natural frequencies and mode shapes as input patterns. This method was applied on ten-storey with two bay frame structures as depicted in Fig. 13. Based on this Figure the frame structure was contained 44 nodal DOFs and was subdivided into three sub-structures contains an internal and two external sub-structures. In this study, noise was induced in training and testing phases. The prediction of average relative errors for testing data samples were obtained in the range of 9-15%, which demonstrated good agreement and showed the applicability of ANNs using combined modal data based on sub-structuring technique for the detection of damage in large structural systems.

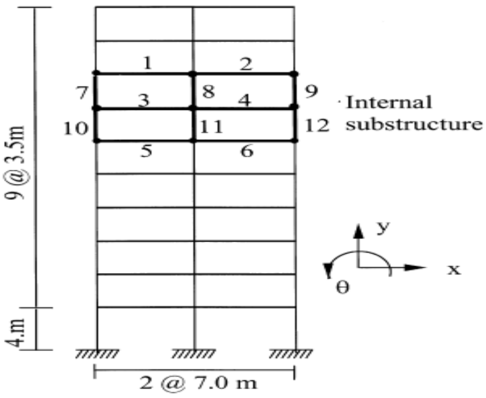


Fig. 13 Sub-structuring of two-bay frame structure (Yun and Bahng 2000)

4.3.3 Bridges

Mehrjoo *et al*. (2008) focused on reporting damage of joints in two truss bridge structures using ANNs. The natural frequencies and mode shapes were applied as inputs to the ANN for damage identification. Accuracy and efficiency of the suggested method was demonstrated using numerical models of the two different truss bridges with five and sixteen joints, respectively. Various types of damages to suspension cables, main members, girders, and joints were considered. The type of damage that was considered in this study was fatigue in the joints, as shown in Fig. 14.

It was assumed for modeling that when a truss joint was damaged, the cross-sectional area of all elements linked to that joint, was reduced in proportion to the damage intensity percentage at that joint. A tiny element was then defined at the end of all elements common to the joint, to facilitate modeling of damage at joints and the cross-sectional area of all the tiny elements connected to that joint, was proportionately reduced. Based on the findings, the average errors for testing the data set in the case of using five modes were demonstrated to be about 1%, which proved the applicability and efficiency of the ANN method to determine the severity and locate damage of the joints in truss bridges. However, the results demonstrated that when only one mode was applied, an average error of more than 8% was obtained. Finally, it was concluded that the optimum number of mode shapes to be included was five to produce a minimum error of about 1%. In this research only investigated data from noise-free analytical modeling and real testing uncertainties such as measurement noise were not applied.

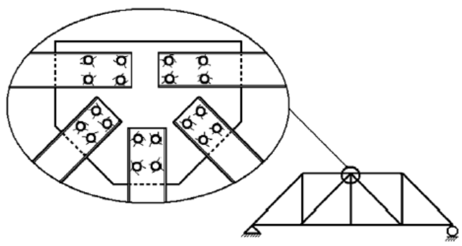


Fig. 14 A schematic picture of fatigue damage in a truss joint (Mehrjoo *et al*. 2008)

A three-step algorithm for identifying existence, location and severity of damage on a finite element model of cable-stayed Kap Shui Mun Bridge located in Hong Kong using modal parameters was utilized by Ko *et al*. (2002) wherein twelve cases were studied. In the first step, natural frequencies of datum and damaged states of structure as inputs for autoassociated neural networks were considered for the purpose of defecting damage. In two of twelve cases studied, this step could not recognize damage and failed to sense the damage. In the second step, modal flexibility index and modal curvature index were used to determine the damage location. It was found that, these modal indices were sometimes unable to locate the damage. Natural frequencies and mode shapes in the third step of this algorithm were used as inputs to Multi-Layer Perceptron (MLP) neural network for identifying damage severity. According the authors, the third step was most promising in terms of damage identification.

The damage assessment of a bridge structure was carried out based on the estimated modal parameters using ANN by Lee *et al*. (2002). As inputs to the neural networks, the ratios of the resonant frequencies between before and after damages and the mode shapes after the damages were used to take into account the mass effect of traffic on the bridge. Ambient vibration testing data caused by traffic loadings was used and the modal parameters were identified from the free-decay signals extracted using the random decrement method. The predicted damage locations and severities were found to compare well with the imposed damages on the structure.

Choi and Kwon (2000) applied a finite element model to develop a damage detection method for a steel truss bridge based on an ANN. Strain data, mode shapes and natural frequencies for training of neural network were obtained through the FEA. The static analysis of the finite element model identified eight truss members subjected to high stress levels, and the stiffness in each of these members was reduced to simulate eight different damage cases. Two different neural networks were developed for damage localization. The first network determined which half, either the left or the right of the midpoint of the bridge, was damaged. The strain readings from seven truss members that were generated from the analytical model have been used as inputs to the first neural network. Binary number corresponding to the left or right side of the bridge was chosen as an output of network. The inputs to the second network were the binary output from the first network, modal parameters, mode shapes, and natural frequencies which were generated from the FEA. The second neural network determines which of the eight truss members are damaged and each output demonstrates the existence of damage at the associated truss member. The authors found that a two-step neural network successfully located the damage in the finite element model.

Feng and Bahng (1999) proposed a method for the monitoring of jacketed RC columns using a combination of ANN, finite element techniques and vibration testing. In this research, the input patterns included the mode frequencies and mode shapes of columns determined from the FEA. Correction coefficients of element stiffness for the column were chosen as the output pattern. A finite element model was built to predict the baseline vibration characteristics of a small-scale bridge model, and the predicted responses were compared with the vibration test data taken from the scale model. After that, damage was defined in the bridge model, and the vibration tests were repeated for several cases of damage. ANN was trained using data taken from the finite element model and the damage bridge. In this work, the ANN could estimate changes in the stiffness based on the measured dynamic characteristics.

4.3.4 Trusses

A technique for predicting the sub-structural stiffness parameters of a truss with two-span planar by using an ANN with natural frequencies and mode shapes as input patterns was described

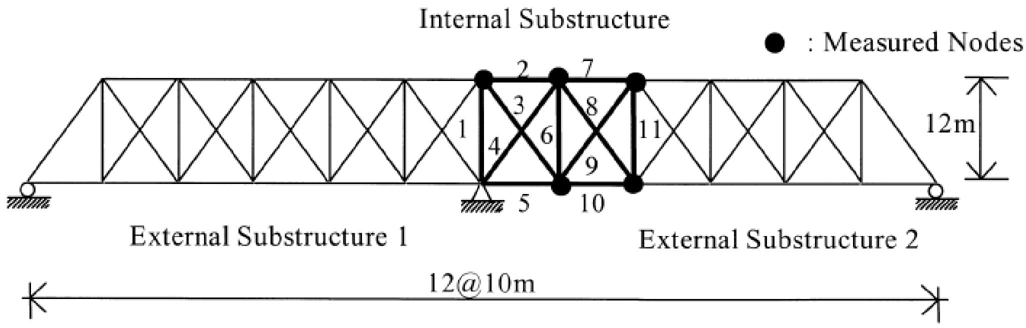


Fig. 15 Sub-structuring of truss structure (Yun and Bahng 2000)

by Yun and Bahng (2000). As shown in Fig. 15, the truss was contained 90 nodal DOFs and three sub-structures contains an internal and two external sub-structures. In this research, the estimation of average relative errors for testing data sets were obtained in the range of 9-15%, which showed the applicability of ANNs using natural frequencies and mode shapes based on sub-structuring technique for the damage assessment in truss structure systems.

Identification of damage in a 20-bay planar truss composed of sixty struts was done by Povich and Lim (1994). Removal of struts from the structure simulated damage in the truss. The structure was excited by a shaker and two accelerometers were used to provide input data and frequency range investigated was within the first four bending modes. An ANN was applied to identify the map from the Fourier transform of the acceleration history to damage in each desired member. The network consisted of 394 inputs corresponding to the acceleration FFTs at the frequencies of interest for two points and 60 outputs, one for each strut in the structure. This network could identify the missing strut in 21 cases and was able to localize the damage to two adjacent struts in 38 cases. The authors did not check the generation capabilities of this work and did not carry out verification or testing of the neural network.

4.3.5 Buildings

Gonzalez and Zapico (2008) applied neural networks to identify seismic damage in a 5-storey office building using natural frequencies and mode shapes. In this study, detection and quantification of the global damage at each storey of a Welded Steel Moment Frame (WSMF) building using its low natural frequencies and mode shapes was investigated. The first flexural mode consists of frequencies and mode shapes as inputs and mass and stiffness at each principal direction of the structure was selected as outputs. The finite element model was used to generate the data needed to train the ANNs and an index for damage was defined by comparing the initial and final stiffness. This method was successful in determining which storey of the building was damaged. The results were successful and showed the robustness of the ANN for the prediction of damage. The authors found that ANN was quite sensitive to modal data based on the sensitivity analysis that had been done in this work.

Two different neural networks namely the multilayer perceptron (MLP) network with Back Propagation(BP) algorithm and the Radial Basis Function (RBF) network were evaluated for damage assessment by Rytter and Kirgegaard (1997). A finite element model of a full-scale four-story reinforced concrete building was used for this research work. Random damage states were generated through finite element modeling simulations, which were essentially stiffness reductions in beams and columns. The relative changes in the modal parameters were used as inputs of the network to detect the bending stiffness changes of the beams and columns at the output layer. In this work, four thousand nine hundred sets of mode shapes and natural frequencies were calculated for different damage situations. The MLP network showed the possibility of being used in connection with vibration-based inspection, where else the RBF network completely failed. Based on this research, the performance of the RBF network was highly dependent on an appropriate selection of damage cases used in the training.

Vinayak *et al.* (2008) employed the dynamic properties of four and the eight storey building model for determination of severity and location of damage. In this research natural frequency and mode shape change were applied as inputs of ANN and output was combination of various damage levels of different storey of the building. According to this study accuracy of grade of damage identified in structure increased with the increase in the number of damage cases combination used for ANN training. Also the results confirm that the accuracy to determine extent of damage decreases with increase in the number of storeys being damaged.

4.3.6 Other structures

A substructuring technique was applied with a multistage ANN method to detect the location and extent of the damage in a two-span continuous concrete slab structure by Bakhary *et al.* (2010). Mode shapes and natural frequencies of the substructures were used as the inputs to predict the E values of the segment in the identified substructure. The authors showed that by dividing the structure into substructures and analyzing each substructure separately, local damage can be better identified. Based on this technique, all the simulated damages in the structure were successfully detected.

Bakhary (2006) also investigated the ability of ANNs to detect damage location and severity in a slab-like structure using natural frequencies and mode shapes as the input. Dynamic characteristics of the damage and undamaged structure to train the ANN were obtained from finite elements analysis. In this study, damage modeled by reducing the values of modulus of elasticity of the elements at various locations along the slab and the trained ANN was validated using experimental data. The results demonstrated that ANN is capable to provide reasonable results on damage detection using data generated from FEA. In this study, higher modes provided good performance for training of ANN, but yielded higher error which led to reduce accuracy of ANN.

The use of natural frequencies and mode shape as input variables were successfully implemented by Tsou and Shen (1994) whereby two different neural networks with different input parameters were compared. In the first neural network only changes in natural frequencies were as the inputs while in the second ANN combination of natural frequencies and mode shapes were selected as the inputs. In the architecture of ANN each neuron in the output layer was applied to represent the stiffness loses of each member. In this study, reducing the spring constant to model the damage of system was considered. Both networks were verified with single and multiple damages. In this investigation, finite element simulation of a three degree and eight degree of freedom spring-mass system was applied as examples. According to authors the first ANN with changes in natural frequencies as the input parameters could detect single and multiple damages in a simple system. However for complicated systems the results were not in agreement while the second ANN consists of combination of natural frequencies and mode shapes could identify damage with more accuracy for complicated systems. This highlighted that the mode shapes information is an important indicator in damage detection.

5. Conclusions

Modal parameters consists of natural frequencies, mode shapes, and damping ratios which are functions of the physical features of the structure such as mass, damping, and stiffness. Therefore any changes in the physical features will cause changes in the modal parameters. Damage is assessed via changes in the dynamic characteristics or response of structures and has been given much attention in previous literature. Damage assessment approaches attempt to identify damage by solving an inverse problem, which often requires the construction of numerical models.

A robust damage assessment will be able to identify whether damage happened at a very early stage, locate the damage, and provide some estimate of the severity of the damage. Artificial neural networks are one of the most important ways of solving the inverse problems.

A neural network can be applied to map the inverse relationship between the measured responses and the structural parameters of interest based on training and testing data sets. Based on this review paper, it is evident that over the past two decades there have been numerous studies applying ANN on modal properties of structures in the field of damage detection and structural monitoring. It has been proven that ANNs using modal parameters can provide several advantages over the conventional mathematical approaches and damage detection is much improved. ANNs have the capability to detect damage even when trained with incomplete and insufficient data.

Choosing a suitable architecture of ANN, the number of hidden layers and numbers of hidden neurons in each layer can improve the capability of ANNs. The inputs and outputs of ANNs can be selected with high flexibility without increasing the complexity of the training and testing process.

In this review paper it is also shown that modal analysis data are directly linked to the topology of the structure and can be easily applied for damage assessment and are more accurate for detecting large defects in structures. However the data are very sensitive to noise during acquisition and are not applicable for nonlinear structures.

It can be summarized that earlier studies applied modal frequency changes to detect damage. However recent researches have shown that frequency changes are insufficient and changes in mode shapes are more sensitive and may be more useful for detection of the damage location using ANNs.

Finally, it is noteworthy that most neural networks suffer from a single common difficulty in that the training requires a lot of data sets from both the undamaged and damaged structures. However the trained ANN models are capable of generating effective damage behavior and damage dissipation at different damage levels and are feasible tools for damage detection based on vibration data.

Based on this review, many studies have attempted to generate the training data sets associated with various damage cases from numerical simulations such as FEA and needless to say that the success of artificial neural networks depends on the accuracy of the applied numerical models.

6. Recommendations for future works

Based on this review, further studies on the structural damage detection in the area of ANNs using dynamic modal parameters are recommended. Several specific recommendations for future research are drawn below:

i) According to researchers in this review, the application of ANN based damage assessment methods to a real structure is limited and are usually on small building components of

structures. However the practical structures are usually complex and large. Thus, it is recommended that the feasibility studies of ANNs are conducted on large-scaled and real structures for future works.
ii) Application of ANN using modal parameters to structures with multiple-type damages is limited. Therefore, more study in this field is suggested.
iii) Very little efforts have been directed to the methodology for detecting unanticipated damage cases and further research on different types of damage at the different locations using different damage detection algorithms should be investigated.
iv) Excitation techniques for components of structures can be simply applied by hammer impact. However, when large and complex structures are investigated, the source of excitation should be changed. Further studies regarding the influence of the different sources of excitation such as shaker on large structures should be done.
v) Data samples have very important effect in efficiency of training and testing of ANNs. There is scarcity on the ANN performance under different methods for generating of data for training and testing of network. Thus a comparison study on the ANN implementation under different algorithm for training and testing patterns selection is recommended.
vi) Application of ANN using modal parameters with noisy data is limited. However, accurate prediction of parameters from noisy data can be challenging and improving the capability of measurement noise and reducing the influences of the modeling error need to be further investigated.
vii) Locations and number of measurements points have very important influence on the accuracy of damage assessment results. There is little effort on the effect of numbers and location of measurement points to damage detection algorithm using ANNs and further work is recommended in this area.
viii) Damage detection investigation can be further investigated for nonlinear material behaviors using ANN models with modal parameters as input.
ix) It is also useful to study the performance of various types of ANNs in order to improve damage detection results.
x) Artificial neural networks implemented in this review usually used a supervised-trained method which means that the networks had to be given the input data i.e., modal parameters and theh corresponding output data i.e., damage identification. However, in real life, usually the output data is not available. It is further recommended to investigate the use of unsupervised-trained neural networks for damage identification and make a comparison between using the results for supervised and unsupervised learning for damage identification.
xi) Many researchers have tried to develop reliable methods for damage detection. Current methods produce good results but have their own limitations. However the challenge lies ahead in establishing a method which is applicable for all types of structures and damage scenarios with minimal limitations.

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