Damage Recognition in RCC Building Frame

P.S. Laxmi and Dr.D.K. Kulkarni

Abstract--- *Damage recognition is important to asses the sstructural system and provide safety during their service life. Change in dynamic characteristics from the undamaged state indicates significant damage in the structures. The concept of change in natural frequency due to earthquake has been employed to identify the damage in the structure. A 2D reinforced concrete building frame is analyzed for different levels of damage using structural engineering software STAAD.Pro V8i. Further, an artificial neural network using backpropagation algorithm is trained to develop the correlation between the damage in the frame with its known dynamic characteristics. Efficiency of artificial neural network to predict the damage for untrained parameters is studied.*

Keywords--- *Artificial Neural Network, Damage Index, Dynamic Characteristics, Finite Element Software, Stiffness.*

I. Introduction

CIVIL Engineering structures are more susceptible to damage and deterioration during their service life and the need of damage detection is widely increasing for the maintenance of existing civil infrastructure. The damage to a building structure may be due to natural hazards such as earthquakes and windstorms, and due to long-duration ageing under hostile environment. For the purpose of providing seismic safety, it is necessary to monitor the damage for its existence, location and extent. Usually damage can be detected by visual inspection which is the most common type. But, this method doesn't hold good for large and complex structures due to the problem of accessibility and imprecise.Hence from last few decades, a research is made to detect the damage in structures by varying the dynamic response of a structure.

An attempt has been made to recognize and localize the damage using the changes in curvature mode shapes, natural frequencies, changes in strain energy, modal stiffness, and modal displacement.

The dynamics parameters such as natural frequencies, and mode shapes have been widely used for damage detection, as they are functions of structural properties. This is based on that any degradation of the structural properties results in changes of the modal parameters. Hence, Damage is defined as reduction in stiffness of elements making the structure weak which cause undesirable displacements or vibrations to the structure leading to sudden and catastrophic failure. Variation in natural frequency from undamaged state indicates the damage in the structure.

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Cawley and Adams [1]proposed the first model by varying natural frequencies and also adopted finite element model, to recognize the damage in the structures. They have shown that how measurements made at a single point in the structure can be used to recognize, locate and estimate the damage. Hearn and Testa following the works of Cawley and Adams, they have reported the non-destructive inspection of structures by modal analysis of vibration response.Z.Y. Shi et.alstudied on locating damage in the structure based on modal strain energy method.From few years an attempt has been made to employ artificial neural network in Structural Engineering for recognizing damage in structures. Artificial Neural Network resembles human brain. It consists of interconnected neurons (processing units) which exchange messages among themselves. ANNs are used when the relationship between input and output is complicated or when the use of another technique requires large computational time. In this paper MATLAB Neural Network Toolbox is used to develop and train the neural network, efficiency of neural network to predict the values which are not trained is verified.

A. *Recognition of Structural Damage*

Occurrence of damage in the structure affects its functionality and decreases the load carrying capacity of structures hence making it unsafe. Therefore it is necessary to monitor the structure regularly to detect the damage in the structure. If minor or moderate damages are detected they can be retrofitted or damaged structures are replaced and the collapse of the structure can be prevented otherwise the structure leads to catastrophic failure. It is important to consider the cause of deterioration, if ignored the deterioration repeats.

Four stages of damage identification classification are as follows:

Level 1: Identification that the damage is there in the structure.

Level 2: level 1 plus identification of the geometric location of the damage

Level 3: level 2 plus computation of the severity of the damage

Level 4: level 3 plus estimating the remaining service life of the structure

B. *Damage Index for Different Damage Stages*

Damage is minor if the damage indexis in the range of 0 to 0.15, damage is moderate and repairable if the damage index is between 0.15 to 0.3, damage is severe and irrepairable if the damage index is between 0.3 to 0.8, damage leads to collapse of the structure if damage index is more than 0.8.

C. Neural Network Theory

Two primary elements that make a neural network are: neurons and interconnection weights between the neurons. These determine the nature and strength of the connection between the neurons. A neural network consists of layers and each layer contains neurons (processing units) that act parallel within the layer. To create the model network must be trained with the training data. Input data in the form of vector or matrix is transferred through the layers. Each data value in the input vector is multiplied by the weights associated with each neuron in a layer and the results are summed at each neuron input creating a new vector with the size equal to the number of neurons in that layer. Later, the transfer function at each neuron converts its input, which is a sum of weighted input and bias, into a neuron layer output. In hidden layers, neuron layer output vector is used as input to the next layer. Then, the output vector represents the final output of the entire neural network.

The neural network uses two types of learning methods. One is supervised training and the other is unsupervised training. Supervised training is employed in back-propagation neural network and unsupervised is employed in Counterpropagation neural network (feed-forward artificial neural network).

1) Back-Propagation Neural Network

In this type of training, both inputs and outputs are provided. It has input layer, output layer and hidden layers that must be defined by the developer. The network processes the inputs and then compares the resulting outputs with the desired outputs. Errors are then propagated back through the system, making the system to adjust the weights that control the network. This process occurs again and again till the weights are continually adjusted.

2) Counterpropagation Neural Network

This network is referred as self-organization. This network consists of three layers: An input layer, a competing layer that functions as a clustering device, an interpolation layer. The network is provided with inputs but not with desired outputs. The system itself must decide what features must be used to group the input data. In this network for any pair of input, only the weights of the winning processing elements in the competing layer are adjusted. Hence, most of the computing time is saved as compared with back-propagation network. With training, the neural network reaches a stabilizing stage, and the solution is obtained using an averaging scheme with the interpolation layer. The advantage of this type of neural network is that it can work with incomplete data and data containing system electrical noise.

D. Methods of Damage Detection by Direct Use of Modal Parameters

1) Change in Natural Frequencies

Change in natural frequency is the general method of damage detection. If damage exists in the structure, stiffness reduces and corresponding decrease in natural frequency can be observed. Natural frequency is the function of mass and stiffness. It varies directly with stiffness and inversely with mass.

2) Change in Damping

Damping changes and dissipative effects due to the friction between crack surfaces is another interesting indicator for damage detection. The undetectable cracks by using changes in natural frequencies can cause important changes in the damping factor allowing damage detection is the advantage of using change in damping. Hence, damping factor increases with increase in crack severity.

3) Mode Shapes

Mode shapes are the vibrational deformation. Mode shapes can give more information than natural frequency and are more sensitive to system damage. Hence, extent and location of damage are the parameters affecting the change in mode shapes and the spatial description in magnitude change varies fromone to another with respect to each node due to the crack location.

4) Modal Assurance Criterion

The Modal Assurance Criterion is related only to the mode shapes.It relates test and analytical mode shapes.A separate frequency comparison must be used in combination with the modal assurance criterion values to determine the correlated mode pairs because MAC considers only the mode shapes.

E. Objectives of the Project

This paper presents response spectrum analysis of a rcc four storey building frame to obtain base shear and frequency using STAAD.Pro software and the results from STAAD.Pro software are used to train the artificial neural network. Damage in frame is determined by reducing the flexural rigidity of the frame and the efficiency of the artificial neural network is checked.

II. METHODOLOGY

A. Damage Modeling

The damage is induced in the structure based on the concept of reducing the stiffness. Damage index is the basis for predicting the damage state hence, it is calculated as

DI = 1-(Kfinal/Kinitial)

Where Kinitial= building stiffness without damage, Kfinal= stiffness of the building with damaged, K= (base shear/storey drift)

Example model considered is a four storied building frame and description is as follows:

Table 1: Frame Details

Floor number	*Load*	*Column size*	*Beam size*
First floor	W1=17kN/m	C1=0.28X0.28	0.3X0.3
Second floor	W2=17kN/m	C2=0.28X0.28	0.3X0.3
Third floor	W3=17kN/m	C3=0.28X0.28	0.3X0.3
Fourth floor	W3=15kN/m	C4=0.23X0.23	0.3X0.3

Modulus of rigidity, E=2.17 x 10^7kN/m^3

The frame is subjected to response spectrum analysis using STAAD.Pro for zone-4. 18 sets of results are obtained from STAAD.Pro by decreasing the modulus of elasticity of the frame. In the first case the frame is analysed without any damage and in the second case 5% damage is induced in the first storey by reducing the value of 'E' and no damage to other stories and in the third case 10% damage in first storey and 5% damage in the second storey is induced whereas other stories are undamaged. This process continues till 85% damage is induced in the first storey. Then the stiffness in damaged state and damage index is calculated for each storey. From the damage index the extent of damage in the structure is determined.

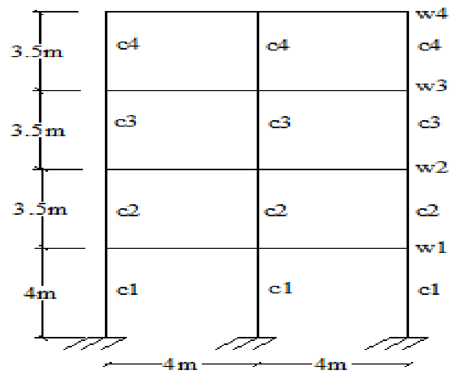

Figure 1: Four Storey Plane Frame

Table 2: Results from STAAD.Pro Software (case-1 to case-8)

Modulus of rigidity value	*Mode shape coefficient*	*Storey drift*	*Initial stiffness*	*Final stiffness*	*Damage index*	*Reduction in modulus of rigidity*	*Frequency*
SET-1							
2.17E+07	0.3153	15.537	2.566				0.855
2.17E+07	0.6068	28.178	1.415				
2.17E+07	0.8255	36.615	1.089				
2.17E+07	0.9999	42.717	0.9336				
SET-2							
2.06E+07	0.3253	16.327	2.566	2.442	0.048	5%	0.843
2.17E+07	0.6155	29.186	1.415	1.366	0.034		
2.17E+07	0.8298	37.649	1.089	1.059	0.0274		
2.17E+07	0.9999	43.759	0.9336	0.9113	0.0238		
SET-3							
1.95E+07	0.3319	17.245	2.566	2.312	0.09	10%	0.825
2.06E+07	0.6264	30.779	1.415	1.295	0.084	5%	
2.17E+07	0.8363	39.409	1.089	1.012	0.0709		
2.17E+07	0.9999	45.543	0.9336	0.875	0.062		
SET-4							
1.84E+07	0.3351	18.263	2.566	2.184	0.149	15%	0.804
1.95E+07	0.6317	32.569	1.415	1.224	0.134	10%	
2.06E+07	0.8421	41.66	1.089	0.957	0.121	5%	
2.17E+07	0.9999	47.904	0.9336	0.832	0.1		
SET-5							
1.74E+07	0.3351	19.301	2.566	2.066	0.195	20%	0.782
1.84E+07	0.6321	34.44	1.415	1.157	0.181	15%	
1.95E+07	0.8425	44.05	1.089	0.905	0.168	10%	
2.06E+07	0.9999	50.633	0.9336	0.787	0.156	5%	
SET-6							
1.63E+07	0.3564	20.837	2.566	1.913	0.254	25%	0.761
1.74E+07	0.67	37.773	1.415	1.055	0.253	20%	
1.84E+07	0.8884	48.28	1.089	0.826	0.241	15%	
1.95E+07	1	53.728	0.9336	0.742	0.204	10%	
SET-7							
1.52E+07	0.3386	22.056	2.566	1.808	0.295	30%	0.734
1.63E+07	0.6358	39.228	1.415	1.016	0.281	25%	
1.74E+07	0.8444	50.472	1.089	0.79	0.274	20%	
1.84E+07	0.9999	58.591	0.9336	0.68	0.27	15%	
SET-8							
1.41E+07	0.3406	23.753	2.566	1.678	0.345	35%	0.708
1.52E+07	0.6383	42.151	1.415	0.946	0.331	30%	
1.63E+07	0.8462	53.686	1.089	0.742	0.318	25%	
1.74E+07	0.9999	61.508	0.9336	0.648	0.305	20%	

Table 3: Results from STAAD.Pro Software (case-9 to case-16)

Modulus of rigidity value	*Mode shape coefficient*	*Storey drift*	*Initial stiffness*	*Final stiffness*	*Damage index*	*Reduction in modulus of rigidity value*	*Frequency*
SET-9							
1.03E+07	0.3426	25.74	2.566	1.549	0.396	40%	0.682
1.41E+07	0.6407	45.596	1.415	0.874	0.382	35%	
1.52E+07	0.8476	57.985	1.089	0.687	0.368	30%	
1.63E+07	0.9999	66.348	0.9336	0.601	0.356	25%	
SET-10							
1.19E+07	0.3449	28.092	2.566	1.419	0.446	45%	0.654
1.30E+07	0.6434	49.662	1.415	0.803	0.432	40%	
1.41E+07	0.8493	63.043	1.089	0.632	0.419	35%	
1.52E+07	0.9999	72.028	0.9336	0.553	0.406	30%	
SET-11							
1.09E+07	0.3459	30.651	2.566	1.301	0.493	50%	0.627
1.19E+07	0.6451	54.187	1.415	0.735	0.48	45%	
1.30E+07	0.8506	68.728	1.089	0.58	0.467	40%	
1.41E+07	0.9999	78.434	0.9336	0.508	0.455	35%	
SET-12							
9.76E+06	0.3505	34.161	2.566	1.167	0.545	55%	0.596
1.09E+07	0.6492	60.035	1.415	0.664	0.53	50%	
1.19E+07	0.8529	75.925	1.089	0.525	0.52	45%	
1.30E+07	0.9999	86.479	0.9336	0.461	0.5	40%	
SET-13							
8.68E+06	0.3544	38.393	2.566	1.038	0.595	60%	0.564
9.76E+06	0.6545	67.312	1.415	0.592	0.581	55%	
1.09E+07	0.8558	84.807	1.089	0.47	0.568	50%	
1.19E+07	0.9999	96.351	0.9336	0.413	0.557	45%	
SET-14							
7.59E+06	0.3593	43.822	2.566	0.91	0.645	65%	0.531
8.68E+06	0.6601	76.502	1.415	0.521	0.631	60%	
9.76E+06	0.8597	96.09	1.089	0.415	0.619	55%	
1.09E+07	0.9999	108.8	0.9336	0.366	0.607	50%	
SET-15							
6.51E+06	0.3654	51.0491	2.566	0.781	0.695	70%	0.494
7.59E+06	0.6668	88.624	1.415	0.449	0.682	65%	
8.68E+06	0.8634	110.81	1.089	0.359	0.669	60%	
9.76E+06	0.9999	125.059	0.9336	0.318	0.658	55%	
SET-16							
5.42E+06	0.3738	61.147	2.566	0.652	0.745	75%	0.455
6.51E+06	0.676	105.366	1.415	0.378	0.732	70%	
7.59E+06	0.8687	130.957	1.089	0.304	0.72	65%	
8.68E+06	0.9999	147.116	0.9336	0.271	0.709	60%	

Table 4: Results from STAAD.Pro Software (case -17 to case18)

Modulus of rigidity value	*Mode shape coefficient*	*Storey drift*	*Initial stiffness*	*Final stiffness*	*Damage index*	*Reduction in modulus of rigidity value*	*Frequency*
SET-17							
4.34E+06	0.3855	76.2523	2.566	0.523	0.796	80%	0.412
5.42E+06	0.6885	130.0184	1.415	0.306	0.783	75%	
6.51E+06	0.8758	160.274	1.089	0.248	0.771	70%	
7.59E+06	0.9999	178.952	0.9336	0.222	0.76	65%	
SET-18							
3.25E+06	0.4034	101.318	2.566	0.393	0.846	85%	0.362
4.34E+06	0.7067	170.009	1.415	0.234	0.834	80%	
5.42E+06	0.8856	207.077	1.089	0.192	0.823	75%	
6.51E+06	0.9999	229.241	0.9336	0.173	0.813	70%	

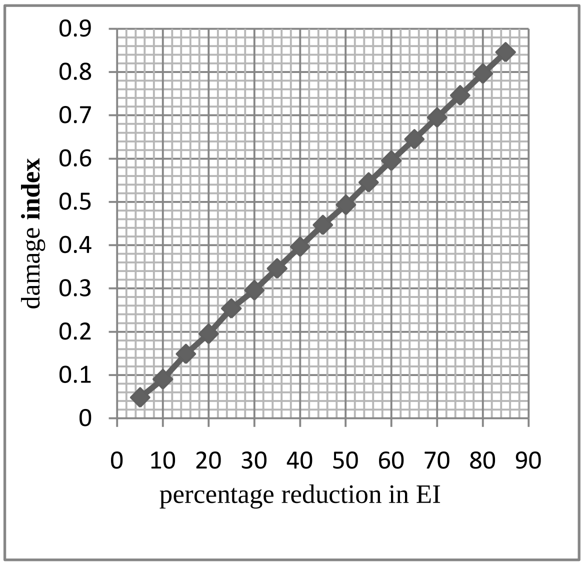

Figure 2: Percentage Reduction in EI vs Damage Index for First Storey

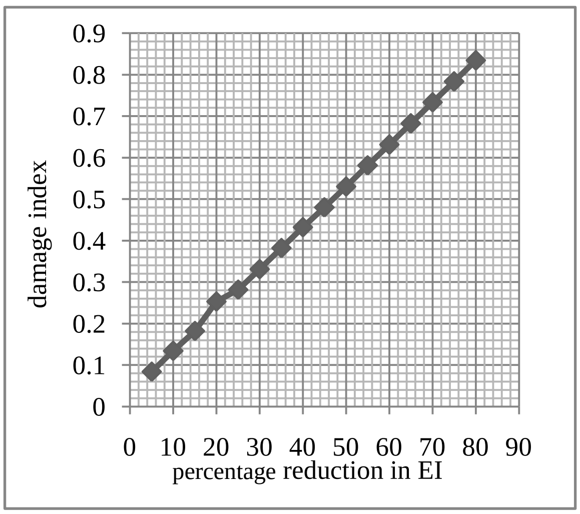

Figure 3: Percentage Reduction in EI vs Damage Index for Second Storey

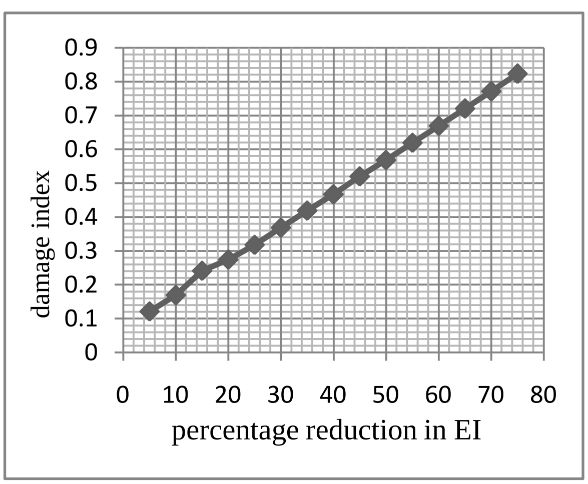

Figure 4: Percentage Reduction in EI vs Damage Index for Third Storey

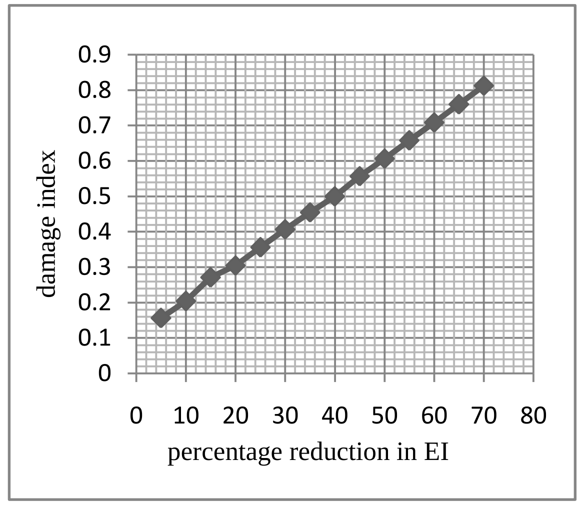

Figure 5: Percentage Reduction in EI vs Damage Index for Fourth Storey

B. *Artificial Neural Network Modeling*

Outputs from STAAD.Pro is used as inputs values and target values for artificial neural network. It is provided with three input parameters and one output parameter. Inputs are: storey height, mode shape coefficients, frequency. Output is damage index. Neural network is trained by back propogation method.

Artificial neural network is efficient when it can give the values for which it is not trained. Hence, some of the patterns are skipped ie., pattern-4,8,12,16 from training and the efficiency of the network is determined by giving same inputs and checking the output. A graph is plotted between the calculated damage indices and predicted damage indices. The calculated and predicted values are almost same and hence artificial neural network is efficient enough to predict the damage in the structures. Graphs are as below

C. *Comparision Between Calculated and Predicted Values*

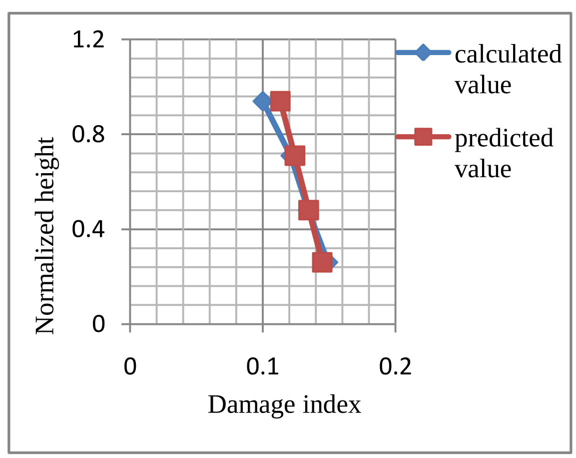

Figure 6: Damage Index vs Normalized Storey Height for Case 4

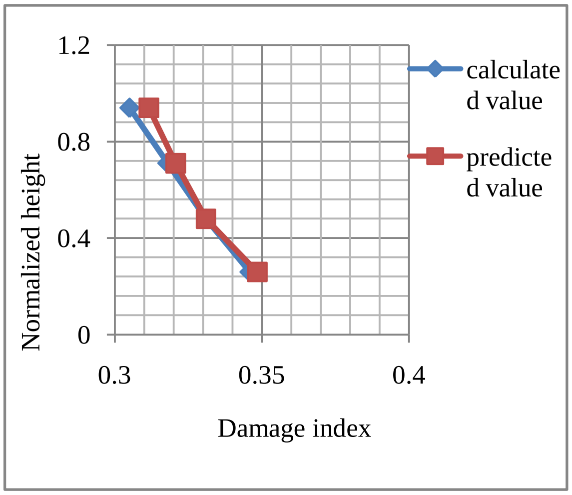

Figure 7: Damage Index vs Normalized Storey Height for Case 8

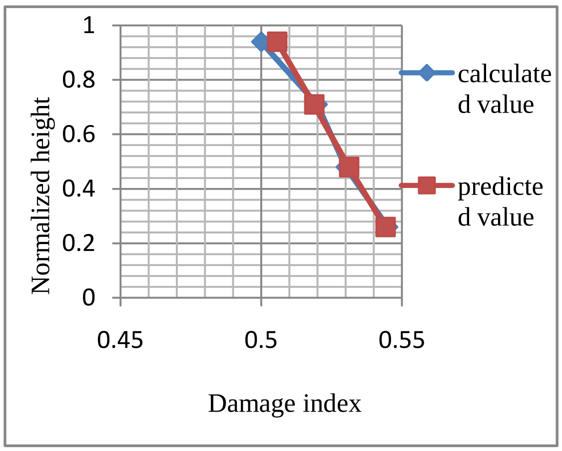

Figure 8: Damage Index vs Normalized Storey Height for Case 12

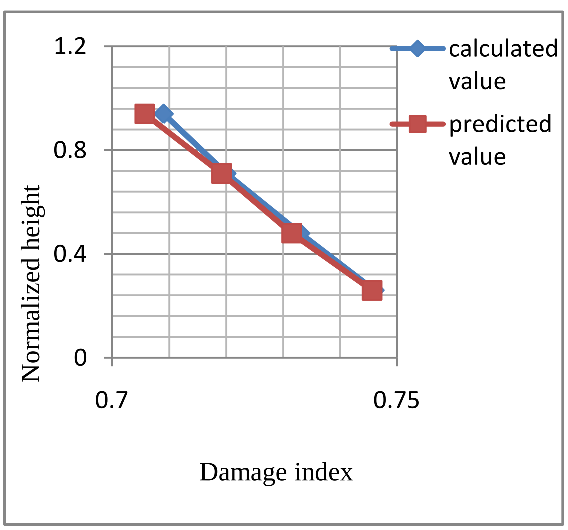

Figure 9: Damage Index vs Normalized Storey Height for Case 16

III. Discussion

For pattern 4 from figure 6 the percentage variation between the calculated damage index and predicted damage index for first storey is 2.8% and for second storey is 0.6% and for third storey is 2.5% and for fourth storey is 9%. Similarly percentage variation for 8th, 12th and 16th is calculated and most of the variations are within 6% and are within the limits ie., 10%.

IV. Conclusion

Following conclusions are arrived from the present study

1. Frequency decreases as damage index increases.
2. Damage is minor till 15% reduction in flexural rigidity. This type of damage is neglisible and do not cause much disturbance to the buildings.
3. Damage is moderate and repairable from 20% to 30% reduction in flexural rigidity. This type of damage can be repaired by retrofitting.
4. Damage is severe and irrepairable from 35% to 80%.
5. Frame collapses when the flexural rigidity reduces to 85%.
6. The efficiency of calculated and predicted value is less than 6% and hence within the limits.
7. Efficiency of neural network increases with increase in the number of patterns.

V. Scope for Future Work

This work can be extended for steel frames. Comparision of efficiency can be made between artificial neural network and genetic algorithm.

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