NN based Damage Detection in Multistory Buildings from Modal Parameter Changes

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ABSTRACT

To determine the relative status of the damaged floors of a building after an earthquake using building modal characteristics, instrumentation of the building is not required throughout its lifetime. In this paper, comparison of neural networks accuracy trained with fractional frequency change and mode shape change obtained from combination of three, four and five damage levels of different storeys of the building is evaluated. The network trained with combination of three damage levels of four and eight storey building is incapable of giving acceptable results. However, for four-storey building, network trained with four damage levels predicted good results and networks trained with five damage levels predicted excellent results. For eight-storied building, network trained with four damage levels gave acceptable results for storey level damage. The accuracy of damage severity, decrease with the increased number of building storey.

Keywords: Damage detection, Neural Network, Frequency, Mode shape, stiffness

INTRODUCTION

The need to interpret the correlation between the input and the output values, which do not have a mathematical relationship, has led to the development of techniques such as neural networks. The neural networks (NN) approach tries to map the given input and output obtained from the system. The network tries to recognize the pattern by analyzing the data and further utilize these patterns for solving the problems. The nonlinear operation during the training of the network generates the output. In neural networks, the pattern recognition being data dependent is 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 applications i.e. problems in pattern recognition, data processing, and non-linear control has made neural networks a complementary to conventional approaches (Bishop 1994). To test the capabilities of the neural network in order to recognize the pattern of the different outputs, Elkordy et al. (1993) trained three backpropagation networks with the normalized reduced mode shapes. The mode shapes were obtained from a simplified two-dimensional frame with beam elements and detailed finite element model. Barai and Pandey (1995) generated training examples with various combinations of damage in the bottom chord steel bridges and identified the reduced stiffness in the form of cross sectional area. Zhao et al (1998) concluded that the natural frequencies or slope arrays sometimes provide better result than mode shapes and state arrays and the prediction of one-element damage states is more accurate than the multiple damage states. Slope arrays are the slope between two adjacent points in a mode shape and State arrays are the difference in nodal values between two mode shapes. Hou et al. (2000) showed that occurrence of damage and the moment when it occurs can be clearly determined in the details of the wavelet decomposition of considered vibration data. Sun and Chang (2000) used Wavelet Packet Transform based component energies as input to the neural network models for damage assessment. Yun and Bahng (2000) studied the sub structuring 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 with the negligible modal strain energy for a particular mode. Marwala (2000) study the performance of committee of neural networks technique, that used frequency response functions, modal properties (natural frequencies and mode shapes), and wavelet transform data simultaneously to identify damage in structures. The author showed that the data noise does not influence performance of the approach. The proposed method identified damage cases better than the three approaches used individually. The committee approach gives results that have a lower mean square error (MSE) than the average MSE of the individual methods. Ni et al. (2002) proposed the strategy to locate the joint damage and identify damage extent in existing building using the modal component as input for the three layered neural network configuration with back propagation algorithm. Zapico and Gonzalez (2003) utilized the natural frequencies obtained from finite element model to train the multi-layer perceptron network for assessing the overall damage at each floor in composite two-storey frame. Qian and Mita (2007) applied Parzen window method for structural damage location and feed forward back propagation neural network for identifying degree of damage in a 5- storey shear building. The proposed algorithm uses only a small number of training data. Zapico (2005) and Gonzalez (2008) worked on two different approaches for seismic damage identification in buildings with steel moment-frame structure based on artificial neural network and modal variables. The statistical analysis of the results is successful, but it showed that the predictions are quite sensitive to the data errors and modal errors. Bakhary (2009) presented an approach on the three storey frame to detect small structural damage using ANN method with progressive substructure zooming. The study used the substructure technique together with a multi-stage ANN models to detect the location and extent of the damage. Modal parameters i.e. frequencies and mode shapes are used as input to ANN. Lautour (2010) used Autoregressive(AR) model to fit the acceleration time histories. The coefficients of the AR models were input and damage cases or remaining structural stiffness were output to an ANN. The author concludes that the combination of AR models and ANNs perform well using even small number of damage-sensitive features and limited sensors. Taha (2010) described a damage detection method based on using artificial neural network (ANN) to compute the wavelet energy of acceleration signals acquired from the structure.

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 shape of the structures to indicate the probable existence of damage (Salawu 1995; Yuen 1985). To determine the level of damage in different storeys of a Reinforced Concrete building, an approach using neural network is work out in which the modal parameters change 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 the steel members which have been subject to the ultimate stress leading to the reduction in the story stiffness can be worked. Since nonlinear behaviour of steel are normally idealised as a bi-linear relationship with no stress carrying capacity in the structural members after yielding. Hence after the steel member has yielded the stiffness is zero, however, once unloaded, elastic behaviour is retained although the stiffness may or may not be the same as undamaged structure. Thus the limitation of this study is that it would be able to determine only the reduction in the story stiffness of the building and would not be able to determine the member stiffness reduction. The modal parameters depend on the physical characteristics of the structural member, which are environmental condition sensitive; and environmental conditions are bound to affect the modal parameters. However, in the present case since the fractional frequency change is considered for neural network training the variation in the frequency in no case would greater than 0.1 with the assumption that the maximum variation in the frequency between the sunny day and during cold weather is not more than 10%. The fractional frequency change in case of that same environmental condition after earthquake damage will be

$$[(F_{DA} - F_U)]/F_U$$

On contrary, incase of frequency of the structure determined in a non-similar environmental condition the fractional frequency change could be

$[(F_{DA} \pm \Delta F_{DA})- F_U]/F_U$ or $[F_{DA} - F_U]/F_U \pm \Delta F_{DA})/F_U$ or $[F_{DA} - F_U]/F_U \pm 0.1*F_U/F_U$ or

$[F_{DA} - F_U]/F_U \pm 0.1$

For the calculation purpose, the variation of frequency due to environmental factor is considered as the 10% of the undamaged structure, which would be highly conservative in respect of the scenarios in which the temperature variation is not extremely high. Further, this assumption is considered since the actual frequency of the damaged structure cannot be extracted.

Where, F_U is the frequency of the undamaged structure in a particular environmental condition.

F_{DA} is the actual frequency of the damaged structure in the same environment condition in which the frequency of the undamaged structure is determined.

ΔF_{DA} is the variation due to the environmental factor of the extracted frequency of the damaged structure.

Thus, from above calculation, the variation in the frequency will not be constant for the different environmental condition but the maximum error in frequency variation can be considered 0.1 for extreme case. Further the mode shape used for the neural network training being normalized to the top of the building the environmental factor should not be of concern. The variation in the error of the estimated damage at various floor levels due to change in environmental condition can be studied which is beyond the scope of the present work. Further, the acceleration record determined from the ambient vibration recorded might be contaminated by the noise. However, this contamination will not affect the results, since the neural network training is being carried out by the frequency domain parameters and not from the time domain parameter. Although, the frequency extraction from the frequency response spectrum, is subjected to the judgment of the users, but with the mode shape associated with the extracted frequency the misinterpretation can be reduced. In addition, since the modal parameter is used to the train the network to determine the relative state of floor hence the accuracy of the experimental results would not matter. The accuracy would be of interested incase of the severity is directly related to the exact quantity of the retrofitting to be carried out. In the present study, the neural network training is based on the unidirectional extraction of the modal parameters and not on the bi direction acquisition of the records. The objective has been to determine relative damage with minimum extracted modal parameter. The limitation of the present study is that since only the unidirectional extracted mode shape of the damaged building can be considered for damage quantification. The situations in which the mode shapes of the considered direction incase become torsional mode shape or starts vibrating in the other direction after damage then that particular mode could not be extracted. In such case the study may not be able to produce effective results due insufficient input data. The accuracy of the severity of damage for the same level would change incase of bi directional modal parameters are considered for the unsymmetrical building. Thus, accuracy of the equivalent 2D model for neural network based storey level damage severity is studied. The capabilities of the trained networks are checked to detect the location of damage. Two case studies on only analytical models of four and eight-storey building which are common in India are presented here. The case studies have not been verified with the experimental results as the study focused on the comparison of the damage levels to be considered for the neural network training for the most probable floor damage severity value.

Neural Network Modeling **–** In this study, neural networks are trained using Multilayer Layer Perceptron (MLP) of the programme NeuroSolutions 5.0. The cross validation data set considered during the training of the network is 10% of the input data. The convergence criteria for terminating the training of the data is the increase of cross validation values. The various parameters assumed for training of networks are given in Table 1.

FOUR STOREY BUILDING

In the first case study a two bay by two bay four-storey building has been considered. The modeling of the building is carried out in SAP2000 as shown in Figure 2, depicting vertical columns, horizontal beams, and infill as equivalent struts in the form of line sketch. Appropriate dead and live load along with the wall thicknesses are considered for the modal analysis of the structure. The contributing area of load shared by each node has been used to determine the lumped mass at each storey. The floor stiffness is calculated from the deflection obtained by the unit load applied at the upper floor of the storey. The stiffness and mass values of each storey of the undamaged frame shear building is given in Table 2. The derived storey stiffness and masses are the characteristic of equivalent stick model consisting of the link elements and the lumped mass at the designated storey of the structure. The stiffness values assigned to the link elements represent the combined stiffness of all the respective columns in that storey and the lumped masses represent the total mass of the particular storey. The modal parameter i.e. the frequency and the mode shape of this 2D model is used for the neural network training. The variations in the lateral stiffness of the elements represent the different levels of damage in the different floor of the building. The variation of the stiffness of the different link elements generated different structural models and accordingly the different frequency and mode shapes of the buildings are obtained. The damage values are considered as combination of 0%, 35%, 75% for three damage levels, 0%, 25%, 50%, 75% for four damage levels and 0%, 20%, 40%, 60%, 75% for five damage levels. The various damage levels that have been considered correspond to light damage moderate damage, severe damage and extremely severe damage. The damages as high as 75% is easily visible by the naked eye, yet the quantification through visual inspection about the severity of the damage in a particular floor would always be questionable which involved human judgment at the various locations of the damage. Further the neural network's prediction of 75% damage would suggest replacement of the damage elements hence considering damages more 75% would be an irrelevant damage level for the present study. Also only considering lower level damages would make the neural network unstable for the higher level damages severity determination. The different possible damage combinations are governed by $N_{dc} = N_{dv}{}^{Ns}$ where, N_{dc} is the total number of cases or combinations of damages, N_{dv} is the number of damage values, Ns is the number of storeys in the structure. Thus, for four-storied building, three damage levels give 81 combinations; four damage levels give 256 combinations whereas five damage levels give 625 combinations. The damage combination levels related to various state of the damaged building cases required for the neural training being large have not been mentioned since it would be difficult to establish the trend of the various damage level cases through the frequency changes. These combinations have been generated through a FORTRAN code. The stiffness values K, 0.8K, 0.75K, 0.65K, 0.6K, 0.5K and 0.25 K are assigned to the link for the respective damage values of 0%, 20%, 25%, 35%, 40%, 50%, 60% and 75%, 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. A MATLAB code is developed to calculate the following

(i) The fractional frequency change, which is the relative change of natural frequencies of the damaged with respect to that of undamaged structure. For four-storey building, four fractional frequency change values for each damage case have been calculated.

(ii) The mode shape change is the difference in the mode shapes of damaged structure with respect to the mode shapes of undamaged structure. All mode shapes of damaged as well as undamaged cases are normalized with respect to the top floor. For the four storey building, 12 mode shape change values for each damage case are calculated.

(iii)The fractional frequency and mode shape change is considered as input to the neural network and its corresponding storey damage levels for each floors as the output

1 Three, four and five damage level based network

1.1 ***Network Training*** - The training of network with the data containing three, four and five damage level values has been carried out using three randomly shuffled data sets i.e. Data set 1, Data set 2 and Data set 3. The selection of number of neurons in the hidden layer was not based on some thumb rule but the trials of networks have been carried out with single hidden layer and with two hidden layers with nodes ranging from 4 to 32 in numbers. The selection of the best network, which should be used for training was determined from the criteria of minimum mean square error (MSE) obtained after few seconds of training. The networks selected for training of three damage levels have been 16-16-4, 16-16-4,16-4-4, in case of four damage levels 16-16-4, 16-16-4, 16-16-16-4 and in case of five damage level 16-16-4, 16-16-4, 16-16-4 for data set 1, data set 2 and data set 3 respectively. All the data sets are trained upto 40000 epochs. After training, network of 16-16-4 of data set 2 has been found to give best results for three damage levels. Similarly, network of 16-16-4 of data set 2 and network of 16-16-4 of data set 3 for four damage levels and five damage levels respectively have given best results. These networks are subsequently used for all studies.

1.2 ***Testing of network*** **-** Testing of the above selected trained network is carried out using randomly selected damage values (rsdv). Total 81 test samples as detailed below are used for testing, although the test set data points are small but test set have been kept same for the comparison of the different combination of damage levels considered for training. The test data set that have been taken contain atleast that number of value that are used for training the network:

◊ The first sample is the undamaged state of the structure.

◊ 20 samples of combination of rsdv1 in 1st storey and no damage in 2nd to 4th storeys.

◊ 20 samples of combination of rsdv2 in 1st storey, rsdv1 in 2nd storey and no damage in the 3rd and 4th storeys.

◊ 20 samples of combination of rsdv3 in 1st storey, rsdv2 in 2nd storey, rsdv1 in 3rd storey and no damage in 4th storey.

◊ 20 samples of 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.

The absolute difference between the predicted percentage and actual percentage of damage value for each storey is calculated and the maximum difference is considered error for the particular case. The median, which reflect the numerical value separating the higher half of a sample from the lower half; Mean which reflects central tendency of the sample and 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 was to remove the effect of any wild result obtained for the testing of the neural network. Median mean and standard deviation of error 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) are tabulated in Table 3.

2 Comparison of three, four and five damage level based networks

The accuracy of the results obtained from the trained network has been grouped into accurate, substantially accurate, moderately accurate and incorrect.

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

The efficiency of the results obtained from the networks trained with three, four and five damage levels have been plotted in Figure 5. The network trained with data set of combination of three damage values has given several incorrect results during testing. The network trained with data set of combination of four damage values has given either accurate or substantially accurate values. The network trained with the data set of combination of five damage values has given all accurate values even in 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. Higher number of damaged storey gives less accurate results. Results obtained from the network trained with set of data consisting of the fractional frequency change, mode shape changes and five levels of damage are accurate enough to be relied upon for the damage location and severity in four storied structure.

EIGHT STOREY BUILDING

In the second case study a four bay by four bay eight-storey building is assumed. The model is generated in SAP2000 as shown in Figure 6. As in case of four-storied building, an equivalent stick model is generated. The derived stiffness and mass values of each storey for the stick model have been tabulated in Table 4.

1 Three and four damage level based network

1.1 ***Network Training*** - The case study to quantify the damage in eight-storey building is checked on three and four damage level based network. The training samples for both three damage level and four damage level based network have been considered same to difference in the efficiency of both the networks. In case of three damage level based network, training data set consisted of $3^8 = 6561$ samples, whereas in case of four damage level total $4^8 = 65{,}536$ combination are possible which were randomized and reduced data set with 6553 samples approximately 10% of the total combinations were considered for training. The effect of the variation of the samples to be considered for neural network training is beyond the scope of the present study. A MATLAB code was developed to find fractional frequency change and mode shape change as done for four-storied building. This provides 64 inputs to the neural network with eight outputs (damage in various floors). The data sets are checked for the best network as explained in section 3.2. In case of three-damage level, network 64-48-48-8 while for four damage level, network 64-64-64-8 is selected for testing.

1.2 ***Testing of Network*** - The test set consists of 81 test samples, which comprises of first sample as the undamaged state and further 10 samples with the following combinations each

- rsdv-a in 1st and no damage in 2nd to 8th storeys.

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

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

As for four storied building, difference between expected and output damage values for each storey is calculated, maximum of the difference is extracted as error. Median mean and standard deviation of errors have been given in Table 5.

2 Comparison of three and four damage based networks

The results have been grouped into the category as explained in Section 3.3. The efficiency of from the trained networks has been shown in Figures 7 and 8. It can be seen from these figures that networks trained with data set of combination of three damage values give some incorrect results while networks trained with the data set of combination of four damage values has given accurate and substantially accurate values considering the worst case of all the storey damage. Thus, the results obtained from the network trained with set of data consist of the fractional frequency change, mode shape changes and the four levels of damage are accurate enough to be relied upon for the damage location and severity in the eight storied structure.

DISCUSSION OF RESULTS

The results of study have been discussed in reference to the two considered models i.e. four and eight-storey building.

1 Four story building

The number of training samples generated with the combination of three damage values is not sufficient with the procedure followed to quantify the damage, as the accuracy of the results has not been satisfactory. The number of training samples generated with the combination of four damage values is quite satisfactory with the procedure followed for quantifying the damage but the desired best results are achieved with the combination of five damage values. The standard deviation showed that the variation in the results decreased with the increase in the number of the damage level considered for the training of the data.

2 Eight storey building

Although, the number of training samples used for training the network with the combination of three damage values although is quite large but the data set lacks the sufficient information for the neural network to generate the pattern and quantify the damage successfully. The number of training samples generated with the combination of four damage values is huge hence the reduced number approximately the same as the three damage values case study was taken and the result have been 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 the higher storey of the building. The damages quantified for four-storey building with the four damage values combination were much better than the damages quantified for eight storey building with the four damage values combination with more than 25 times the samples used for four storey building.

To summarize the method for the real world application, the following steps are to be followed to determine the damaged storeys and quantify the damages at various storeys.

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

2. 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.

3. 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 implies the damages at different storeys.

4. 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.

5. The difference of the mode shape of damaged state with respect to the undamaged state with the top node normalized to unity is 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 the earthquake strikes.

8. Ambient vibration of the building should be done again after occurrence of earthquake and the frequency and mode shape of the structure is determined.

9. 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.

CONCLUSIONS AND FUTURE RESEARCH

The combination of the frequency change and mode shape change can be used to locate and quantify the damage in an important building in the event of an earthquake. The database of modal parameters of various important buildings can be kept as signature of the building as a record and can be used to determine the building deterioration in the event of an earthquake.

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

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

This study has been focused only on the stiffness reduction of the storey of the building. The future work can be directed towards predicting stiffness reduction of various members in the buildings.

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Table 1 Parameters for neural network with two hidden layers

Description	Hidden layer	Hidden layer	Output
Transfer	Tanhaxon	Tanhaxon	Sigmoid
Learning Rule	Momentum	Momentum	Momentum
Step Size	1.0	0.1	0.01
Momentum	0.7	0.7	0.7

Table 2 Details of four storey building

Stiffness and mass		
Storey's	**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

Table 3 Error from trained network for four storey building

Damage combination		D1	D1-2	D1-3	D1-4
Three Damage level	**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 level	**Median**	1	3	2	3
	Mean	1.4	3	2	2.8
	Standard deviation	1	1	1	1
Five Damage level	**Median**	1	1	1	1
	Mean	1	1.7	1.2	1.3
	Standard deviation	0	0.8	0.5	0.7

Table 4 Details of eight storey building

Stiffness and mass		
Storeys	**Stiffness x 10^3 KN/m**	**Mass x 10^2 Kg**
First	1256	3659
Second	1838	3501
Third	1811	3394
Fourth	1623	3288
Fifth	1623	3288
Sixth	1607	3193
Seventh	1445	3098
Eight	1412	2477

Table 5 Error from networks for eight storey building

Tested Damage combination random values		a	b	c	d	e	f	g	h
Three Damage level	**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	0	0.7	0.5	0.7	0.5	0.3	0.7	1.1
Four damage level	**Median**	5	5	4	4	3	4	4	3
	Mean	5.1	5	4	4	3.4	3.8	3.9	2.7
	Standard	0.3	0	0	0	0.5	0.4	0.3	0.5

Where a, b, c, d, e, f, g, h represent the damage in (1^{st} storey only), (1^{st} and 2^{nd} storey), (1^{st}, 2^{nd} and 3^{rd} storey), (1^{st}, 2^{nd}, 3^{rd} and 4^{th} storey), (1^{st}, 2^{nd}, 3^{rd}, 4^{th} and 5^{th} storey), (1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th} and 6^{th} storey), (1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th}, 6^{th} and 7^{th} storey) and finally all storeys respectively.

List of Captions of illustrations

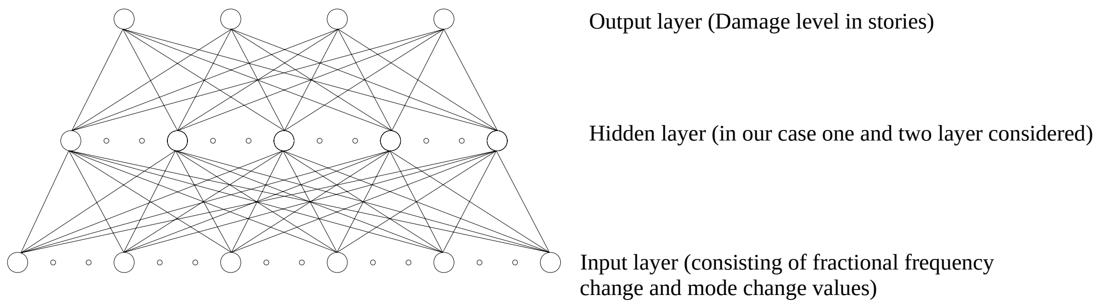


Fig. 1 Typical MLP neural network model with reference to present study

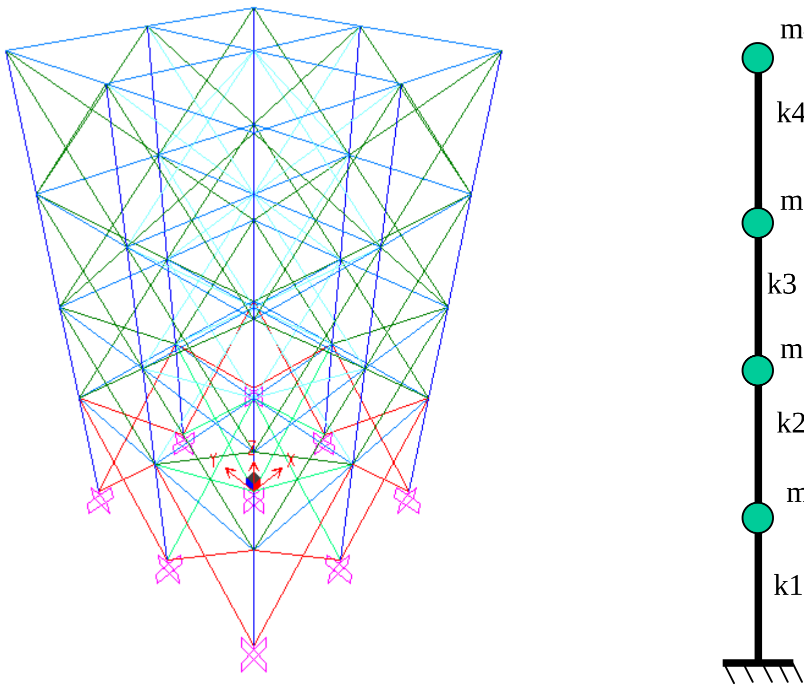


Fig. 2 Four storey building - study model with equivalent stick model

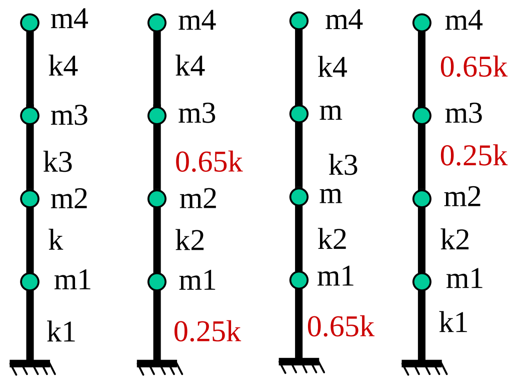


Fig. 3 Typical set of damage combinations for training Neural Network

Test set – 81 samples – (1 undamaged) + (20 samples each x 4)

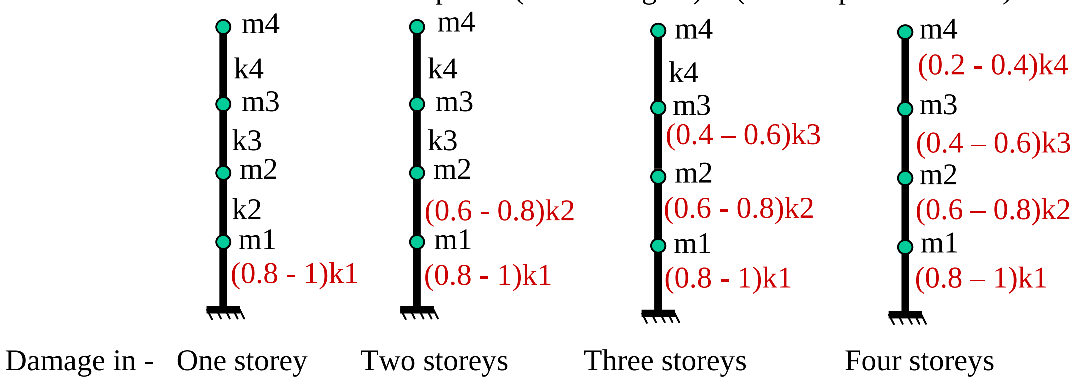
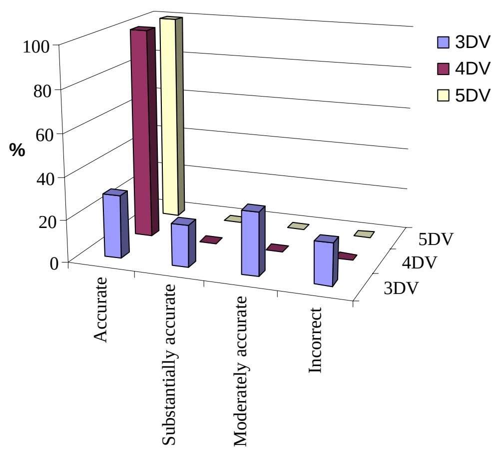
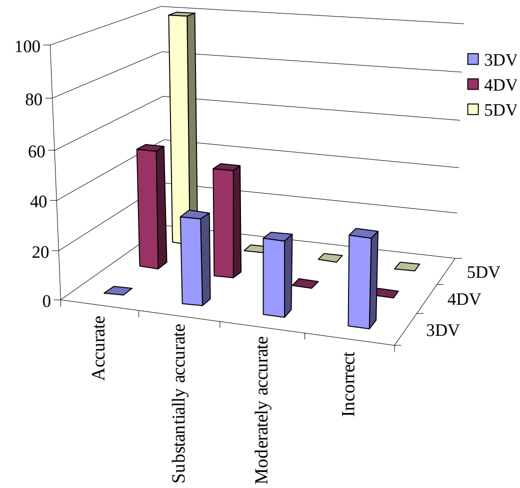


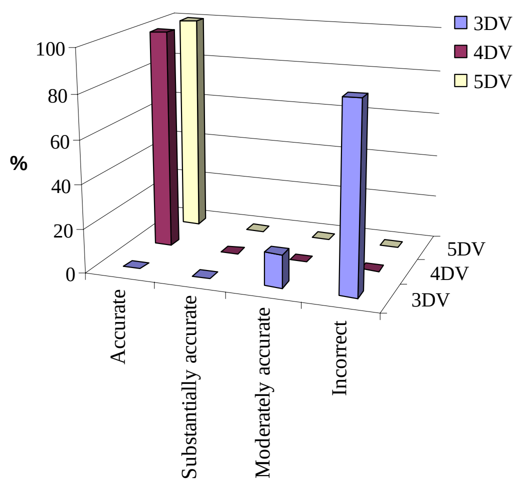
Fig. 4 Test set for testing of trained neural networks



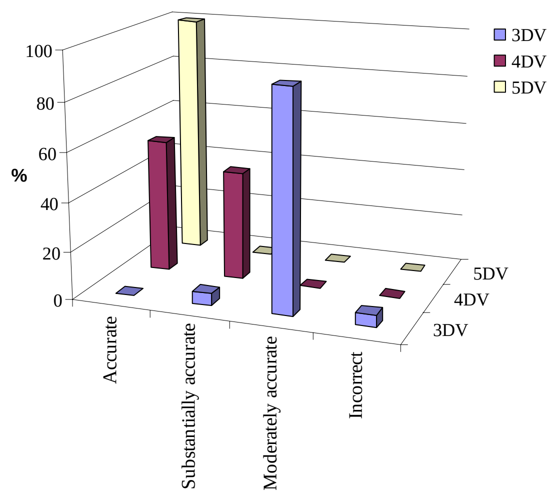
(a)



(b)



(c)



(d)

Fig. 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

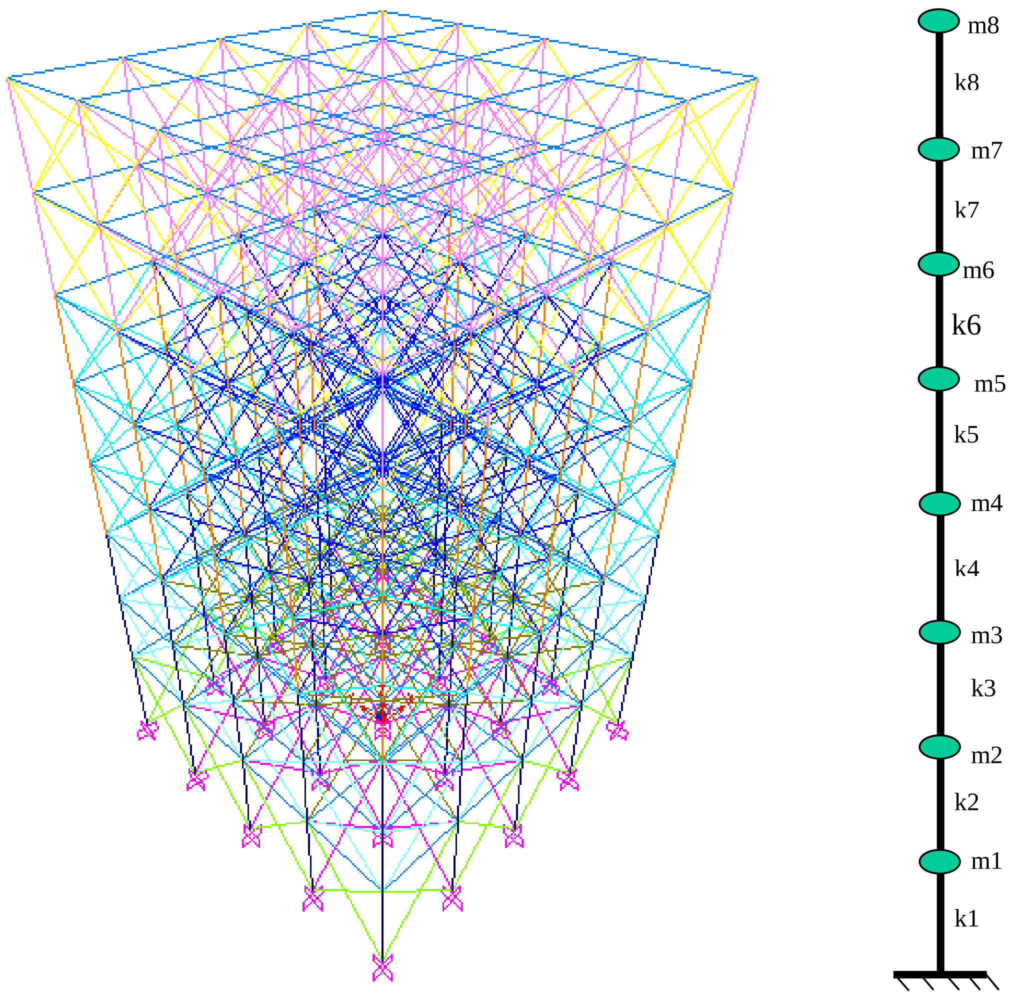


Fig. 6 Eight storey building study model with equivalent stick model

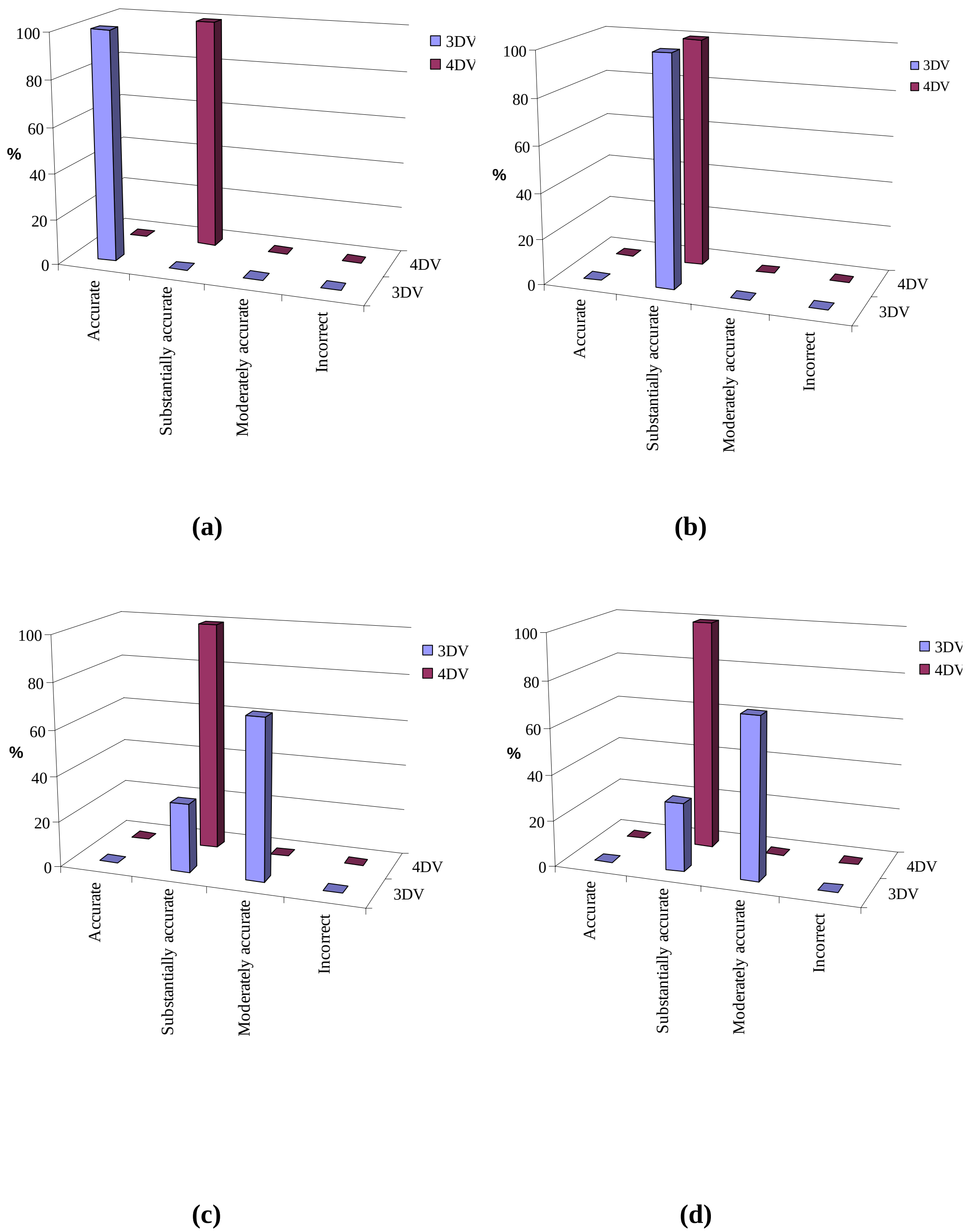


Fig. 7 Efficiency of three and four damage based networks for randomly damaged (a) only first storey (b) first and second storey (c) first to third storey (d) first to fourth storey in eight storey building

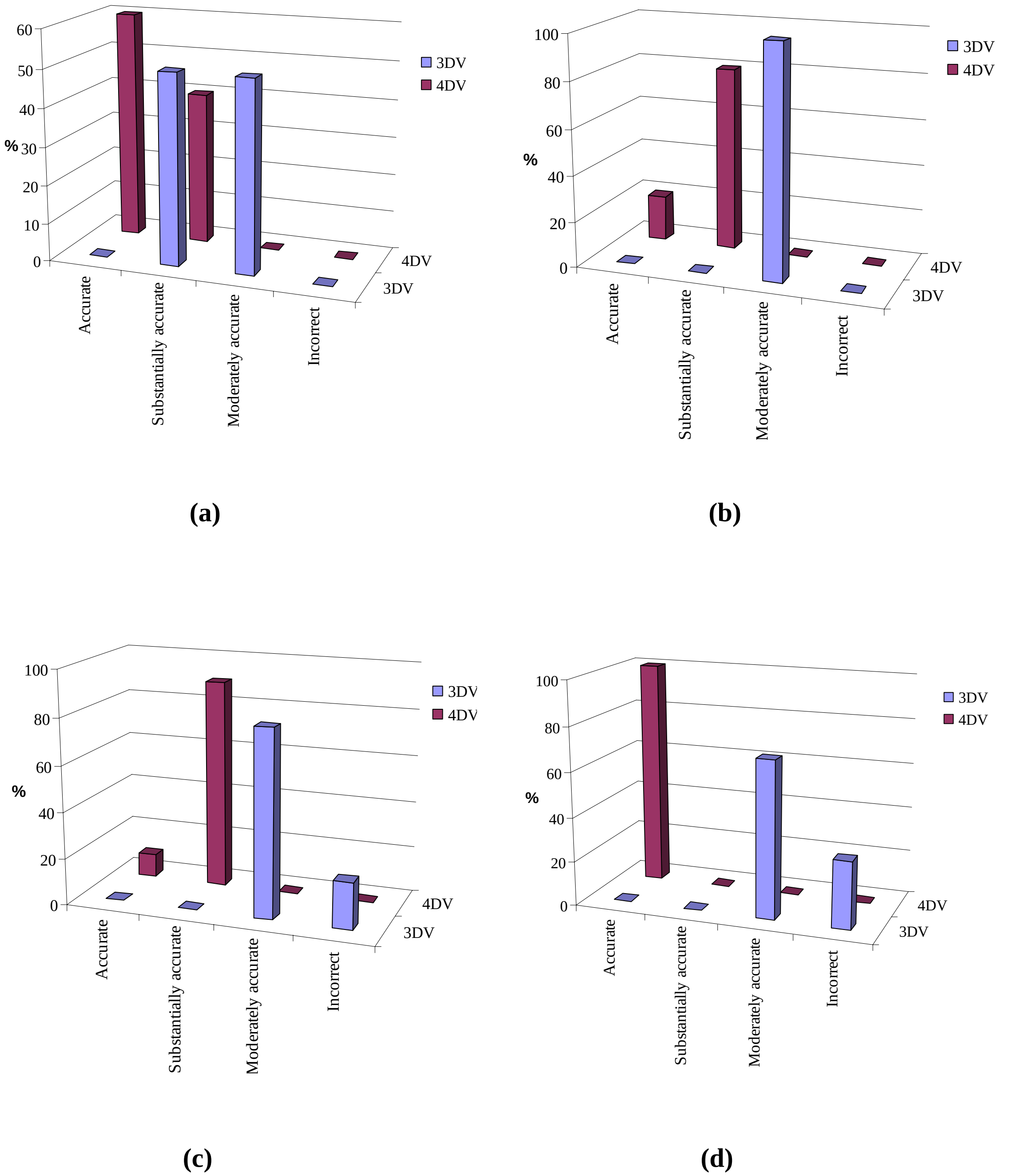


Fig. 8 Efficiency of three and four damage based networks for randomly damaged (a) first to fifth storey (b) first to sixth storey (c) first to seventh storey (d) first to eight storey in eight storey building