NN based Damage Detection from Modal Parameter Changes

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ABSTRACT

This paper deals with the determination of severity of damage in a structure from modal parameter changes using neural network approach. The input data was fractional frequency and mode shape change and the output data was combination of different defined damage levels of various storey of the building. The neural network was used to map the corresponding level of damage in the structure with the input data which reflects the changes in the structure. The input data of fractional changes of dynamic characteristics for different damage combinations was generated from the mathematical model updated from the experimentally obtained modal parameters determined from the ambient vibration testing of the structure. The approach was validated on four and the eight storey building model. The study was first carried out with different combinations of levels of damage to determine the suitable network to identify the degree of damage in the building. It was possible to obtain satisfactorily accurate degree of damage in floors of the building. The training of the network was carried out for different combination of damage cases and the result showed that the accuracy of degree of damage detected in structure increased with the increase in the number of combination of damage cases considered for training of neural network. It has been found that the accuracy to determine severity of damage decreases with increase in the number of storeys being damaged.

KEYWORDS – Damage detection, neural network, natural frequency, mode shape

1. INTRODUCTION

The problems in the several fields of science and engineering with not so clearly defined procedures to obtain the solutions have led to the development of techniques such as neural network which were based on the interpretation of the correlation of the input values and the output values [2]. The neural networks (NN) approach is one such technique which is being used to map the given input and the output obtained from the system through its self learning mechanism in which the network tries to recognize the pattern by analyzing data and further utilize these patterns for solving the problems. The input given to a trained network is combined in some way and a nonlinear operation is performed which generates the output. To explore the capability of neural network in recognizing the patterns, Elkordy et al (1993) trained networks with normalized reduced mode shapes of a five story steel frame to locate the damage for which the network were trained[3]. Barai and Pandey (1995) generated various combination of damage in the bottom chord of steel bridges using FEM program and identified the reduced stiffness [1]. Zhao et al (1998) tried to locate structural damage through nodal static displacements natural frequencies, mode shapes and slope array [11]. For the assessing the overall damage at each floor in composite two storey frame, Zapico and Gonzalez (2003) applied the natural frequencies obtained from the finite element model to train the multi-layer perceptron network and found the difference of about 10% between the stiffness matrix obtained from testing of trained network and pseudo-dynamic test[10]. Xu et al (2004) developed a strategy for the identification of stiffness and damping from the velocities and displacements of the structure under dynamic loading which did not require the information about the undamaged structure. The root mean square difference vector generated during the training of the neural network used to evaluate its performance was used as index for system identification [8]**.** Qian and Mita (2007) applied Parzen window method for structural damage location using only a small number of training data for identifying degree of damage in a 5 storey shear building [6]. A typical Multi Layer

Perceptron (MLP) neural network with reference to present study is shown in Figure 1.

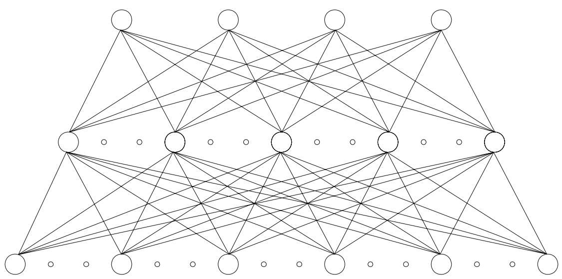

Figure 1 Typical MLP neural network model with reference to present study

2. DAMAGE QUANTIFICATION METHODOLOGIES

The detection of the location of damage in a structure allows the engineer to take up the decision regarding retrofitting measures but the extent of retrofitting that is to be carried out is always of concern since some time the damage location is inaccessible and hence an approximate prior knowledge of location would always be helpful in carrying out the repair. The damage quantification would also help to judge about the stability of the structure and the approximate cost that would be incurred in carrying out the repair. The measured frequency changes in the structure indicate the probable existence of damage and the changes in mode shape, mode shape curvature allow locating damage in the structure. But determining the degree of damage from changes in mode shape is not possible. Damage detection through neural network is one such approach in which the complete database of the derived parameter with the respective damage is fed to the network. The derived parameters are the input for the network and the damage location are the desired output. Once the trained network is given the input for the given problem, it should be able to detect the correct location of damage and also provide quantified damage.

In this part of the work, it is assumed that natural frequencies and mode shapes (modal parameters) of undamaged buildings are known using ambient vibration studies or earthquake records. It is also assumed that analytical results of frequencies and mode shapes of undamaged building match well with experimental results. This mathematical model is then analytically damaged and modal parameters are determined for a number of combinations of different level of damages at different locations. These results are then used to train the neural network [4]. The trained neural network then should be able to determine which storey is damaged by what amount. Further the damages occurred either in beam, column, wall of the particular identified damaged storeys will have to be located through visual inspection or various other techniques. In the present neural network studies following steps have been worked out.

A particular building is considered for study. It is assumed that through the ambient vibration response of the structure the frequency and mode shape of the undamaged structure is determined. This frequency and mode shape of the structure is used for the modal updating of a spring mass model. It is assumed that the mass matrix is known quite accurately. The stiffness of the spring element is updated as per the requirement. The stiffness matrix of the undamaged structure is then obtained from the unit load method. Thus the stiffness matrix and mass matrix of the undamaged structure is known. The set of frequency and modes shapes are generated for undamaged and combination of damaged cases. A computer program was made to generate the damage combinations for the specific number of damages in a building with particular number of storeys.

3. FOUR STOREY BUILDING

In this example a two bay by two bay four story building was chosen for study. The mathematical model was generated in SAP2000 [7] as shown in Figure 2 which is a line sketch depicting the vertical columns, horizontal

beams, equivalent struts representing infill. The stiffness assigned to the elements represented the combined stiffness of all the respective columns in that storey. The lumped masses represented the total mass of the particular storey. The stiffness reductions of the links represented the damage in the structures. The variation of the stiffness of the different link elements generated different structural models. The damage values considered are the representative values: slight damage, moderate damage and extreme damage. For training of neural network the damages in the storeys of the structure were considered to be in the combination of three damage values, four damage values and five damage values. The different possible damage combination is governed by $N_{dc} = N_{dv}^{\ Ns}$ Where, N_{dc} is the total number of cases or combinations of damages, N_{dv} is the total number of damage values, Ns is the number of storeys in the structure. For four storied building and different damage values the possible damage combinations are:
for three damage values i.e. 0%, 35%, 75% - 81 combinations,
for four damage values i.e. 0%, 25%, 50%, 75% - 256 combinations
and for five damage values i.e. 0%, 20%, 40%, 60%, 75% - 625 combinations.

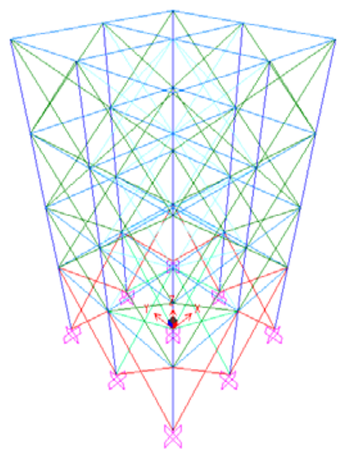

Figure 2 Mathematical model of four storey building

These combinations were generated through a FORTRAN code. The stiffness values assigned to the link for the damage values; 0%, 20%, 25%, 35%, 40%, 50%, 60% and 75% were K, 0.8K, 0.75K, 0.65K, 0.6K, 0.5K, 0.25K respectively, where K is the respective storey stiffness of undamaged structure. A typical set of damage combinations with three damage values is shown in Figure 3.

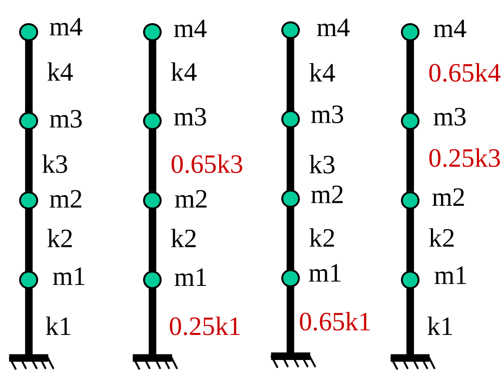

Figure 3 Typical Set of Damage Combinations for Training Neural Network

A MATLAB code calculated the frequency and mode shapes for the respective damaged cases with the stiffness, mass and damage combinations given as an input. The mode shapes obtained for the different cases were first normalized with respect to the top storey. One of the outputs obtained from the computer programme was the relative decrease of the frequency of the damaged structure with respect to the undamaged case (Ni et al, 2002). The difference in the mode shapes of different cases with respect to the undamaged cases were another set of output from the MATLAB programme. The complete input for the neural network was fractional frequency change, mode shape changes, and the corresponding damage values given in the structure.

Neural Network Modeling - The network of the input and the output was generated using NeuroSolutions 5.0 [4]. The neural network models for all the cases were generated using Multilayer Layer Perceptron (MLP). The cross validation data set considered was 10% of the input data used for training the network. The convergence criterion of the training of the neural network was increase of cross validation values. The various parameters assumed for the considered network are given in Table 2. The same parameters were used for single layer network.

3.1 Three Damage Based Network

The data combination set for training of network containing only three damage values i.e. 0%, 35%, 75% were randomized to generate three random data sets i.e. Data set 1, Data set 2, Data set 3 . The network has been trained considering these three stages of damage. These three data sets were checked independently for the best network. Network that would give the minimum mean square error (MSE) was selected for our use. From the trials the network 16 - 16 - 4, 16 - 16 - 4 and 16 - 4 - 4 were considered for the training of the Data set 1, Data set 2, and Data set 3 respectively. The network 16-16-4 trained with data set 2 for 30000 epochs (number of training cycles) which had least mean square error was selected for testing. It may be mentioned again that NN was trained using various damage combinations of 0%, 35%, and 75%. Test set consisted of randomly selected damage values (rsdv). Total of 81 test samples as shown in Figure 4 comprised of :
First sample - undamaged state of the structure,
20 samples - combination of rsdv1 in 1st storey and no damage in 2nd to 4th storeys,
20 samples - combination of rsdv2 in 1st storey, rsdv1 in 2nd storey and no damage in the 3rd and 4th storeys.
20 samples - combination of rsdv3 in 1st storey, rsdv2 in 2nd storey, rsdv1 in 3rd storey and no damage in 4th storey.
20 samples - combination of rsdv4 in 1st storey, rsdv3 in 2nd storey, rsdv2 in 3rd storey and rsdv1 in 4th storey.
Where rsdv1, rsdv2, rsdv3, rsdv4 represents randomly selected damage values between 0 - 20%, 21 - 40%, 41 - 60%, 61 - 80% respectively.

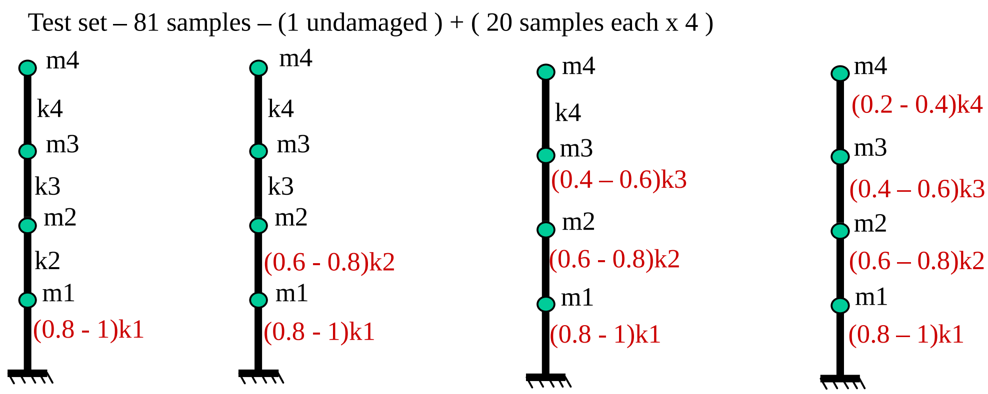

Figure 4 Test set 2 for testing of trained neural networks

The actual difference between the damage values for each storey was calculated and the maximum actual difference was extracted. The calculated median and mean of absolute error in percentage between predicted damage and actual damage from trained network with three damage values for only first storey damage (D1), first and second storey damage (D1-2), first, second and third storey damage (D1-3) and all storey damage (D1-4) is tabulated in Table 1. The median and mean for one storey damage, two storey damage, three storey damage and four storey were almost equal. The mean of the error increased with the increase in the number of stories being damaged except for the situation in which all the stories were damaged.

Table 1 Error from three damage based network for four storey building

Tested Damage combination		D1	D1-2	D1-3	D1-4
Test set -random damage values	Median	6	9	12	9
	Mean	6	8	11	8

3.2 Four Damage Based Network

The results obtained from the networks trained with three damage values were not satisfactory since there were large differences in desired values of damage, as is evident from the Table 1. Hence the training of the network was carried out with samples with four damage values that is, 0%, 25%, 50% and 75%. Same procedure was followed as in the case with three damage values. The network 16 – 16 – 4 trained with data set 2 for 40000 epoch was selected for testing.

Test set consisted of rsdv which is same as has been explained earlier in the case of testing of trained network with three damage values. The calculated median and mean of absolute error in percentage between predicted damage and actual damage from trained network with four damage values for only first storey damage (D1), first and second storey damage (D1-2), first, second and third storey damage (D1-3) and all storey damage (D1-4) for Test set is tabulated in Table 2. The median and mean for all the cases were exactly equal. The mean for only one storey damage was as desired and the mean of absolute error between predicted damage and actual damage from trained network for other cases were quite acceptable.

Table 2 Error from four damage based network for four storey building

Tested Damage combination		D 1	D 1-2	D 1-3	D 1-4
Test set - random damage values	Median	1	3	2	3
	Mean	1	3	2	3

3.3 Five Damage Based Network

The median and mean values tabulated in Table 1 and Table 2 clearly reveal that by training of the network with combination of four damage cases substantially reduces the error in comparison with three damage cases. Although the result obtained from the networks trained with four damage values improved drastically as is evident from the Table 2 but there were still some unacceptable errors in some of the sample. Hence the training of the network was carried out with 5^4 = 625 samples with five damage values that is, 0%, 20%, 40%, 60% and 75%. Same procedure was followed as in the case with four damage values. The network 16 – 16 – 4 trained with data set 3 for 40000 epoch was selected for testing. Test set (using rsdv) was the same as has been explained in the case of testing of trained network with three damage values. The calculated median and mean of absolute error in percentage between predicted damage and actual damage from trained network with five damage values for only first storey damage (D1), first and second storey damage (D1-2), first, second and third storey damage (D1-3) and all storey damage (D1-4) for Test set is tabulated respectively in Table 3.

Table 3 Error from four damage based network for four storey building

Tested Damage combination		D 1	D 1-2	D1-3	D1-4
with random damage	Median	1	1	1	1
	Mean	1	1	1	1

3.4 Comparison of Three, Four And Five Damage Based Networks

The results obtained from the testing of networks trained with the following combinations and levels of damages are tabulated as follows.

- 81 Combinations of three damage values (0%, 35 % and 75%),
- 256 Combinations of four damage values (0%, 25%, 50% and 75%),
- 625 Combinations of five damage values (0%, 20% 40%, 60% and 75%),

The accuracy of the results has been further grouped into accurate, substantially accurate, moderately accurate and incorrect.

- Result with maximum difference of ± 3% and less is grouped as accurate results.
- Results with maximum difference of ± 3 - 6% are grouped as substantially accurate.
- Result with maximum difference of ± 7 - 9% efficiency are moderately accurate.
- Result with maximum difference more than ± 9% are called incorrect.

The efficiency of the results obtained from the networks trained with three (3DV), four (4DV) and five damage values (5DV) has been categorized as mentioned above and is tabulated in Table 4. The following can concluded from Table 4.

- The networks trained with data set of combination of three damage values gave several incorrect results during testing considering worst case of all storeys damage.
- The networks trained with data set of combination of four damage values gave either accurate or substantially accurate values considering worst case of all storey damage.
- The networks trained with the data set of combination of five damage values during testing gave only accurate values considering the worst case of all the storey damage.

The accuracy of the output obtained from the network is dependent on the extent of damage i.e. the number of storeys in which the damage has occurred. Higher number of damaged storey gives less accurate results. The result obtained for the network trained with set of data consisting of the fractional frequency change, mode shape changes and the five levels of damage are accurate enough to be relied upon for the damage location and severity in the four storied structure.

Table 4 Efficiency of three, four and five damage based networks for four storey building

Trained Network tested with combination of random damage values (Figure 5)												
Efficiency	D1			D1-2			D1-3			D1-4		
	3DV	4DV	5DV	3DV	4DV	5DV	3DV	4DV	5DV	3DV	4DV	5DV
Accurate	30	100	100	0	50	100	0	100	100	0	55	100
Substantially accurate	20	0	0	35	45	0	0	0	0	5	45	0
Moderately accurate	30	0	0	30	0	0	15	0	0	90	0	0
Incorrect	20	0	0	35	0	0	85	0	0	5	0	0

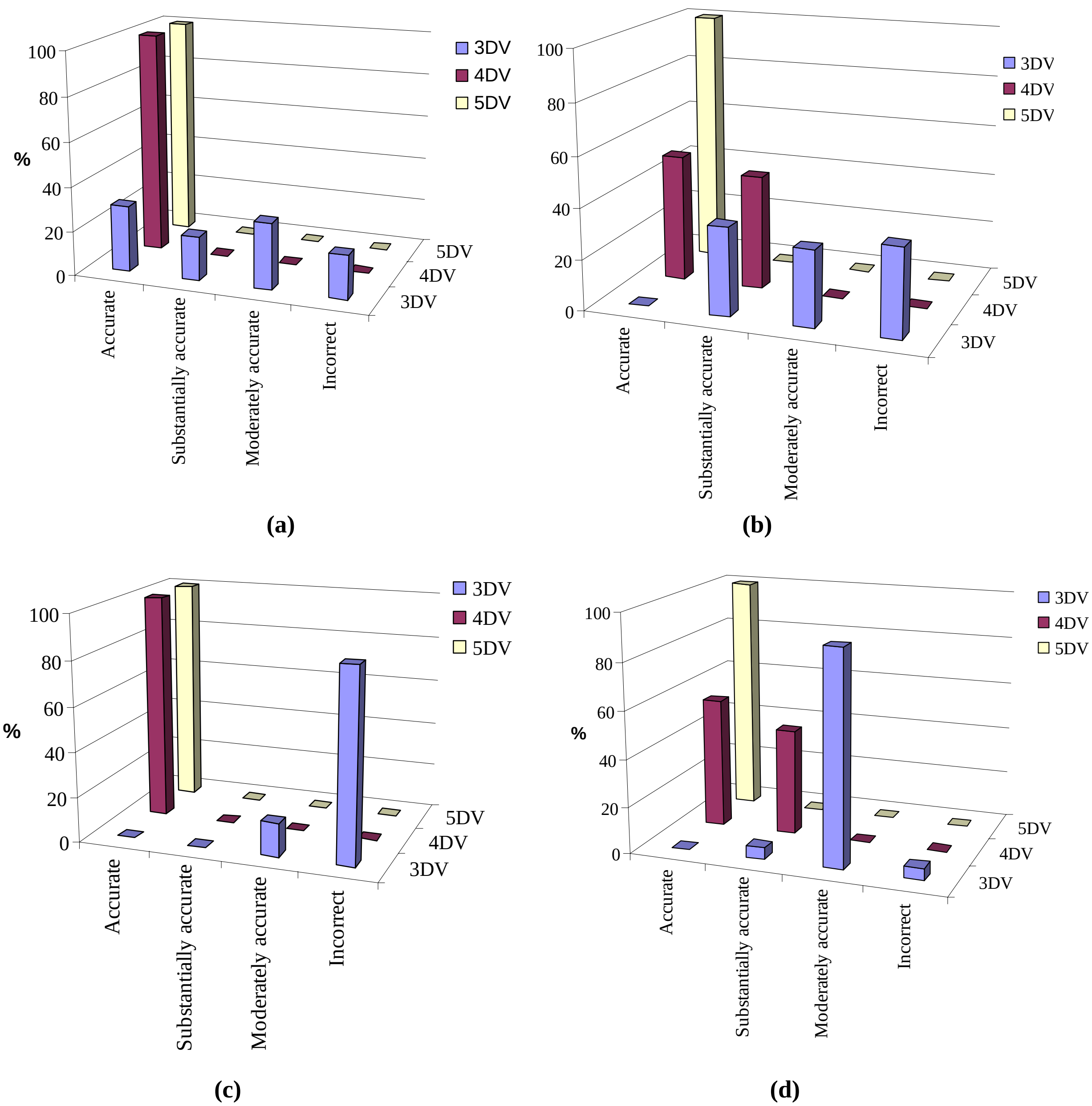

Figure 5 Efficiency of three, four and five damage based networks for randomly damaged (a) Only first storey (b) first and second storey (c) first, second and third (d) All storeys in four storey building

4. STEPS FOR LOCATING AND QUANTIFYING DAMAGE BY NN

The following steps are to be followed to determine the damaged storeys and quantify the damages at various storeys.

i. Ambient vibration test should be carried out to determine the frequency and mode shape of the undamaged building.

ii. Mathematical model of the building should be generated and updated in any standard structural analysis program such that the frequencies of the building should match the experimental frequency.

iii. The set of frequency and mode shape should be determined for various damage combinations of different storeys from the analytical model which represent the set of damage state, where a set of damage set means the damages at different storeys.

iv. The ratio of difference between undamaged state and damaged state to the undamaged state is used as one part of input for neural network training as far as the frequency parameter is concerned.
v. The difference of the mode shape of damaged state with respect to the undamaged state with the top node normalized to one is another part which is also used as input for the neural network as far as the mode shape parameter s concerned.
vi. This combination of the relative frequency change ratio and change in mode shape is finally used for training the neural network.
vii. The trained network should be used to determine the damage once the earthquake strike.
viii. Ambient vibration of the building should be done again and the frequency and mode shape of the structure after the occurrence of earthquake.
ix. This frequency and mode shape is given as an input to the neural network to locate the damage and to determine the extent of damage.

5. CONCLUSIONS

The following conclusions are derived from the study:
i The combination of frequency change and mode shape changes can be used to locate and quantify the damage.
ii The number of training samples used for training the network should be sufficient enough as well the data set should contain sufficient information so that the neural network can generate the pattern from the data.
iii. The number of training samples generated with the combination of three damage values was not sufficient with the procedure followed to quantify the damage as the accuracy of the results was not satisfactory.
iv. The number of training samples generated with the combination of four damage values was quite satisfactory with the procedure followed for quantifying the damage but the desired best result was achieved with the combination of five damage values.

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