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NN-BASED DAMAGE DETECTION IN MULTI-STOREY BUILDINGS FROM MODAL PARAMETER CHANGES

Hemant Kumar Vinayak*, Ashok Kumar**, Pankaj Agarwal** and Shashi Kant Thakkar**

*Department of Civil Engineering
National Institute of Technology Hamirpur, Hamirpur-177005
**Department of Earthquake Engineering
Indian Institute of Technology Roorkee, Roorkee-247667

ABSTRACT

To determine the relative status of the damaged floors of a building after an earthquake by using modal characteristics of the building, instrumentation of the building is not required throughout its lifetime. In this paper, the accuracy of neural networks trained with fractional frequency and mode shape changes, as obtained from the combinations of three, four and five damage levels of different storeys of the building, is evaluated. The networks trained with a combination of three damage levels are found to be incapable of giving acceptable results in the case of four- and eight-storey buildings considered. However, for the four-storey building, the networks trained with four damage levels predict good results and the networks trained with five damage levels predict excellent results. For the eight-storied building, the networks trained with four damage levels give acceptable results for storey level damage. Further, the accuracy of damage severity is found to decrease with an increase in the number of building storeys.

KEYWORDS: Damage Detection, Neural Network, Frequency, Mode Shape, Stiffness

INTRODUCTION

The need to interpret correlation between input and output values, which do not have a mathematical relationship, has led to the development of techniques such as neural networks. The neural network (NN) approach tries to relate the given input and output obtained from the system. A network tries to recognize the pattern by analyzing the data and then utilize these patterns for solving problems. The nonlinear operation during the training of the network generates the output. In neural networks, the pattern recognition is data dependent and is thus not a closed-form solution. In reference to the present study, a typical multi-layer perceptron (MLP) neural network model is shown in Figure 1. The ability to solve real-world problems, e.g., problems in pattern recognition, data processing and nonlinear control, has made neural networks complementary to the conventional approaches (Bishop, 1994). To test the capabilities of the neural networks in order to recognize the patterns of different outputs, Elkordy et al. (1993) trained three backpropagation networks with normalized reduced mode shapes. The mode shapes were obtained from a simplified two-dimensional frame with beam elements and from a detailed finite element model. Barai and Pandey (1995) generated training examples with various combinations of damage in the bottom chord of steel bridges and identified the reduced stiffness in terms of cross-sectional area. Zhao et al. (1998) concluded that natural frequencies or slope arrays sometimes provide better results than mode shapes and state arrays and that the prediction of one-element damage states is more accurate than the multiple damage states. Slope arrays describe the slopes between two adjacent points in a mode shape and state arrays give the differences in the nodal values between two mode shapes. Hou et al. (2000) showed that the occurrence of damage and the moment when this damage occurs can be clearly determined in the details of the wavelet decomposition of the considered vibration data. Sun and Chang (2002) used the wavelet packet transform based component energies as input to the neural network models for damage assessment. Yun and Bahng (2000) studied the substructuring technique on a two-span truss and a multi-storey frame and found that the elements with large modal strain energy are easily detectable than those with negligible modal strain energy for a particular mode. Marwala (2000) studied the performance of a committee of neural network technique that used frequency response functions, modal properties (i.e., natural frequencies and mode shapes), and wavelet transform data simultaneously in order to identify damage in structures. It was shown that data noise does not influence the performance of the approach. The method proposed in the paper identified damage cases better than the three approaches used individually. The committee approach is known to give results that have a lower mean-square error (MSE) than the average MSE of the individual methods. Ni et al. (2002) proposed a strategy to locate joint damage and to identify the extent of damage in existing buildings by using the modal component as an input for the three-layered neural network configuration with back propagation algorithm. Zapico and Gonzalez (2006) utilized the natural frequencies obtained from a finite element model to train the multi-layer perceptron network for assessing the overall damage at each floor in a composite two-storey frame. Qian and Mita (2007) applied the Parzen window method for structural damage location and a feed-forward back propagation neural network for identifying the degree of damage in a 5-storey shear building. The proposed algorithm uses only a small number of training data. Zapico et al. (2005) and Gonzalez and Zapico (2008) worked on two different approaches for seismic damage identification in buildings with steel moment-frame structures based on artificial neural network and modal variables. The statistical analysis of the results was successful, but it was shown that the predictions are quite sensitive to the data and modal errors. Bakhary et al. (2010) presented an approach to detect small structural damage in a three-storey frame by using the artificial neural network (ANN) method with progressive substructure zooming. They used the substructure technique together with a multi-stage ANN model to detect the location and extent of the damage. The modal parameters, i.e., frequencies and mode shapes, are used as inputs to ANN. Lautour and Omenzetter (2010) used an auto-regressive (AR) model to fit the acceleration time histories. The coefficients of the AR model were the input and the damage cases or remaining structural stiffness were the output to an ANN. It was concluded that the combinations of AR models and ANNs perform well even on using a small number of damage-sensitive features and limited sensors. Reda Taha (2010) described a damage detection method based on ANN to compute the wavelet energy of acceleration signals acquired from the structures.

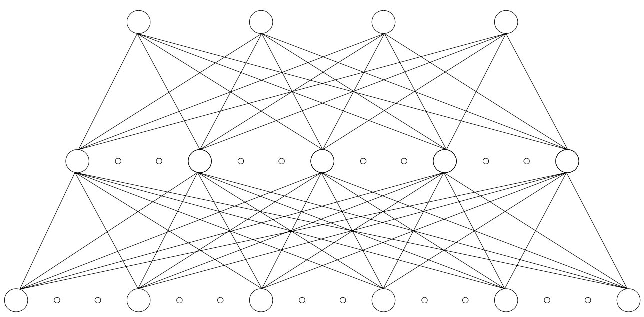


Fig. 1 Typical MLP neural network model with reference to present study

DAMAGE QUANTIFICATION USING MODAL PARAMETERS

The extent of retrofitting at the determined damage location is always of concern. The stability of the structure and approximate cost of repair depend on the quantification of damage in the structure. Many researchers have used frequencies and mode shapes of the structures to indicate the probable existence of damage (Salawu, 1997; Yuen, 1985). In order to determine the level of damage in different storeys of a reinforced concrete building, an approach using neural network is worked out in which changes in the modal parameters of the building as input and respective damages as output are fed to the network for training. This method would be equally applicable to steel structures as well, with the limitation that only those steel members which have been subjected to the ultimate stress, leading to the reduction in story stiffness, can be considered. The nonlinear behaviour of steel is normally idealized as a bilinear relationship, with no stress carrying capacity in the structural members after yielding. Hence, after a steel member has yielded, its stiffness is considered to be zero; however, once it is unloaded, the elastic behaviour is retained, although the stiffness may or may not be same as that in the undamaged structure. Thus, the limitation of this study is that it would be able to determine only the reduction in the storey stiffness of the building and would not be able to determine the reduction in the member stiffness.

The modal parameters of a structure depend on the physical characteristics of the structural members, which are in turn sensitive to the environmental conditions; the environmental conditions are thus bound to affect the modal parameters. However, in the present case, since fractional frequency change is considered for neural network training, variation in frequency in no case would be greater than 0.1 under the assumption that maximum variation in frequency between sunny days and cold weather is not more than 10%. The fractional frequency change in the case of the same environmental conditions after earthquake damage will be $\left(F_{DA}-F_U\right)/F_U$. On the contrary, in the case of the frequency of the structure determined in non-similar environmental conditions, the fractional frequency change would be $\left[\left(F_{DA}\pm \Delta F_{DA}\right)-F_U\right]/F_U$ or $\left(F_{DA}-F_U\right)/F_U \pm \Delta F_{DA}/F_U$ or $\left(F_{DA}-F_U\right)/F_U \pm 0.1 * F_U/F_U$ or $\left(F_{DA}-F_U\right)/F_U \pm 0.1$. Here, F_U denotes the frequency of the undamaged structure in the particular environmental conditions, F_{DA} denotes the actual frequency of the damaged structure in the same environment conditions in which the frequency of the undamaged structure is determined, and ΔF_{DA} denotes the variation due to the environmental factor in the extracted frequency of the damaged structure. For the purpose of calculations, the variation in frequency due to the environmental factor is considered as 10% of the frequency of the undamaged structure, which would be highly conservative in respect of the scenarios where the temperature variations are not extremely high. Further, this assumption is made because the actual frequency of the damaged structure cannot be extracted.

In the above calculations, variation in frequency will not be constant for different environmental conditions, but the maximum relative error in frequency variation can be considered as 0.1 for the extreme case. Further, since the mode shape used for neural network training is normalized to the top of the building, the environmental factor should not be of any concern. The variations in the errors of the estimated damage at various floor levels due to a change in the environmental conditions can be studied, but such a study is beyond the scope of the present work. Further, the acceleration records determined from the recorded ambient vibrations might be contaminated by noise. However, this contamination will not affect the results since the neural network training is carried out by using frequency-domain parameters, not time-domain parameters. Although frequency extraction from a frequency response spectrum is subjected to the judgment of the users, with the help of the mode shape associated with the extracted frequency, the possibility of any misinterpretation can be reduced. In addition, since modal parameters are used to train the network to determine the relative state of floor, the accuracy of experimental results would not matter. The accuracy would be of interest, in case the severity of damage is directly related to the exact quantity of retrofitting to be carried out.

In the present study, the neural network training is based on the unidirectional extraction of modal parameters and not on the bidirectional acquisition of records. The objective is to determine relative damage with a minimum extraction of modal parameters. A limitation of the present study is that only the unidirectional extracted mode shape of the damaged building can be considered for damage quantification. When the mode shape of the considered direction becomes torsional mode shape or the vibration starts in the other direction after damage, that particular mode cannot be extracted. In such a case the study may not be able to produce effective results due to the insufficient input data. The accuracy of the severity of damage for the same level would change, in case bidirectional modal parameters are considered for the unsymmetrical building. Therefore, the accuracy of the equivalent 2D model for neural network based storey level damage severity is studied. The capabilities of trained networks are checked to detect the locations of damage. Two case studies on the analytical models of four- and eight-storey buildings, which are common in India, are presented here. These case studies are not verified with any experimental results, as the study focuses on the comparison of the damage levels to be considered for the neural network training for the most probable floor damage severity.

In this study neural networks are trained by using the MLP of the programme NeuroSolutions (NeuroDimension, 2006). The cross-validation data set considered during the training of the network is 10% of the input data in size. The convergence criterion used for terminating the training of the data is the increase in cross-validation values. Various parameters assumed for the training of networks are given in Table 1.

Table 1: Parameters for Neural Network with Two Hidden Layers

Description	Hidden Layer 1	Hidden Layer 2	Output Layer
Transfer Function	Tanhaxon	Tanhaxon	Sigmoid
Learning Rule	Momentum	Momentum	Momentum
Step Size	1.0	0.1	0.01
Momentum	0.7	0.7	0.7

FOUR-STOREY BUILDING

In the first case study a two bay by two bay four-storey building is considered. The modeling of the building is carried out in SAP 2000 (CSI, 2002) as shown in Figure 2, depicting vertical columns, horizontal beams, and infills as equivalent struts in the form of line sketch. Appropriate dead and live loads along with the wall thicknesses are considered for the modal analysis of the structure. The contributing area of the load shared by each node is used to determine the lumped mass at each storey. The floor stiffness is calculated from the deflection obtained by applying unit load at the upper floor of the storey. The stiffness and mass values of each storey of the undamaged shear frame building are given in Table 2. The derived storey stiffnesses and masses are the characteristics of the equivalent stick model consisting of link elements and lumped masses at the designated storeys of the structure. The stiffness value assigned to a link element represents the combined stiffness of all the respective columns in that storey and the lumped mass value represents the total mass of that particular storey. The modal parameters, i.e., the frequencies and mode shapes of this 2D model, are used for the neural network training. The variations in the lateral stiffnesses of the elements represent the different levels of damage in the different floors of the building. The variations in the stiffnesses of different link elements generate different structural models and accordingly different frequencies and mode shapes of the buildings are obtained. The damage values are considered as the combinations of 0%, 35% and 75% for three damage levels, 0%, 25%, 50% and 75% for four damage levels, and of 0%, 20%, 40%, 60% and 75% for five damage levels. The various damage levels that are considered correspond to light damage, moderate damage, severe damage and extremely severe damage. The damage as high as 75% is easily visible by the naked eye, yet the quantification through visual inspection about the severity of damage in a particular floor would always be questionable, as this involves human judgment at various locations of the damage. Further, a prediction of 75% damage by the neural network suggests replacement of the damaged elements; hence, damage of more than 75% would be an irrelevant damage level for the present study. Also, consideration of only the lower level damage would make the neural network unstable for the determination of a higher level damage severity. The different possible damage combinations are governed by $N_{dc} = N_{dv}^{Ns}$, where N_{dc} is the total number of cases or damage combinations, N_{dv} is the number of damage values, and Ns is the number of storeys in the structure. Thus, for a four-storied building, three damage levels give 81 combinations, four damage levels give 256 combinations, and five damage levels give 625 combinations. The damage combination levels related to various states of the damaged building cases required for the neural network training being large are not mentioned, since it would be difficult to establish the trend of various damage level cases through the changes in frequencies. The stiffness values K, $0.8K$, $0.75K$, $0.65K$, $0.6K$, $0.5K$ and $0.25K$ are assigned to the links for the respective damage values of 0%, 20%, 25%, 35%, 40%, 50%, 60% and 75%, where K denotes the respective storey stiffness of the undamaged structure. A typical set of damage combinations with three damage values is shown in Figure 3. A MATLAB code (MathWorks, 2006) is developed to calculate the following:

a) The fractional frequency change, which is relative change in the natural frequencies of the damaged structure with respect to those of the undamaged structure. For the four-storey building, four values of fractional frequency change for each damage case are calculated.
b) The mode shape change, which is the difference in the mode shapes of the damaged structure with respect to the mode shapes of the undamaged structure. All the mode shapes of the damaged as well as undamaged cases are normalized with respect to the top floor. For the four-storey building, 12 values of mode shape change for each damage case are calculated.
c) The fractional frequency and mode shape changes are considered as input to the neural network and the corresponding storey damage levels for each floor as the output.

1. Three, Four and Five Damage Levels Based Networks

1.1 Network Training

The training of networks with the data containing three, four and five damage level values are carried out by using three randomly shuffled data sets, i.e., Data Set 1, Data Set 2 and Data Set 3. The selection of the number of neurons in the hidden layer is not based on some thumb rule, but the trials of networks are carried out with a single hidden layer and with two hidden layers with the nodes ranging from 4 to 32 in numbers. The selection of the best network, which should be used for training, is determined from the criterion of minimum mean-square error (MSE) obtained after few seconds of training. The networks selected for the training of three damage levels are (i) 16-16-4, 16-16-4, 16-4-4, (ii) 16-16-4, 16-16-4, 16-16-16-4 in the case of four damage levels, and (iii) 16-16-4, 16-16-4, 16-16-4 in the case of five damage levels, for Data Set 1, Data Set 2 and Data Set 3, respectively. All the data sets are trained upto 40,000 epochs. After the training, the network of 16-16-4 of Data Set 2 is found to give best results for three damage levels. Similarly, the network of 16-16-4 of Data Set 2 and the network of 16-16-4 of Data Set 3 for four damage levels and five damage levels, respectively, give best results. These networks are subsequently used for all studies.

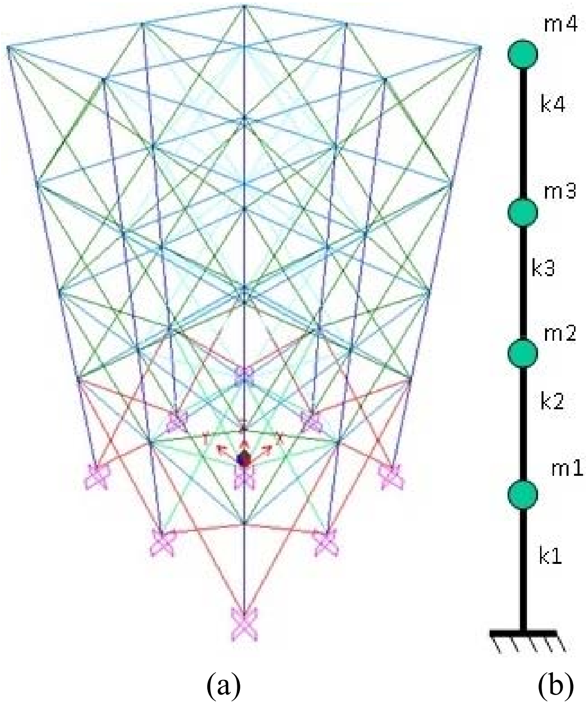


Fig. 2 Four-storey building: (a) study model, (b) equivalent stick model

Table 2: Stiffness and Mass Details of Four-Storey Building

Storey	Stiffness (kN/m)	Mass (kg)
First	323×10^3	89×10^3
Second	450×10^3	86×10^3
Third	450×10^3	86×10^3
Fourth	443×10^3	64×10^3

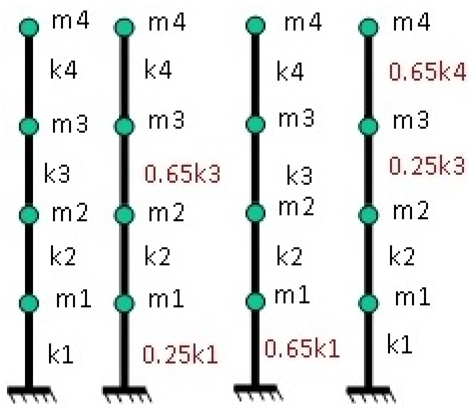


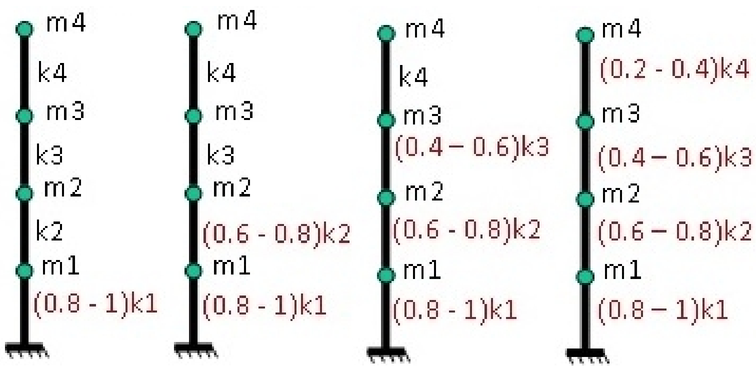
Fig. 3 Typical set of damage combinations for training neural network

1.2 Testing of Network

The testing of the above-selected trained networks is carried out by using randomly selected damage values (RSDV). A total of 81 test samples as detailed below are used for testing; although the test-set data points are small, the test sets are kept same for the comparison of different combinations of damage levels considered for training. The test data sets that are taken contain at least that number of values that are used for training the network:

- the first sample is the undamaged state of the structure;
- 20 samples of the combination of RSDV-1 in the 1st storey and no damage in the 2nd to 4th storeys as in Figure 4(a);
- 20 samples of the combination of RSDV-2 in the 1st storey, RSDV-1 in the 2nd storey and no damage in the 3rd and 4th storeys as in Figure 4(b);
- 20 samples of the combination of RSDV-3 in the 1st storey, RSDV-2 in the 2nd storey, RSDV-1 in the 3rd storey and no damage in the 4th storey as in Figure 4(c); and
- 20 samples of the combination of RSDV-4 in the 1st storey, RSDV-3 in the 2nd storey, RSDV-2 in the 3rd storey and RSDV-1 in the 4th storey as in Figure 4(d);

where RSDV-1, RSDV-2, RSDV-3 and RSDV-4 represent randomly selected damage values between 0–20%, 21–40%, 41–60% and 61–80%, respectively.



(a) (b) (c) (d)

Fig. 4 Test set of 81 samples (1 undamaged + 20 damaged samples each for 4 storeys) for testing of trained neural networks with damage in (a) one storey, (b) two storeys, (c) three storeys, (d) four storeys

The absolute difference between the predicted percentage and actual percentage of the damage values for each storey is calculated and the maximum difference is considered as the error for that particular case. The median, which reflects the numerical value separating the upper half of a sample from the lower half, the mean, which reflects the central tendency of the sample, and the standard deviation, which measures the variability or diversity from the mean, are determined for the different test damage cases to determine the variation from the expected value. The objective of considering the median is to remove the effect of any wild result obtained for the testing of the neural networks. The median, mean and standard deviation of the error for only the first-storey damage (i.e., D1), first- and second-storey damage (i.e., D1-2), first-, second- and third-storey damage (i.e., D1-3) and all-storey damage (i.e., D1-4) are tabulated in Table 3.

2. Comparison of Three, Four and Five Damage Levels Based Networks

The accuracy of the results obtained from the trained networks is grouped into accurate, substantially accurate, moderately accurate and incorrect:

- results with a maximum difference (among any of the four storeys) of ±3% and less are grouped as accurate,
- results with a maximum difference of ±3–6% are grouped as substantially accurate,
- results with a maximum difference of ±7–9% are moderately accurate, and
- results with a maximum difference more than ±9% are called incorrect.

Table 3: Errors from Trained Networks for Four-Storey Building

Damage Combination		D1	D1-2	D1-3	D1-4
Three Damage Levels	Median	6	9	12	9
	Mean	5.9	7.8	11.2	8.5
	Standard Deviation	3.5	2.3	1.5	0.9
Four Damage Levels	Median	1	3	2	3
	Mean	1.4	3	2	2.8
	Standard Deviation	1	1	1	1
Five Damage Levels	Median	1	1	1	1
	Mean	1	1.7	1.2	1.3
	Standard Deviation	0	0.8	0.5	0.7

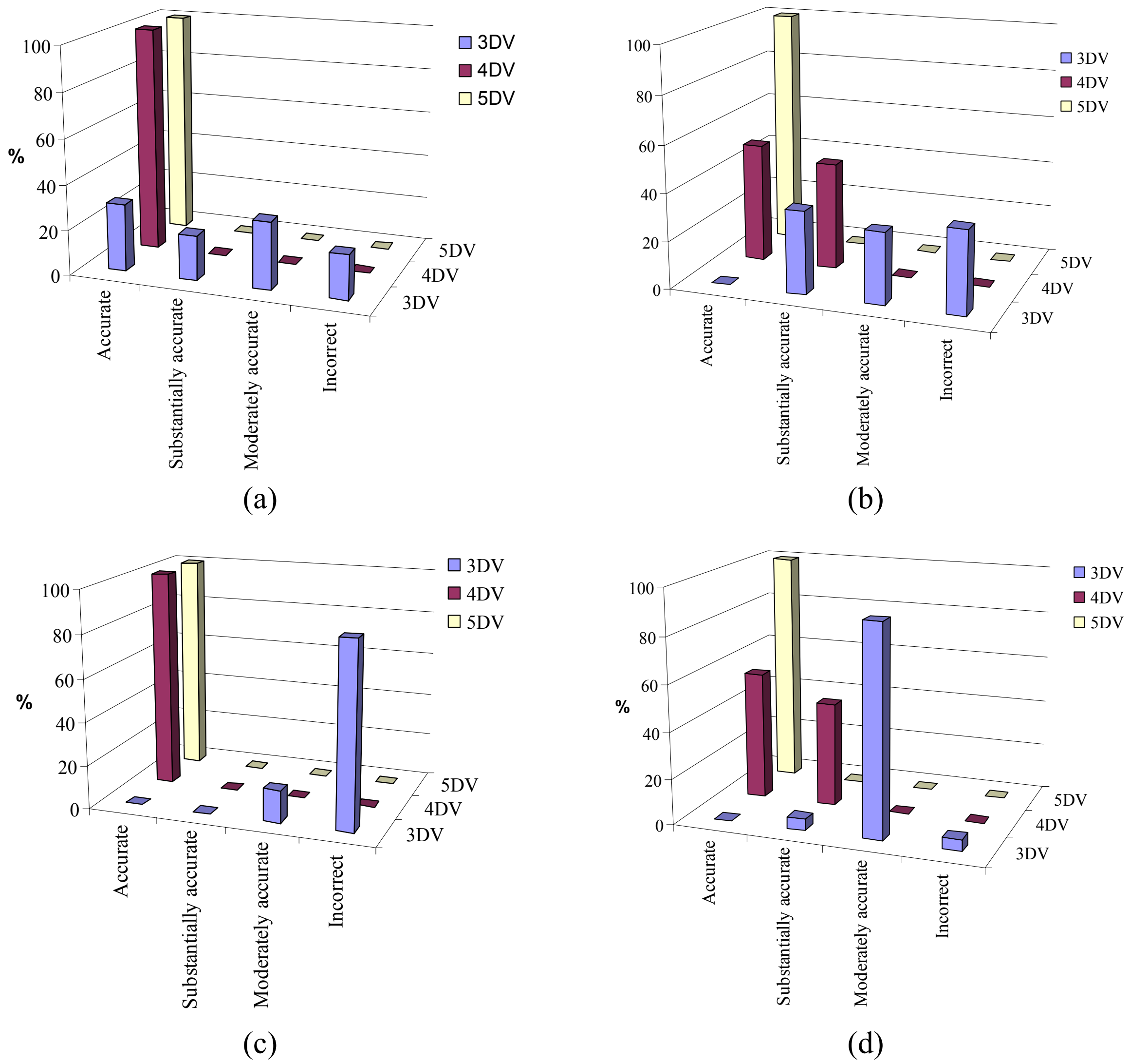
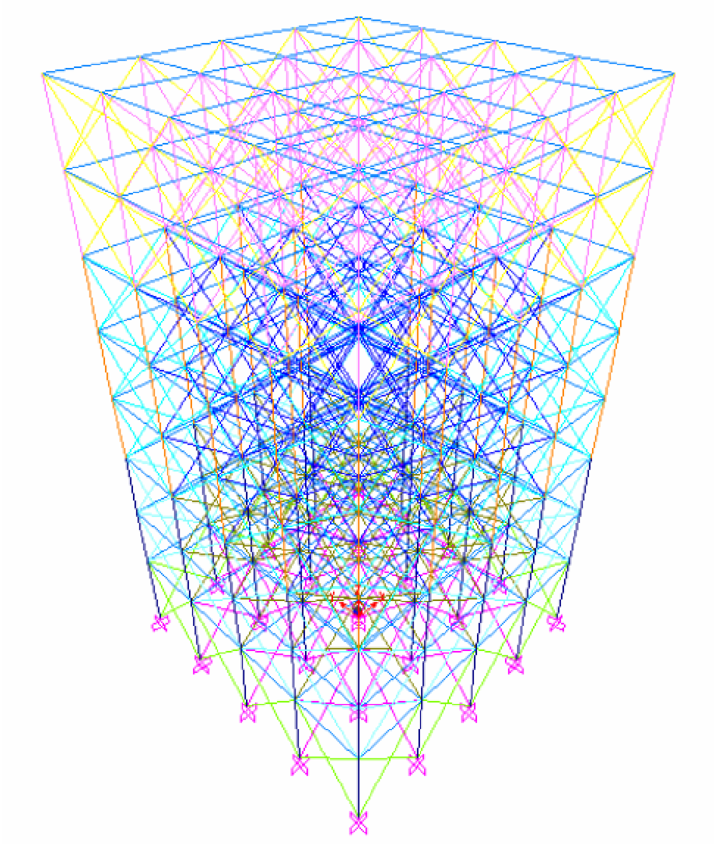


Fig. 5 Efficiencies of three, four and five damage level based networks for randomly damaged (a) only first storey, (b) first and second storeys, (c) first, second and third storeys and (d) all storeys, in four-storey building

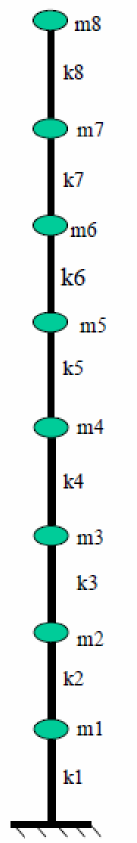
The efficiencies of the results obtained from the networks trained with three, four and five damage levels are plotted in Figure 5. The network trained with the data set of the combinations of three damage values is found to give several incorrect results during the testing. The network trained with the data set of the combinations of four damage values gives either accurate or substantially accurate values. The network trained with the data set of the combinations of five damage values gives all accurate values even in the case of all-storey damage. The accuracy of the output obtained is dependent on the extent of damage, i.e., the number of storeys in which the damage has occurred. A higher number of damaged storeys gives less accurate results. The results obtained from the networks trained with the data sets consisting of fractional frequency changes, mode shape changes and five levels of damage are accurate enough to be relied upon for the location and severity of damage in the four-storey structure.

EIGHT-STOREY BUILDING

In the second case study a four bay by four bay eight-storey building is considered. The model is generated in SAP 2000 (CSI, 2002) as shown in Figure 6. As in the case of four-storey building, an equivalent stick model is generated. The derived stiffness and mass values of each storey for the stick model are tabulated in Table 4.



(a)



(b)

Fig. 6 Eight-storey building: (a) study model, (b) equivalent stick model

Table 4: Stiffness and Mass Details of Eight-Storey Building

Storey	Stiffness (kN/m)	Mass (kg)
First	1256×10^3	3659×10^2
Second	1838×10^3	3501×10^2
Third	1811×10^3	3394×10^2
Fourth	1623×10^3	3288×10^2
Fifth	1623×10^3	3288×10^2
Sixth	1607×10^3	3193×10^2
Seventh	1445×10^3	3098×10^2
Eighth	1412×10^3	2477×10^2

1. Three and Four Damage Levels Based Network

1.1 Network Training

The case study to quantify damage in the eight-storey building is checked on three and four damage level based networks. The training samples for both three damage level and four damage level based networks are considered as same to appreciate the difference in the efficiencies of both the networks. In the case of three damage level based network, the training data set consists of $3^8 = 6{,}561$ samples, whereas in the case of four damage levels a total of $4^8 = 65{,}536$ combinations are possible. These combinations are randomized and a reduced data set of 6553 samples, which are approximately 10% of the total number of combinations, is considered for training. The effect of variations in the samples to be considered for neural network training is beyond the scope of the present study. A MATLAB code (MathWorks, 2006) is developed to find the fractional frequency changes and mode shape changes as in the case of four-storey building. This provides 64 inputs to the neural network with eight outputs (i.e., the damage in various floors). The data sets are checked for the best network as explained in the previous section. The network 64-48-48-8 in the case of three damage levels and the network 64-64-64-8 for four damage levels are selected for testing.

1.2 Testing of Network

The test set consists of 81 test samples, which comprise first sample as the sample in the undamaged state and further 10 samples with the following combinations:

- RSDV-a in the 1st storey and no damage in the 2nd to 8th storeys;
- RSDV-b in the 1st storey, RSDV-a in the 2nd storey and no damage in the 3rd to 8th storeys;
- RSDV-c in the 1st storey, RSDV-b in the 2nd storey, RSDV-c in the 3rd storey and no damage in the 4th to 8th storeys;
- RSDV-d in the 1st storey, RSDV-c in the 2nd storey, RSDV-b in the 3rd storey, RSDV-a in the 4th storey and no damage in the 5th to 8th storeys;
- RSDV-e in the 1st storey, RSDV-d in the 2nd storey, RSDV-c in the 3rd storey, RSDV-b in the 4th storey, RSDV-a in the 5th storey and no damage in the 6th to 8th storeys;
- RSDV-f in the 1st storey, RSDV-e in the 2nd storey, RSDV-d in the 3rd storey, RSDV-c in the 4th storey, RSDV-b in the 5th storey, RSDV-a in the 6th storey and no damage in the 7th and 8th storeys;
- RSDV-g in the 1st storey, RSDV-f in the 2nd storey, RSDV-e in the 3rd storey, RSDV-d in the 4th storey, RSDV-c in the 5th storey, RSDV-b in the 6th storey, RSDV-a in the 7th storey and no damage in the 8th storey; and
- RSDV-h in the 1st storey, RSDV-g in the 2nd storey, RSDV-f in the 3rd storey, RSDV-e in the 4th storey, RSDV-d in the 5th storey, RSDV-c in the 6th storey, RSDV-b in the 7th storey and RSDV-a in the 8th storey;

where RSDV-a, RSDV-b, RSDV-c, RSDV-d, RSDV-e, RSDV-f, RSDV-g and RSDV-h represent randomly selected damage values between 0–10%, 11–20%, 21–30%, 31–40%, 41–50%, 51–60%, 61–70% and 71–80%, respectively.

As for the four-storey building, difference between the expected and output damage values for each storey is calculated and the maximum of the differences over all the storeys is extracted as the error. The median, mean and standard deviation of errors are given in Table 5.

2. Comparison of Three and Four Damage Levels Based Networks

The results are grouped into different categories of accuracy as explained in the previous section. The efficiencies of different trained networks are shown in Figures 7 and 8. It is seen from these figures that the networks trained with the data set of the combinations of three damage values give some incorrect results, while the networks trained with the data set of the combinations of four damage values give accurate and substantially accurate values on considering the worst case of "all storeys" damage. Thus, the results obtained from the networks trained with the data set consisting of the fractional frequency changes, mode shape changes and four levels of damage are accurate enough to be relied upon for the location and severity of damage in the eight-storey structure.

Table 5: Errors from Networks for Eight-Storey Building

Tested Damage Combination Random Values		a	b	c	d	e	f	g	h
Three Damage Levels	Median	3	6	7	7	6	8	9	9
	Mean	3	5.4	6.7	6.6	6.4	8.1	8.9	8.7
	Standard Deviation	0	0.7	0.5	0.7	0.5	0.3	0.7	1.1
Four Damage Levels	Median	5	5	4	4	3	4	4	3
	Mean	5.1	5	4	4	3.4	3.8	3.9	2.7
	Standard Deviation	0.3	0	0	0	0.5	0.4	0.3	0.5

Here, a, b, c, d, e, f, g and h represent the damage in the "1st storey only", "1st and 2nd storeys", "1st, 2nd and 3rd storeys", "1st, 2nd, 3rd and 4th storeys", "1st, 2nd, 3rd, 4th and 5th storeys", "1st, 2nd, 3rd, 4th, 5th and 6th storeys", "1st, 2nd, 3rd, 4th, 5th, 6th and 7th storeys" and "all storeys" cases, respectively.

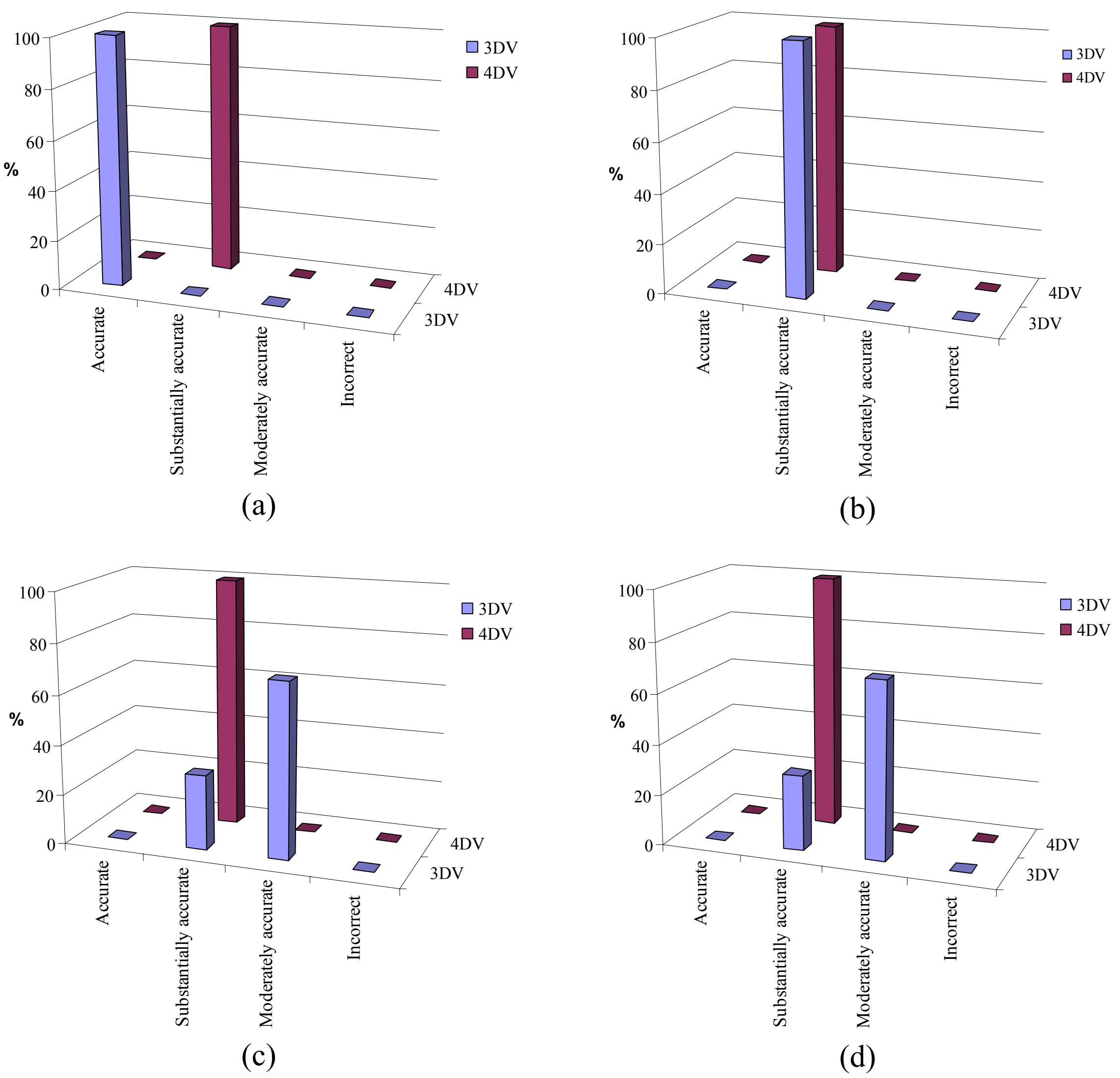


Fig. 7 Efficiencies of three and four damage level based networks for randomly damaged (a) only first storey, (b) first and second storeys, (c) first to third storeys and (d) first to fourth storeys, in eight-storey building

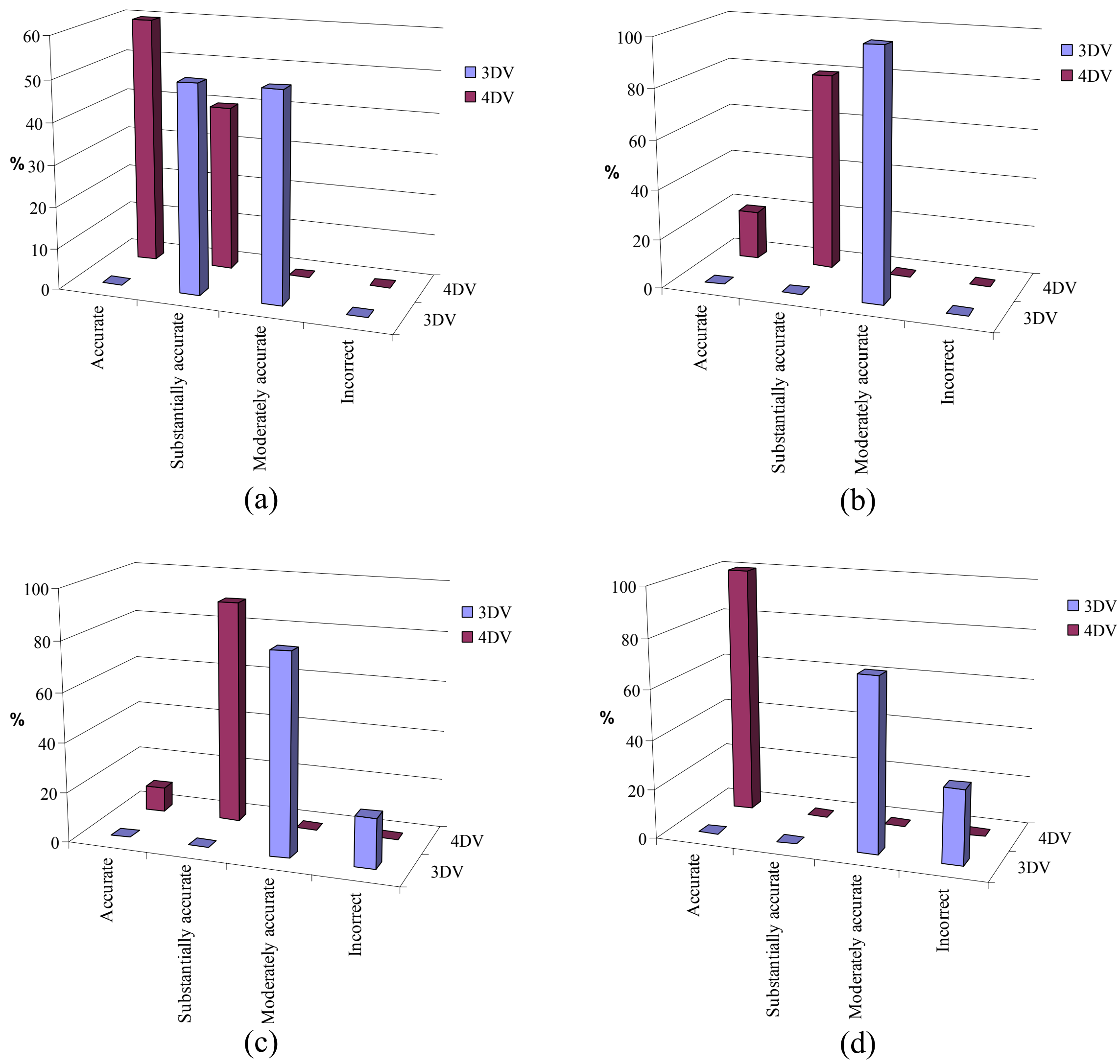


Fig. 8 Efficiencies of three and four damage level based networks for randomly damaged (a) first to fifth storeys, (b) first to sixth storeys, (c) first to seventh storeys and (d) first to eight storeys, in eight-storey building

DISCUSSION OF RESULTS

The results of study are discussed with reference to the two models considered, i.e., four- and eight-storey buildings.

1. Four-Storey Building

The number of training samples generated with the combinations of three damage values is not sufficient for the procedure followed to quantify the damage, as the accuracy of the results is not found to be satisfactory. The number of training samples generated with the combinations of four damage values is quite satisfactory, but the best results are achieved with the combinations of five damage values. The standard deviations show that variations in the results decrease with an increase in the number of damage levels considered for the training of the data.

2. Eight-Storey Building

Although the number of training samples used for training the network with the combinations of three damage values is quite large, the data set lacks sufficient information for the neural network to generate the pattern and quantify the damage successfully. The number of training samples generated with the combinations of four damage values is huge, hence a reduced number, approximately same as that for the case of three damage values, is taken and the results are observed to be satisfactory. The middle storey of the eight-storey building is found to be more unpredictable for quantifying the damage than with respect to the lower and higher storeys of the building. The damage quantified for the four-storey building with four damage value combinations is more accurate than the damage quantified for the eight-storey building with four damage value combinations and more than 25 times the samples used for the four-storey building.

To summarize the method for the real-world applications, following steps are to be followed for identifying the damaged storeys and for quantifying damage in various storeys:

1. Ambient vibration testing should be done to determine the frequencies and mode shapes of the undamaged building.
2. The mathematical model of the building should be generated and updated in any standard structural analysis program, such that the frequencies of the building match the experimental frequencies.
3. The sets of frequencies and mode shapes should be determined for various damage combinations of different storeys from the analytical model. These damage combinations represent a set of damage states, whereas a set of damage sets implies damage in different storeys.
4. The ratio of difference between the undamaged and damaged states to the undamaged state is used as one part of the input for neural network training as far as the frequency parameter is concerned.
5. The differences in the mode shapes of the damaged state with respect to the undamaged state, with the top node normalized to unity, form another part which is also used as input for the neural network as far as the mode shape parameter s concerned.
6. This combination of the relative frequency change ratio and change in mode shape is finally used for training the neural network.
7. The trained network should be used to determine the damage, once an earthquake occurs.
8. The ambient vibration testing of the building should be done again after the occurrence of the earthquake and the frequencies and mode shapes of the structure should be determined.
9. The so-obtained frequencies and mode shapes should be given as input to the neural network to locate the damage and to determine the extent of damage.

CONCLUSIONS AND FUTURE RESEARCH

The combination of frequency change and mode shape change can be used to locate and quantify damage in an important building in the event of an earthquake. The database of the modal parameters of various important buildings can be maintained as signatures of those buildings in records. This database can be used to determine the extent of deterioration in such buildings in the event of an earthquake.

It is evident from the comparison of different damage level combinations considered that the number of training samples used for training a network should be sufficient and the data set should contain sufficient information so that the neural network can generate a correct pattern from the data set. Thus, the information about a particular building can be increased by considering a 3D model of the building, instead of the 2D model considered in the present study.

The probability of predicting accurate damage in a building decreases with an increase in the number of damaged storeys. Hence, damage prediction in different storeys of the building should be complemented with the other methods of damage prediction.

This study has focused only on the stiffness reduction of the storeys of the building. Future work can be directed towards predicting stiffness reduction of various members in the buildings.

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