The Three Stage Damage Identification Method for Building Structures Using Frequency Response Functions (FRFs) and Neural Networks (NNs)

Rupika P. Bandara*, Tommy H.T Chan*, David P. Thambiratnam*

* *Science and Engineering Faculty Queensland University of Technology, 2 George Street, Brisbane, QLD 4001, Australia (E-mail: arachchillage.bandara@student.qut.edu.au; tommy.chan@qut.edu.au; d.thambiratnam@qut.edu.au)*

ABSTRACT
A challenging problem in structural health monitoring systems is the requirement of a systematic, effective method for locating damage and severity estimation of structures, based on vibration data measured by sensors. To address this issue, a novel technique is proposed using “damage index” derived from Frequency Response Functions (FRFs) with the three stage neural network method to detect the location and estimate the severity of the existing damage. The basic idea of this method is to establish features of damaged structure using FRFs from different measurement points of different sub-sets of frequency points. Then using these features, damage indices of different damage cases of the structure are identified after reconstructing of available FRFs data using Principal Component Analysis (PCA). Damage indices corresponding to different damage locations and severities are introduced as input variable to developed neural networks. Once the location of a damaged floor has been determined in the first stage using FRFs measured from the whole structure, damage element and the magnitude of damage of the affected elements are then determined using FRFs measured from the damaged floor in the second and third stage respectively. Finally, the effectiveness of the proposed method is illustrated and validated using the finite element model of a ten storey framed structure. The results show that the PCA based damage index is suitable and effective for structural damage detection of building structures even for damage scenarios with small damage severity.

KEYWORDS
Frequency Response Functions (FRFs); Neural Networks (NNs); Damage detection; Principal Component Analysis (PCA).

INTRODUCTION
Neural networks (NNs) are used, for damage detection purposes, because of their ability to solve complex problems and generalisation capability that allows them to produce reasonable outputs from inputs not encountered during learning. However, the range of training samples should be used to cover various damage locations with different damage levels in order to recognize the better ability to ANN’s pattern recognition. Consequently, when dealing with large scale structures, a lot of possible damage locations are available. Hence the network is needed to be trained with an enormous number of sampling data sets which direct long learning process. It significantly jeopardizes the training efficiency and accuracy of the NNs. Thus some researchers have been focused on eschewing the extensive training in using NNs for damage detection.

As an example Jiang et al.(2011) proposed a novel two-stage structural damage detection approach for the cases with enormous measurement data using fuzzy neural networks (FNNs) and data fusion techniques. A 7-degree of freedom 2D building frame was used to prove the feasibility and efficiency of structural damage detection of the proposed approach. The simulation result showed that the identification accuracy can be boosted with the proposed approach instead of FNN models alone. However, this method was not tested with experimental data. A new two stage approach was developed by Pan, et al (2010) to identify the location and extent of structural damage by combining the NNs and Genetic Algorithms (GA). The input parameters of NNs were the changes in the dynamic characteristics of a 3D two storey frame structure for the interval estimation of damage element. Only a few frequencies and modal shapes were needed to accurately assess the location and extent of damage. However, Finite Element Model (FEM) of two storey frame was used to verify the method and experimental verification were not performed. Gonzalez et al. (2008) developed a method for damage identification of buildings with steel moment frame structures. Data for NN training was obtained from a simplified FEM of a five storey building. The proposed method was successful in determining the damaged storey of the building. However, the method was quite sensitive especially to mode shape errors.

Although several NN-based strategies are available for qualitative evaluation of damages of building frames, most of the methods are tested only for small building structures up to five storeys. Moreover, most of the methods are limited to detection of the damaged storey. Hence, detection of damage members was not performed. As a result, the present study is focused on three stage NNs to achieve identifying a damaged floor, damage element and severity estimation respectively. The proposing three stage neural network identification strategies are designed to firstly identify damage floor, secondly locate the damage element and then quantify damage severity. Input vectors with damage index patterns from different damage scenarios and facilitating reduction of training samples are constructed for this purpose. Effectiveness for separate detection of damage location and extent is examined using finite element model of a ten storey frame structure.

METHOD

Proposed algorithm

FRFs measured from different locations are utilized as input parameter to the proposed algorithm. One of the major obstacles in using FRFs for damage identification is the large size of the FRF data as full-size of FRF data result in huge configuration of the network input layer which brings about the problem of iteration divergence in training and computational inefficiency. Hence reducing FRFs data without losing much information is a critical issue. Therefore, PCA, which is one of the most powerful statistical multivariate data analysis techniques for achieving dimensionality reduction, is used to reduce the size of the FRF data. The objective of PCA is to reduce dimensionality by extracting the smallest number of components that account for most of the variation in the original multivariate data and to summarize the data with little loss of information. Besides the benefit of data reduction, PCA is also a powerful tool for disregarding unwanted measurement noise.

Even though PCA can reduce the dimensionality of a data set, the high dimensionality of the FRFs dataset obtained from a complete observation can diminish the effectiveness of PCA (Tang, 2005). Thus, in order to improve the effectiveness of PCA, complete FRFs are divided into sub-observations with low dimensionality and PCA is done for each sub set separately. As direct use of FRFs by compressing PCA also has some drawbacks, it is suggested to develop input patterns from measured FRF data by proposing an algorithm. In this algorithm, damage indices are the output values while directly measured FRFs are the input values. Damage index is computed as a ratio between FRFs data obtained from damaged structure and undamaged structure to enhance the capability of extracting main features of the data sets. As available data set is divided into number of small subsets, each data set has a number of damage indices which is equal to number of data division. Subsequently, these damage indices are arranged according to the frequency range and damage patterns for various damage scenarios are obtained. Proposed algorithm is described below.

Using available FRFs data of the damaged structure, matrix H= [h_{ij} (ω)] which has m rows of FRFs (m observations from different sensors); each with n frequency points is formed. In the present study, numbers of observations (m) depend on number of damaged datasets use for the matrix. Available FRFs data of the undamaged structure are also arranged into a separate matrix and mean values of the each column are obtained. In order to improve the effectiveness of PCA, complete FRFs are divided into sub-observations with low dimensionality where each sub-observation contains r consecutive frequency points ($r<n$). Each column of sub-set FRFs matrix is adjusted to have a zero mean by subtracting the mean of each column of FRFs of the damaged structure and dividing each column by its standard deviation to get a unit variance to yield a response variation matrix $[\tilde{\mathrm{H}}(\omega)_{mxr}]$ as follows.

The mean response of the jth column is given as:

$$\overline{H}_j = \frac{1}{m}\sum_{i=1}^{m} h_{ij}(\omega) \tag{1}$$

The corresponding standard deviation S_j can be defined as

$$S_j{}^2 = \frac{1}{m}\sum_{i=1}^{m}(h_{ij}(\omega) - \overline{H}_j)^2 \tag{2}$$

A typical element of the FRF matrix can now be replaced by:

$$\tilde{h}_{ij}(\omega) = \frac{h_{ij}(\omega) - \overline{H}_j}{S_j\sqrt{m}} \tag{3}$$

The correlation matrix can be defined as:

$$[C]_{rxr} = [\tilde{H}]^T_{rxm}[\tilde{H}]_{mxr} \tag{4}$$

By definition, the principal components are the eigenvalues and associated eigenvectors of the correlation matrix:

$$[C]\{\Psi_i\} = \lambda_i\{\Psi_i\} \tag{5}$$

where i is the principal component index.

The first principal component, i.e. the highest eigenvalue and its associated eigenvector, represents the direction and amount of maximum variability in the original data. The next principal component, which is orthogonal to the first component, represents the next most significant contribution from the original data, and so on. New FRFs for the detection stage is obtained and it is represented as new. The projection of the response variation matrix $(\tilde{H}_{new})_{mxr}$ on the r principal components derived from baseline FRFs of the intact structure is written as (Ni et al., 2006)

$$(A)_{mxr} = (\tilde{H}_{new})_{mxr}(\Psi)_{rxr} \tag{6}$$

The projection matrix [A] and the eigenvector matrix [Ψ] can be partitioned into two sub-matrices with p principal components and (r-p) principal components. Setting those sub-matrices representing principal components (r-p) to zero, once obtains:

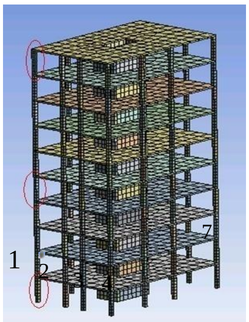
$$(\tilde{H}_R)_{mxr} = [A][\Psi]^T = [[A_{rxp} : [0_{rx(r-p)}][[\Psi]_{rxp} : [0]_{rx(r-p)}]^T \approx [A]_{mxp}[\Psi^T_{pxr}] \tag{7}$$

To compare the new constructed signal $(\tilde{H}_{new})_R$ with the baseline signal H which is the mean response of the r observations of the intact structure, the damage index (DI) is defined as,

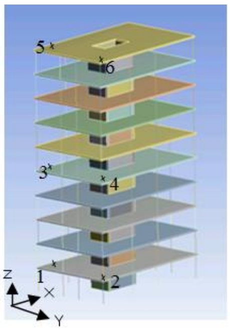
$$DI = (H_{new})_R/(H)_{baseline} \tag{8}$$

Illustrative example

A low rise building with 10 floors (floor height- 4m) shown in Figure 1(a) is used to demonstrate the feasibility of the methodology described above. Numerical simulations for the concrete framed structure are performed using ANSYS (ANSYS Inc., 2007), general-purpose FEM analysis software. The damage in an element is simulated by reducing its stiffness by a specified ratio. Total of 60 damage cases corresponding to three damaged floors with five single damage columns in each floor with four severities are used for numerical simulations. FRFs are measured from twelve different locations of the structure as shown in Figure 1(b). Five columns (first to fourth and seventh column as shown in Figure 1(a)) in the first floor, fifth floor and tenth floor are damaged separately and damages are introduced as reduction of stiffness by 10%, 25%, 40% and 55% of each element. In order to increase the number of training samples for NN training the structure is excited at four different excitation levels (1000N, 1500N, 2000N and 2500N) and FRFs are measured at each excitation level separately. The damage cases only for first column of floor level 1, 5 and 10 are tabulated in Table 1.



(a)



(b)

Figure 1 (a) Damaged elements at first floor (b) FRFs measurement locations (Measurement points '7', '8', '9', '10', '11' and '12' are at mirror image of measurement points '1', '2', '3', '4', '5' and '6' respectively)

Table 1 Description of damage cases

	$EI_{damaged}/EI_{intact}$ (%)	Description (damage floor)
HS	00	Intact structure (Healthy State)
DS_{1-1}	10	First floor
DS_{1-2}	25	
DS_{1-3}	40	
DS_{1-4}	55	
DS_{5-1}	10	Fifth floor
DS_{5-2}	25	
DS_{5-3}	40	
DS_{5-4}	55	
DS_{10-1}	10	Tenth floor
DS_{10-2}	25	
DS_{10-3}	40	
DS_{10-4}	55	

Three stage NN model

Three stage NN model is adopted in this research in order to decrease computational time of the NN training. In the first stage of the approach, damage floor is found and then damage element and damage severity are identified in the second stage and third stage respectively. Three ANNs named network type A, network type B and network type C are developed to utilize in three stages. FRFs from the measurement points distributed along the whole structure are used to train network type A and FRFs from the damaged floor are used to train network type B and C. As only the elements of the damaged floor are needed to be taken as possible damage components in the second stage and third stage of this method, complexity of the NNs are efficiently reduced.

Architecture of the Neural Network

The architecture of the NNs are selected after conducting a series of studies to compare the performance of various alternatives for the number of hidden layers, the number of neurons in individual layers, transfer functions, training algorithm and size of the training data set. The back-propagation network, one of most fully developed and commonly used multi layer networks is chosen in the present work to determine the location of damage and the extent of damage. In the present study, the damage index patterns obtained from the proposed algorithm for a variety of specified locations and magnitudes of damages are used to train the backpropagation neural network. The NN architecture selected in this study consists of 4 layers, the input layer, two hidden layers and one output layer.

To avoid over-fitting during training and to increase the generalisation capability of the proposed NN, a validation data set, which is different from the training data set, is employed. The error on the validation set is monitored during the training process. After the NN has been trained, it is fed with data, which was not present in the training data set, to test the generalisation capability of the NN. The available data are divided into 50%, 25% and 25% respectively for training, validation and testing purposes. To examine the performance of the NNs, the damage predictions are evaluated by normalized errors (NE_{loc} for damage location and NE_{sev} for damage severity) which are calculated using Equation 9 and 10.

$$NE_{loc} = \frac{T_d - O_d}{N_{\max}} \tag{9}$$

$$NE_{sev} = \frac{T_d - O_d}{S_{\max}} \tag{10}$$

where d is the damage scenario, T_d the target value of d, O_d the neural network output value of d, $N_{\max}$ the maximum number of floors in the structure and $S_{\max}$ the maximum severity of the damage.

RESULTS AND DISCUSSION

Identification of Damaged Floor

First stage of the proposed methodology is to find damaged floor of the structure. Totally thirteen NNs representing twelve NNs from each measurement points and one NN from summation FRFs are created. Summation FRFs are also utilized to respect the different characteristics obtained by individual measurements from various sensor locations. Numerical data are polluted with three noise levels of 1%, 3% and 5% to simulate field testing conditions. FRFs data of the damaged structure are reconstructed from FRFs data of the intact structure and fifteen samples are obtained by combining FRFs of different excitation levels. As there are 60 damage cases, totally 2700 data sets are available (60 damage cases x 15 datasets x 3 noise levels) for NN training. The numbers of samples for the training, validation and testing sets for all data categories are listed in Table 2. Damage patterns from measurement point “2” for 40% and 55% damage severity levels for the three damaged floors are shown in Figure 2.

Table 2 Training, validation and testing partitioning of all FRFs data

Data Set	Samples	Remarks
Training	1350	30 damage cases x 15 samples x 3 noise levels
Validation	675	15 damage cases x 15 samples x 3 noise levels
Test	675	15 damage cases x 15 samples x 3 noise levels

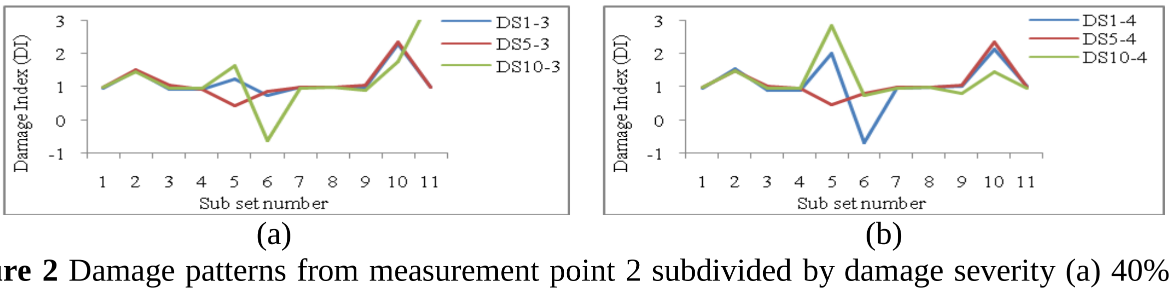


Figure 2 Damage patterns from measurement point 2 subdivided by damage severity (a) 40% and (b) 55%

One input layer of 11 nodes, two hidden layers with 8 and 4 nodes and an output layer with three nodes are used for the NN-type A. Input layer represents the number of subsets of FRFs data set. A log sigmoid transfer function is chosen for the output layer and hidden layer. First NNs are trained with training data and then test data which is not used in the training stage is used to determine the damaged floor of the structure. Accordingly, output value of test data are considered as the damaged floor. Performance of NNs is determined as normalized error for the three data sets. For the better view of the results, normalized errors of individual NNs subdivided by training, validation and test data set are plotted in the Figure 3.

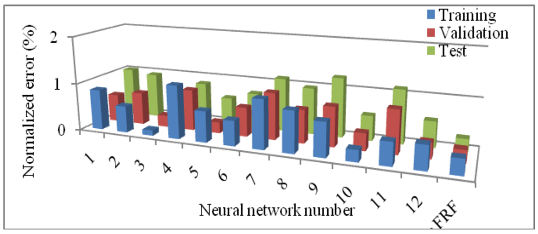


Figure 3 Performance of networks trained with Damage Index (*DI*) values to identify damaged floor

From the results above, maximum error for all trained individual NNs is 1.521% while error of NNs trained with summation FRFs is 0.262%. It is noticed that training a network with the summation of FRFs improves damage detection results as it gives more accurate results than any of the outcomes of the individual NNs. These damage identification outcomes clearly show the efficiency of the NNs training with summation FRFs. Furthermore, as normalized error is very less, it can be concluded that a damage floor can be identified accurately in the first stage.

Identification of Damage Element

In the second stage, the damaged floor identified in the first stage is considered further to determine damage element. In this stage, FRFs are divided into fifteen subsets representing 180 FRFs in each subset to extract more features from FRFs changes.

Figure **4** shows damage patterns obtained from the first floor when first, second, third, fourth and seventh columns are damaged with 55% and 10% damage severity. Damage index values from different columns for these two damage cases show the signs of clearly distinguishable patterns. It is clear from the figure that shape of damage index values vary according to the column number. Because of this special character, NNs could identify damage element by pattern recognition capability.

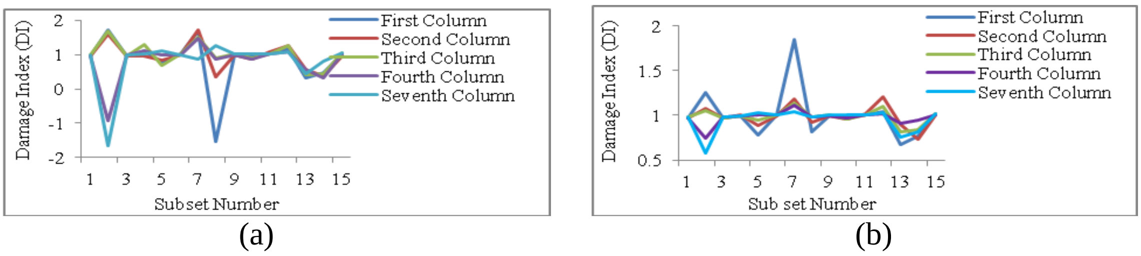


Figure 4 Damage patterns obtained from the first floor when first, second, third, fourth and seventh columns are damaged with (a) 55% and (b) 10% damage severity

To train the network type B, 15 input nodes representing 15 subsets, two hidden layers with 12 and 8 nodes and one output layer with five nodes are used. In this stage FRFs are measured from damaged floor of the structure thus totally four measurements points are available for each floor. NNs are trained with damage patterns of different damage cases of the first floor while NNs are tested with data which is not utilized in the training stage. To evaluate the outcomes of testing data, normalized errors from all damage cases of each data set are determined and compared against each other. 50% of available data are used to train networks while each 25% of data use to validate and to test the networks. Data division for NN training is presented in Table 3. NN performance (in normalized error) trained with data to identify damage element at the first floor is tabulated in Table 4.

Table 3 Data division for NN training for stage 2

Severity (%)	Damage Element				
	1	2	3	4	7
10	Train	Val	Train	Train	Val
25	Val	Train	Test	Train	Train
40	Test	Train	Train	Test	Train
55	Train	Test	Val	Val	Test

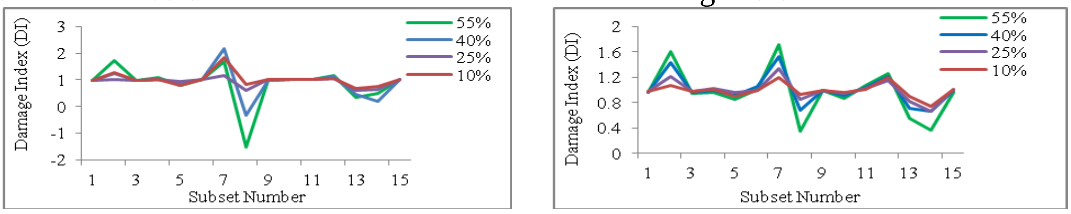
Table 4 NN performance (in normalized error %) trained with summation FRFs to identify damage element at the first floor

Network No	Normalized Error
Training	0.033
Validation	0.058
Testing	0.156

In this case also, NNs trained with summation FRFs give precise results compared with other four individual networks. The outstanding damage localisation results, giving testing error of 0.156% for the summation network and all investigated damage cases, show great potential of the proposed damage identification approach for detecting damaged column. These outcomes show that the defect of columns of multi-storey buildings can be successfully identified even by the FRFs measurements from the floor of the structure.

Quantification of Damage Severity

The final stage of the damage detection approach is to identify damage severity of the damaged element. Damaged element identified from second stage of the approach is further investigated in this stage. Damage Index values from measurement point ‘1’ for different severities when damage is at column ‘1’and column ‘2’of the first floor are shown in Figure.5.



(a) (b)

Figure.5 Damage Index values from measurement point ‘1’ for different severities when damage is at (a) column ‘1’ and (b) column ‘2’

After identifying damaged column, damage patterns only from damaged column for various severities are used to train NN type C. Five columns of first floor are tested to figure out testing performance of NNs when NN is trained with patterns corresponding to different damage levels. FRFs from measurement points ‘1’, ‘2’, ‘7’ and ‘8’ which are located at the first floor are used to train NNs. Only one hidden layer NN is used to determine the damage severity of the element. 5 NNs representing four measurement points and one summation FRFs are developed. Data division for training NNs are tabulated in Table 5. Results obtained only for summation FRFs are presented in Table 6.

Table 5 Data separation for NN type C training

Damage severity	Column Number				
	1	2	3	4	7
10	Train	Val	Train	Test	Train
25	Val	Train	Test	Train	Val
40	Test	Train	Train	Val	Test
55	Train	Test	Val	Train	Val

Table 6 Training, Validation and test performance of the NNs trained with summation FRFs subdivided by column number

Column No	Training	Validation	Testing
1	0.145	0.247	0.354
2	0.256	0.342	0.178
3	0.287	0.411	0.426
4	0.125	0.265	0.469
7	0.109	0.200	0.266

The output results shows that damage severities are correctly identified by ANNs without depending on the damage severity of training data. As an example NN trained with 10% and 55% damage severity data give precise performance for test data which consists of 40% damage severity. For this case, normalized error is 0.354% for identifying severity of column number ‘1’ from damage patterns of 40% severity data. These results show the pattern recognition and prediction capability of NNs with damage index values. It proves that the multi stage ANN concept with three steps can identify the damage floor, damage element and severity of damage precisely. These outstanding results confirm the accuracy of proposed damage detection approach and effectiveness of transforming FRFs data to damage index values using proposed algorithm.

CONCLUSIONS

This paper presents a structural damage detection method for multi-storey structures using vibration measurements from the floors of the structure. The proposed method is based on FRFs obtained from vibration and utilizes data partitioning into small subsets to reduce dimensionality of the data set and to extract main features corresponding to different frequency range. PCA is used for noise filtering and ANN technique is utilized to match damage patterns to identify a damage floor, damage element and severity. The proposed approach consists of three stages. In the first stage damage floor of the structure is identified. Subsequently, FRF measurements of the identified floor in the first stage are used for damage element identification. Finally severity of the damaged element is accomplished using a few damage patterns measured only at the damage region.

The method is tested on finite element model of a ten-storey framed structure introducing different damage scenarios by reducing the local stiffness of the selected elements at different locations of the structure. Numerical data are polluted with three noise levels to simulate field testing conditions as real measured signals are degraded by various sources. The proposed damage detection method is operated in three phases therefore the proposed approach is effective in reducing the size of NN model. As a result of this computational effort is reduced substantially in this research.

Damage patterns from the proposed algorithm are introduced as input parameter for NN training. The illustrative example shows the capability of the proposed damage detection method in locating and quantifying damages. By partitioning the large set of FRFs data, main features of small sub-sets are extracted by PCA effectively. As a result even small damages could identify from the proposed algorithm precisely for noise polluted data. Since the strategy does not require structural modes or frequencies extraction, it is computationally efficient, thus providing a possibly viable tool for structural identification and damage detection of large-scale infrastructures.

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