Structural damage identification utilising PCA-compressed frequency response functions and neural network ensembles

U. Dackermann, J. Li & B. Samali
Centre for Built Infrastructure Research, Faculty of Engineering, University of Technology, Sydney, Australia

ABSTRACT: This paper presents a damage detection method that utilises FRF data to identify damage in beam structures. The proposed method uses artificial neural networks (ANNs) to map changes in FRFs to damage characteristics. To obtain suitable patterns for ANN inputs, the size of the FRFs is reduced adopting Principal Component Analysis (PCA) techniques. A hierarchy of neural network ensembles is created to take advantage of individual differences from sensor signals. To simulate field applications, the time history data are polluted with white Gaussian noise. The method involves finite element modelling of undamaged and damaged steel beams. By performing transient analysis with the numerical beams, the time histories are obtained and subsequently polluted with different levels of white Gaussian noise. FRFs are determined and compressed utilising PCA techniques. The PCA-reduced FRFs are then used as input patterns for training and testing of neural network ensembles giving the characteristics of the damage.

1 INTRODUCTION

Civil engineering structures continuously accumulate damage during their service life, which may be caused by harsh environmental conditions, ageing materials, overloading or inadequate maintenance. Early damage detection in a structure is important in order to prolong its service live and to prevent catastrophic failures. Current non-destructive damage detection methods are based, for instance, on visual inspection, stress wave, ultrasonic, X-ray, acoustics or radiography. Most of these methods, however, are restricted to local observations in a limited area and rely on a presumption of the likely area of damage. Further, when these methods are applied to large structures, they are very time consuming and costly.

Vibration based damage detection techniques are global methods and are based on the fact that damage alters both, the physical as well as the dynamic properties of a structure. Therefore, by utilising the dynamic quantities from structural vibration, damage can be identified. These dynamic quantities, for instance, can be time histories, frequency response functions (FRFs) and modal parameters such as natural frequencies, mode shapes and damping ratios. Traditionally, modal parameters are the most used dynamic quantities in damage detection (Adams et al. 1978; Pandey et al. 1991; Stubbs et al. 1992). However, modal-based damage identifications have some shortcomings. Firstly, these methods are based on complicated data processing procedures such as modal analysis in which the results can be contaminated by modal extraction errors. Secondly, in most practical applications, the completeness of the modal data cannot be assured as usually only coarse sensor arrays are available. Therefore, directly measured FRF data with their abundance of information is a more desirable dynamic quantity for vibration based damage detection.

Artificial Neural Networks (ANNs) are artificial intelligence, which are capable of learning, i.e. pattern recognition and classification. Using a combination of FRFs and ANNs in structural damage identification is therefore very promising. However, a very significant obstacle is the large size of the FRF data. Utilising full-size FRFs in neural networks will result in a large number of input nodes, which will cause problems in training convergence and computational efficiency. If only partial sets of FRF data are used, an improper selection of data points from frequency windows will result in loss of important information and errors will be introduced to the detection scheme (Ni et al. 2006). Principal Component Analysis (PCA) is a statistical technique for achieving dimensional data reduction and its application for vibration based damage detection is reported in several papers (Ni et al. 2006; Trendafilova et al. 2008; Zang & Imregun 2001). By projecting data onto the most important principal components, its size can greatly be reduced without significantly affecting the data.

2 METHODOLOGY

This paper present a non-destructive, global, vibration based method that locates and quantifies damage in numerical beam structures from differences in FRF data. ANNs are utilised to map pattern changes from FRF data to damage characteristics. To obtain suitable input data for network training, the FRFs are compressed to a few principal components adopting PCA techniques. To simulate field-testing conditions, white Gaussian noise is added to numerical data and issues with limited number of sensor arrays are incorporated. To respect the different characteristics obtained by individual sensors from various locations, a hierarchy of neural network ensembles is utilised to identify damage.

Firstly, numerical models of beam structures, inflicted with damage of various severities and locations, are created. Secondly, time-history data are obtained from transient analysis, which are subsequently polluted with different intensities of white Gaussian noise. Thirdly, from the noise polluted time-history data, FRFs are determined and FRF differences from the undamaged and the damaged beams are obtained. Fourthly, by adopting PCA techniques, the FRF differences are compressed and the most important principal components identified. Fifthly, sets of individual ANNs are trained and tested with the PCA-compressed FRF differences separated by sensor location. Finally, a neural network ensemble fuses the outcomes of the individual networks and a final overall damage prediction is obtained. A flow-chart of the damage identification procedure is presented in Figure 1.

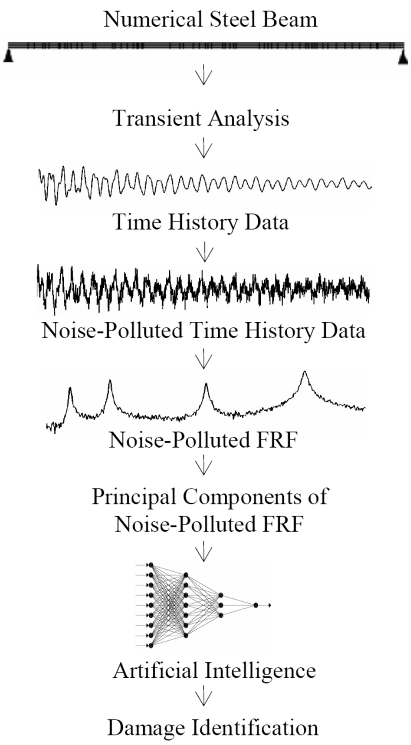

Figure 1. Flow chart of the damage identification procedure.

3 ARTIFICIAL INTELLIGENCE

The term Artificial Intelligence (AI) was coined by John McCarthy who termed it ‘the science and engineering of making intelligent machines’ (McCarthy 1979). ANNs are a type of AI and were originally developed as a methodology for emulating the biology of the human brain. Key properties of ANNs are the capability of pattern recognition and classification, data interpretation and function approximation. ANNs provide a nonlinear parameterised mapping between a set of input and a set of output data. The networks are arranged in layers of input, hidden and output neurons, which are massively interconnected. The layers are linked by transfer functions and the neurons weighted by adjustable variables. The most commonly used networks in damage identification are feed-forward multi-layer neural network. The outputs of these networks are given as

$$a_k(p_i) = \sum_{j=1}^{m} w_{kj}\, f\left(\sum_{i=1}^{d} w_{ji} p_i + b_{j0}\right) + b_{k0} \quad (1)$$

where ‘p_i’ are the input variables, ‘w_{kj}’ and ‘w_{ji}’ the interconnection weights, ‘b_{j0}’ and ‘b_{k0}’ the bias parameter, ‘f’ the transfer function, ‘d’ the number of input units and ‘m’ the number of hidden layer. The weights and biases in the hidden layers are iteratively varied in order to move the network outputs closer to the targets, which is known as training, i.e. learning. The circled illustration of Figure 2 shows the schematic model of a multi-layer feed-forward neural network.

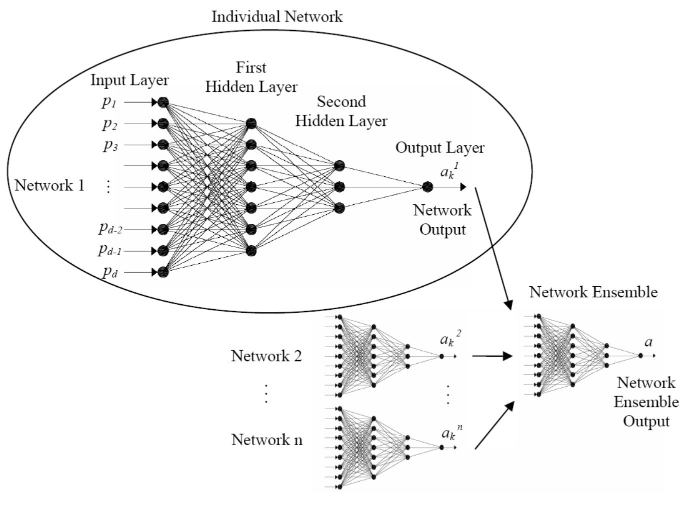

Figure 2. Feed-forward multi-layer neural network ensemble.

When a collection of neural networks is trained simultaneously for the same task a neural network ensemble is created. First, each network in the ensemble is trained individually and then the outputs of each of the networks are combined to produce the ensemble output ‘a’. With the neural network ensemble approach the generalisation ability of a neural network system can significantly be improved (Zhou et al. 2002). A neural network ensemble model is also shown in Figure 2.

4 PRINCIPAL COMPONENT ANALYSIS

PCA was developed by Pearson in 1901 (Pearson 1901) and is one of the most powerful statistical multivariate data analysis techniques for achieving dimensionality reduction. It is a statistical technique that linearly transforms an original set of ‘k’ variables into a smaller set of ‘n’ (n<=k) uncorrelated variables, the so-called principal components (PCs). Eigenvalue decomposition of the covariance matrix forms the basis of PCA. The direction of the resulting eigenvectors represents the direction of the PCs, which are weighted according to value of the corresponding eigenvalues. Each PC is a linear combination of the original variables. All the PCs are orthogonal to each other and form an orthogonal basis for the space of the data. The full set of PCs is equal to the original set of the variables. By removing PCs of low power, a dimensional reduction is achieved without significantly affecting the original data (White et al. 2006). Besides the benefit of data reduction, PCA is also a powerful tool for disregarding unwanted measurement noise. As noise has a random feature, which is not correlated with a global characteristic of the data set, it is represented by less significant PCs. Therefore, by disregarding PCs of low power, measurement noise is filtered.

Following is a description of the derivation of PCA. Given is the data set ‘$[X_{ij}]$’ with ($i = 1, 2, \ldots, m$) and ($j = 1,2,\ldots,k$), where ‘m’ is the total number of observations (i.e. FRFs) and ‘k’ the dimension (variables) of the observations (i.e. spectral lines). First, the mean ‘$\bar{x}_j$’ and the standard derivation ‘s_j’ of the j^{th} column is obtained from

$$\bar{x}_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{2}$$

and

$$s_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij} - \bar{x}_j\right)^2}{m}} \tag{3}$$

Then, the data set ‘[X]’ is transformed into the standard normal space yielding the variation matrix ‘$[\tilde{X}]$’. A normalised element ‘$\tilde{x}_{ij}$’ is given by

$$\tilde{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \tag{4}$$

The covariance matrix ‘[C]’ is expressed as

$$[C] = \frac{[\tilde{X}]^T[\tilde{X}]}{m-1} \tag{5}$$

Finally, the PCs are obtained from

$$[C]\{P_i\} = \lambda_i\,\{P_i\} \tag{6}$$

which is the eigenvalue decomposition of the covariance matrix ‘[C]’, with ‘λ_i’ being the i^{th} eigenvalue and ‘$\{P_i\}$’ the corresponding eigenvector. The first PC, which is the largest eigenvalues and its associated eigenvector, represents the direction and amount of maximum variability in the original data set. The second PC, which is orthogonal to the first PC, represents the second most significant contribution from the data set, and so on. The most significant PCs represent the features that are most dominant in the data set. By discarding components that contribute least to the overall variance, the dimension of the original data set can significantly be reduced (Zang & Imregun 2001).

5 DAMAGE IDENTIFICATION PROCEDURE

5.1 *Numerical Model*

A numerical model of a beam with the dimensions of 12 mm by 32 mm by 2,400 mm is created using the finite element analysis package ANSYS (2005a). The beam model is of steel with a modulus of elasticity of 200,000 N/mm^2. The support conditions are set as pin-pin. The element type used is SOLID45, which is a three dimensional structural solid that is defined by eight nodes having translations in the nodal x, y and z directions. The cross-section is modelled with 4 elements across the height and 4 elements along the width. A division into 201 nodes in the longitudinal direction of the model is chosen in accordance with previous sensitivity studies undertaken by Choi et al. (2007). A schematic model of the numerical beam is shown in Figure 3.

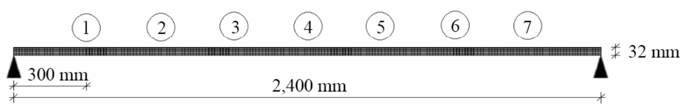

Figure 3. Finite element modelling of a pin-pin supported steel beam.

Four different damage locations are considered, which are located at 4/8th, 5/8th, 6/8th and 7/8th of the span length (denoted as ‘4’, ‘5’, ‘6’, and ‘7’ in Figure 3). For each of these locations four damage severities, termed as extra light (XL), light (L), medium (M) and severe (S), are investigated. All inflicted damage are 1 mm in length and 1 mm, 4 mm, 8 mm and 12 mm, respectively, in height.

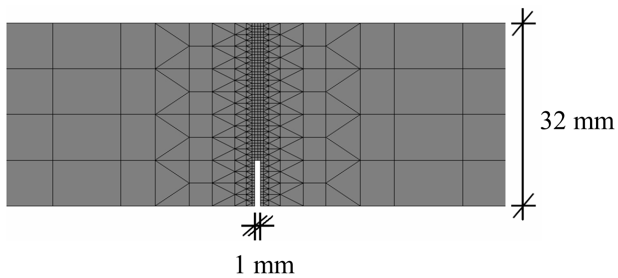

Figure 4. Finite element modelling of medium size damage (8 mm cut).

The damage is modelled by rectangular openings from the soffit of the beam along the span length. The mesh density is refined in the vicinity of the defect as displayed in Figure 4.

5.2 *Pre-Processing*

Following is a description of steps that are performed to generate data, which represents real field-testing data and is suitable as input for ANNs. Firstly, transient analysis is performed with ANSYS. An impact force of 800 N is applied at a reference point (beam location '5') and the time history responses of the beam are recorded at nine equally spaced points. These nine points, which represent sensors of a real test, are situated at the supports and the beam locations '1' to '7'. Secondly, to simulate a real field test, white Gaussian noise of three intensities (2 %, 5 % and 10 %) is added to the excitation signal and the response time histories. For each intensity of noise, three different sets of noise polluted data are generated. Thirdly, the noise polluted time history data are transformed into the frequency spectra using the Fast Fourier Transform (FFT). By dividing the cross spectrum signals of the response data by the auto spectra of the excitation data, the Frequency Response Function (FRF), which comprises of 1638 spectral lines, is obtained. Fourthly, to determine pattern changes caused by damage, differences in the FRF data from the intact and the damaged beams are calculated. Fifthly, by applying PCA following the procedure described in section 4, the FRF differences are projected into the PC space. Sixthly, the most important PCs are chosen and used as input patterns for neural networks.

5.3 *Principal Component Selection*

For each noise level, a set of 144 FRF differences is generated by relating each noise polluted undamaged case to each of the noise polluted damaged case (3 noise polluted undamaged cases x 3 noise polluted damaged cases x 4 damage locations x 4 damage severities). A matrix having 144 rows (FRF differences) and 1638 columns (FRF spectral lines) is formed and subsequently projected onto its PCs utilising the 'princomp' function in MATLAB. It is found that the first 52 PCs account for 99.9 % of the original data. The individual contribution percentage of each of the first five PCs is 38.8 %, 22.3 %, 12.3 %, 5.9 % and 1.3 %. From the 10th PC onwards, each component contributes to less then 1 % to the data. Therefore, the first ten PCs, which represent 85.8 % of the original data, are regarded as most significant components and used as input patterns for the neural networks. By considering only ten PCs, the original data is reduced by 99.4 %. This does not only benefit in a dimensional reduction of the data but does also remove some of the unwanted noise.

A plot of the cumulative contribution percentages of the first 55 PCs, which are obtained from data polluted with 2 % white Gaussian noise, is shown in Figure 5.

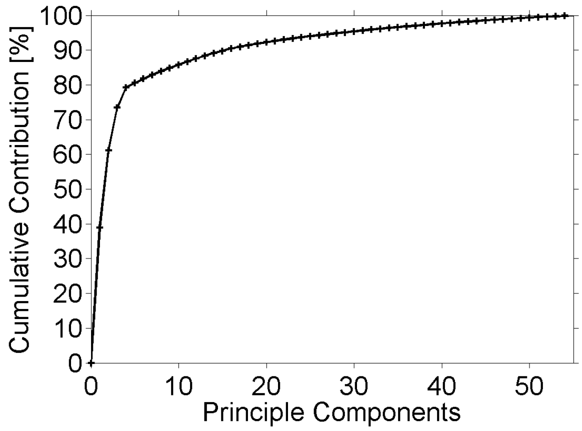

Figure 5. Cumulative contribution percentage of PCs obtained from data polluted with 2 % white Gaussian noise.

5.4 *Artificial Neural Network Model*

Ensembles of supervised feed-forward multi-layer neural networks are designed to identify the damage. The ten most important PCs of the differences of undamaged und damaged FRF are utilised as input patterns to the networks to estimate the location and severity of damage. For each noise intensity level, different neural network ensembles are created. First, individual neural networks are trained with data separated by sensor locations. Then, the outcomes of the individual neural networks are combined in a neural network ensemble and an overall damage prediction is obtained. The individual neural networks comprise of an input layer with ten nodes, representing the ten PCs; four hidden layers of 20, 15, 10 and 5 nodes and one single node output layer estimating the location or the severity of the damage. The network ensemble is designed with nine input nodes, which are the outputs of the nine individual networks; four hidden layers consisting of 20, 15, 10 and 5 nodes and one output node predicting the damage location or severity. The transfer functions used are hyperbolic tangent sigmoid functions. Training is performed utilising the back-propagation conjugate gradient descent algorithm. The input data is divided into three sets; a training, a validation and a testing set. While the network is trained with the training samples, its performance is supervised utilising the validation set to avoid overfitting. The network training stops when the error of the validation set increases while the error of the training set still decreases, which is the point when the generalisation ability of the network is lost and overfitting occurs. The 144 samples of PCs for each noise intensity level are divided into three sets, i.e. 82 for training and 31 each for validation and testing. The design and operation of all neural networks is performed with the software Alyuda NeuroIntelligence version 2.2 from Alyuda Research Inc.

6 RESULTS AND DISCUSSIONS

Individual neural networks are trained with PCA-compressed FRF difference, separated by sensor locations, to identify the location and severity of damage. For each level of noise pollution, separate neural network ensemble sets are created. From the network outcomes, it is observed that the prediction accuracy differs a lot among the individual networks. Whereas some networks precisely identify all damage cases, others give many false predictions. As an example, the outcomes of the individual networks trained with 10 % noise polluted data from sensor locations ‘1’ to ‘7’ to locate damage are displayed in Figure 6 (a) to (g). In the figures, the x-axis displays the 144 samples sorted by their locations (L_4 to L_7) and their severities (S_{XL} to S_S). (Note: All damage cases from the training, the validation and the testing sets are displayed.) The y-axis represents the normalised error, which is defined as $E_{norm}(d) = (T_d - O_d)/L_{max}$, where ‘d’ is the damage case, ‘T_d’ the target value of ‘d’, ‘O_d’ the network output value of ‘d’ and ‘L_{max}’ the total length of the beam (here 2.4 m). The marked bandwidth around the 0 % error axis symbolises the area in which the network estimations must fall in order to correctly locate the damage. Here the bandwidth ranges from -6.25 % to +6.25 % normalised error, representing the mid points in-between two damage locations. From the figures, it can be observed that the networks trained with data from sensor locations ‘3’, ‘4’ and ‘5’ correctly identify all damage cases. The estimations from networks trained with PCs from sensor locations ‘1’, ‘2’, ‘6’ and ‘7’, however, give some false predictions during the validation and testing. It can be seen that all of these misidentifications are from damage cases of extra light or light severity, which are damages of 1 mm respectively 4 mm in height. Further, all incorrectly identified damage cases are situated at locations 5 and 6.

It is obvious that to identify damage only relying on the outcomes of the individual networks can be problematic as their damage predictions differ a lot. To achieve reliable damage identification, a conclusive, intelligent fusion of the network outcomes is necessary. This is achieved by a neural network ensemble, which combines the outcomes of the individual networks. The damage predictions of these neural network ensembles correctly locate and quantify all damage cases for all levels of noise pollution. This is displayed in Figure 7 and Figure 8, which shows the localisation and quantification outcomes of neural network ensembles trained with 2 %, 5 % and 10 % noise polluted data. Final damage identifications clearly show the efficiency of the network ensemble, which gives outcomes that are more accurate than any of the outcomes of the individual neural networks.

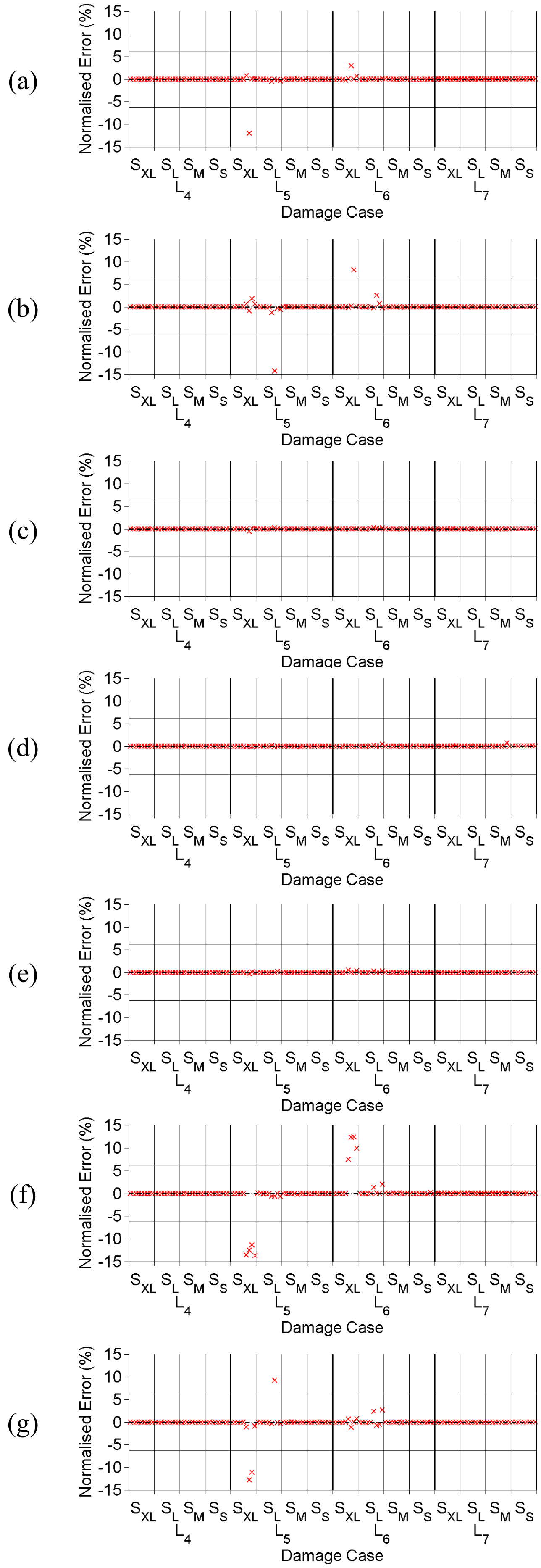

Figure 6. Neural network outcomes trained with 10 % noise polluted data from (a) sensor location 1, (b) sensor location 2, (c) sensor location 3, (d) sensor location 4, (e) sensor location 5, (f) sensor location 6 and (g) sensor location 7.

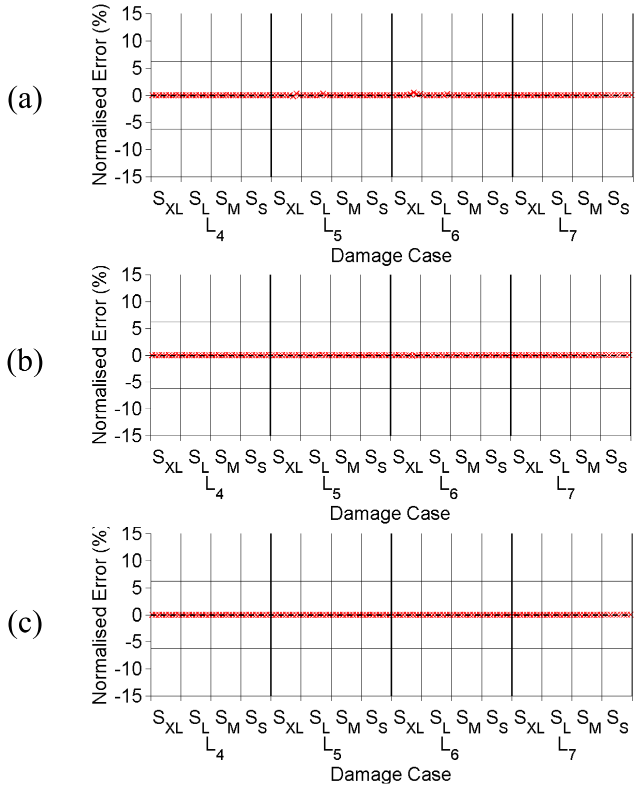

Figure 7. Outcomes of neural network ensembles trained with data polluted with (a) 2 %, (b) 5 % and (c) 10 % of noise to locate damage.

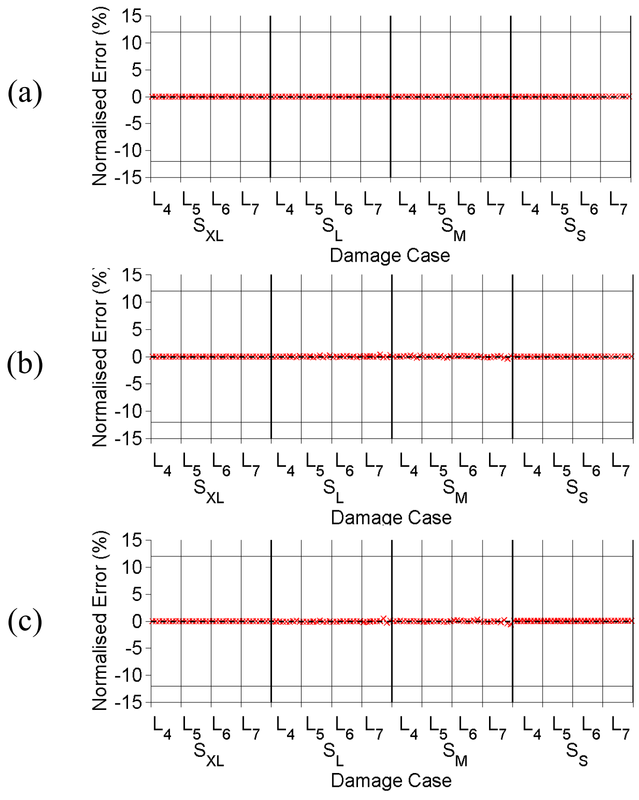

Figure 8. Outcomes of neural network ensembles trained with data polluted with (a) 2 %, (b) 5 % and (c) 10 % of noise to quantify damage.

7 CONCLUSIONS

Authors present a vibration-based damage identification method, which utilises dimensionally reduced FRF data in combination with neural network ensembles to identify location and severity of single damage in beam structures. PCA data reduction technique is adopted to compress the large size of measured FRF data and only the most significant PCs are used as input pattern to neural networks. Real-life field testing associated issues, such as limited number of sensor arrays and measurement noise are incorporated. The damage prediction outcomes of the network ensembles show that the developed method is robust, reliable and precise in identifying structural defects. The results also show the effectiveness of the neural network ensemble approach, which gives outcomes that are more accurate than any of the outcomes of the individual neural networks.

8 REFERENCES

Adams, R.D., et al. 1978. A vibration technique for non-destructively assessing the integrity of structures, *Journal of Mechanical Engineering Science* 20: 93-100.

Choi, F.C. 2007. Assessment of the structural integrity of bridges using dynamic approaches, PhD thesis, University of Technology, Sydney, Sydney, Australia.

McCarthy, J. 1979. Ascribing mental qualities to machines, In M. Ringle (ed.), *Philosophical Perspectives in Artificial Intelligence*, Harvester Press.

Ni, Y.Q., et al. 2006. Experimental investigation of seismic damage identification using PCA-compressed frequency response functions and neural networks, *Journal of Sound and Vibration* 290(1-2): 221-242.

Pandey, A.K., et al. 1991. Damage detection from changes in curvature mode shapes, *Journal of Sound and Vibration* 145(2): 321-332.

Pearson, K. 1901. On Lines and Planes of Closest Fit to Systems of Points in Space, *Philosophical Magazine* 2(6): 559-572.

Stubbs, N., et al. 1992. An efficient and robust algorithm for damage localization in offshore platforms, *Proceedings of the ASCE Tenth Structures Congress,* Antonio, Texas, USA: 543-546.

Trendafilova, I., et al. 2008. Vibration-based damage detection in an aircraft wing scaled model using principal component analysis and pattern recognition, *Journal of Sound and Vibration* 313(3-5): 560-566.

White, P.R., et al. 2006. Analysis of the maximum likelihood, total least squares and principal component approaches for frequency response function estimation, *Journal of Sound and Vibration*, 290(3-5): 676-689.

Zang, C. & Imregun, M. 2001. Combined neural network and reduced FRF techniques for slight damage detection using measured response data, *Archive of Applied Mechanics* 71(8): 525-536.

Zhou, Z.-H., et al. 2002. Ensembling neural networks: Many could be better than all, *Artificial Intelligence*, 137(1-2): 239-263.