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Dynamic Response Of Rc Buildings By Using Artificial Neural Networks

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Abstract

An Artificial Neural Network (ANN) can be defined as a data processing system, consisting of a large number of simple, highly interconnected processing elements (artificial neurons), in an architecture inspired by the structure of the cerebral cortex of the brain. In this study, the dynamic analysis of RC buildings with help of ANN and ETABS is studied.

The objective of this study is to investigate the adequacy of Artificial Neural Networks (ANN) to determine the dynamic response of RC structure in 3 dimensions subjected to earthquake loading. In the ANN model, a multilayer perceptron(MLP) with a back-propagation (BP) algorithm is employed using a scaled conjugate gradient. ANN model is trained, tested in a MATLAB based program. ETABS is used to generate training and testing set of ANN model. Based on this study, it is found that appropriately configured neural network models can successfully learn and simulate the dynamic behaviour of RC structures.

***Key Words**: Dynamic response of RC structure, earthquake loading, artificial neural networks.*

1. INTRODUCTION

Earthquake causes the random ground motions in all directions, radiating from the epicentre. These ground motions causes structure to vibrate and induces inertia forces in them. For the structure to perform better during the earthquakes, it must be analysed and designed as per the Indian seismic code IS 1893 (Part 1) 2002. In the past, several major earthquakes have exposed the shortcomings in buildings, which had caused them to damage or collapse. It has been found that regular shaped buildings perform better during earthquakes.

ANN is a branch of artificial intelligence which attempts to mimic the behaviour of the human brain and nervous system. A neural network can be considered as a black box that is able to predict an output pattern when it recognizes a given input pattern. Neural networks are able to detect similarities in input, even though a particular input may never have been seen previously. This property allows for excellent interpolation capabilities, especially when the input data is noisy.

Mohammad ParsaeiMaram[1] used artificial neural network for predicting seismic behaviour in RC buildings with and without infill walls. The results predicted by the models in their models agrees closely with experimental results. They conclude that, an ANN based model predicts the displacement and base shear at performance point with reasonable accuracy. Hadi [8] discussed the applications of neural networks in concrete structures. Backpropagations networks were chosen for the proposed network, which was written in programming package in MATLAB. The overall results were compared and observed for the performances of the networks. Based on the applications, it was found that neural networks are comparatively effective for a number of reasons, which include the amount of CPU memory consumed by neural networks is less than that consumed by conventional methods, neural networks provide both users and developers more flexibility to cope with different kinds of problems. Hakan Arslan[10] investigated the efficiency of an artificial neural network (ANN) in predicting and determining failure load and failure displacement of multi storey reinforced concrete buildings. Data from the nonlinear analysis were assessed with ANN in terms of failure load and failure displacement. All the ANN models were found to perform well both failure loads and displacements. The present work aims to determine the efficiency of the analysis of the analysis of RC structures using Artificial Neural Network.

1.1. Scope of study

In the present work, Artificial Neural Network (ANNs) are applied to check their efficiency in the analysis of RC structure : 1. To determine dynamic response of buildings for earthquake loads in ETABS. 2. To develop ANN model for the analysis of RC structure. 3. To develop geometry variation, cross-section variation etc., in the analysis procedure. 4. To compare the results which performs better after comparing with ETABS analysis results.

2. THEORY OF DYNAMIC ANALYSIS AND ARTIFICIAL NEURAL NETWORKS

Earthquakes causes ground to vibrate and structures supported on ground are subjected to this motion.

Thus the dynamic loading on the structure during an earthquake is not an external loading, but due to motion of support. And the job of structural engineer is not to make the building earthquake proof, which will be uneconomical and too robust. Instead the building can be design to resist earthquake with certain amount of damage, but without causing the collapse and affecting the livelihood. And the design philosophy lies in between these two earthquake resisting and earthquake proof limits.[14]

2.1. Dynamic Analysis by Response Spectrum Method

The response spectrum represents an interaction between ground acceleration and the structural system, by an envelope of several different ground motion records. For the purpose of the seismic analysis the design spectrum given in fig.2 of IS 1893 (Part 1): 2002 is used. This spectrum is based on strong motion records of eight Indian earthquakes. [11]

Dynamic analysis of the building models is performed using ETABS. The lateral loads generated by ETABS correspond to the seismic zone III and 5% damped response spectrum given in IS 1893 (Part 1): 2002. The fundamental natural period values are calculated by ETABS, by solving the eigenvalue problem of the model. Thus, the total earthquake load generated and its distribution along the height corresponds to the mass and stiffness distribution as modelled by ETABS. Here, as in the equivalent static analysis, the seismic mass is calculated using full dead load plus 25% of live load.

The 5% damped response spectrum is considered for all modes of the building. For the modal combination the square root of sum of squares (SRSS) method is considered, because in this method of modal combination coupling of the modes doesn't take place. For each displacement and force in the structure, the modal combinations produce a single positive results for each direction of acceleration, these directional value for a given response quantity have to be combined to produce a single positive result, and for this directional combination, square root of sum of squares (SRSS) method is adopted. After defining the response spectrum case, analysis is carried out. If the displacements and the base shears obtained by response spectrum method are less than the equivalent static base shear, then as per clause 7.8.2 of IS 1893 (Part 1): 2002, scaling has to be done by multiplying the response spectrum base shear, with the ratio of equivalent static base shear ($\overline{V_B}$) to the response spectrum base shear (V_B). Once the analysis is done the same steps are repeated as explained in the equivalent static method.

2.2. Performance Point

The maximum structural displacement expected for the demand earthquake ground motion represents the performance point. Performance point can also be defined as a condition for which the seismic capacity of the structure is equal to the seismic demand imposed on the structure by the specific ground motion. It can be obtained by the intersection of capacity spectrum and demand spectrum. To get the capacity spectrum it is necessary to convert the capacity curve, which is in terms of base shear and roof displacement, to what is called as capacity spectrum, which is representation of capacity curve in Acceleration-Displacement Response Spectra (ADRS) format[14]. The demand spectrum is the design acceleration spectrum given in IS 1893 (Part 1): 2002 modified for 5% damping (for the concrete structures), based on desired response reduction factor (depending on type of lateral load resisting system) and foundation soil type.[13]

2.3. Artificial Neural Networks

A neural network is a massively parallel distributed processor made up o simple processing units that have a natural tendency for storing experiential knowledge and making it available for us. ANNs have the ability to model linear and nonlinear systems without the need to make assumptions implicitly as in most traditional statistical approaches. Neural networks exhibit characteristics such as mapping capabilities or pattern association, generalization, robustness, fault tolerance, parallel and high speed information processing. So they have been successfully applied to problems in the fields of pattern recognition, image processing, data compression, forecasting and optimization.[15] The neural networks posses the capability to generalize. Thus, they can predict new outcomes from past trends.

In supervised learning, every input pattern that is used to train the network is associated with an output pattern, which is the target or the desired pattern. A teacher is assumed to be present during the learning process, when a comparison is made between the network's computed output and the correct expected output, to determine the error. The error can then be used to change network parameters, which results in an improvement in performance.

Gradient Descent Learning:

This is based on the minimization of error E defined in terms of weights and the activation function of the network. Also, it is required that the activation function employed by the network is differentiable, as the weight update is dependent on the gradient of the error E.

Thus, if ΔW_{ij} is the weight update of the link connecting the i^{th} and j^{th} neuron of the two neighbouring layers, then ΔW_{ij} is defined as :

$$\Delta \mathrm{Wij} = \eta \frac{\partial \mathrm{E}}{\partial \mathrm{Wij}}$$

Where, η is the learning rate parameter and $\frac{\partial \mathrm{E}}{\partial \mathrm{Wij}}$ is the error gradient with reference to the weight $W_{ij.}$ The Widrow and Hoffs Delta rule and Back propagation learning rule are all examples of this type of learning mechanism.

Multi Layer Perceptron (MLP):

MLPs are the most common type of feed-forward networks. Figure-1 shows an MLP which has three types of layers: an input layer, an output layer and a hidden layer. Neurons in input layer only act as buffers for distributing the input signals xi (i=1, 2 …n) to neurons in the hidden layer. Each neuron j (Figure-2) in the hidden layer sums up its input signals xi after weighting them with the strengths of the respective connections wji from the input layer and computes its output yj as a function f of the sum.

$$y_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right)$$

f can be a simple threshold function or a sigmoidal, hyperbolic tangent or radial basis function.

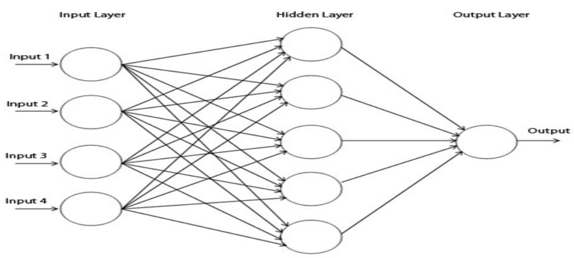

Figure-1: A Multi-Layered Perceptron (MLP) Network

The output of neurons in the output layer is computed similarly. The backpropagation algorithm, a gradient descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δwji the weight of a connection between neurons iand j as follows:

$$\Delta w_{ij} = \eta \delta_j x_i$$

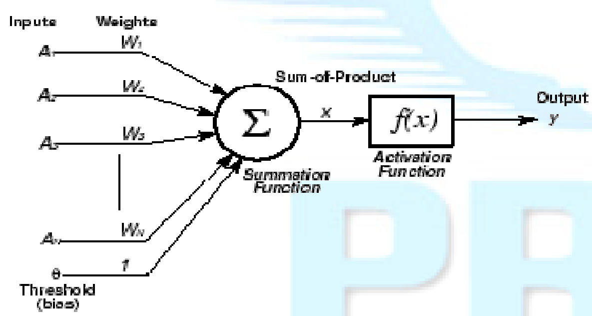

Figure-2: Detail of the Perceptron Process

where η is a parameter called the learning rate and δj is a factor depending on whether neuron j is an input neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\left(y_j^{(t)} - y_j\right)$$

and for hidden neurons

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\left(\sum_q w_{jq} \delta_q\right)$$

Where, netj is the total weighted sum of input signals to neurons j and yj(t) is the target output for neuron j.

As there are no target outputs for hidden neurons, in equations the difference between the target and actual output of a hidden neurons j is replaced by the weighted sum of the δq terms already obtained for neurons q connected to the output of j.

The process begins with the output layer, the δ term is computed for neurons in all layers and weight updates determined for all connections, iteratively. The weight updating process can happen after the presentation of each training pattern (pattern-based training) or after the presentation of the whole set of training patterns (batch training). Training epoch is completed when all training patterns have been presented once to the MLP.

3. EXAMPLE - BUILDINGS STUDIED

In the present study reinforced concrete moment resisting frame building of different storey heights are considered. The plan layout of building with open first storey and unreinforced brick infill walls in the upper storeys models is shown in Fig-3. The 3D view of different building models considered are shown in Fig-4. The bottom storey height is kept 3m and a typical height of 3m is kept for all the other storeys in both the buildings. The building is considered to be located in the seismic zone V and intended for residential use. The input data given for the all buildings are detailed in table 1 and table 2. The nine analytical models considered are as below,

Model 1-9 – Building has no walls in the first storey , one full brick masonry wall in the upper storeys. The model is designed for seismic design from three to eleven storeys.

Table 1 : Design Data For All Building Models

Structure		OMRF
Storey height	Ground storey	3.0 m
	Upper storey	3.0 m
Type of building use		Residential
Seismic zone		V
Material Properties		
Young's modulus of M25 concrete, E		25×10^6 KN/m^2
Grade of concrete		M 25
Grade of steel		Fe 415
Density of reinforced concrete		25 KN/m^3
Modulus of elasticity of brick masonry		21 x 105 KN/m^2
Density of brick masonry		20 KN/m^3
Member Properties		
Beam size (with infill walls)		0.3X0.4 m
Column size (with infill walls)		0.4X0.4 to 0.5X0.5 m
Thickness of slab		0.15 m
Thickness of wall		0.30 m
Floor finishes		1 KN/m2
Live Load Intensities		2 KN/m2
Earthquake LL on slab as per clause 7.3.1 and 7.3.2 of IS 1893 (Part 1): 2002		
Roof		0 KN/m^2
Floor		2 X 0.25= 0.5 KN/m^2

Table 2: Is: 1893-2002 Equivalent Static Method

Zone	V
Zone factor, Z (Table 2)	0.36
Importance factor, I (Table 6)	1.00
Response reduction factor, R (Table 7)	3.0
Damping ratio	5% (for RC framed building)

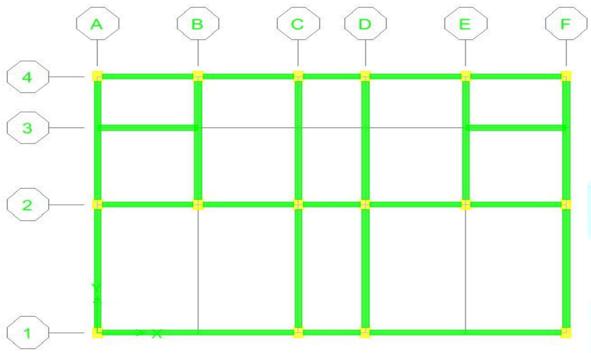

Figure-3: Plan for all building models.

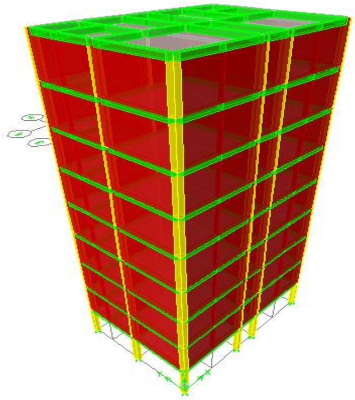

Figure-4: 3d view for all building models with infill walls

4. DESIGNING AND PROGRAMMING ANN MODELS

4.1.Designing ANN Models

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps: (1) collecting data, (2) pre processing data, (3) building the network, (4) train, and (5) test performance of model as shown in Figure-5.

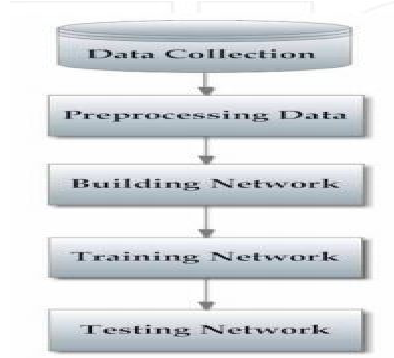

Figure-5: Basic flow for designing artificial neural network model

Data Collection

Collecting and preparing sample data is the first step in designing ANN models. As it is outlined in section 3, data of no of models, height of model, total area of beam(m^2), total area of column(m^2), total area of slab(m^2), total weight of the building(m^2) is collected through the models.

Data Preprocessing

After data collection, three data preprocessing procedures are conducted to train the ANNs more efficiently. These procedures are: (1) solve the problem of missing data, (2) normalize data and (3) randomize data. The missing data are replaced by the average of neighbouring values during the same week. Normalization procedure before presenting the input data to the network is generally a good practice, since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude.

Building of the Network

At this stage, the designer specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function. In this work, multilayer perceptron (MLP) networks are used.

Training the Network

During the training process, the weights are adjusted in order to make the actual outputs (predicated) close to the target (measured) outputs of the network. As it is outlined in section 3, fourteen different types of training algorithms are investigated for developing the MLP network. MATLAB provides built-in transfer functions which are used in this study; linear (purelin), Hyperbolic Tangent Sigmoid (logsig) and Logistic Sigmoid (tansig).

The graphical illustration and mathematical form of such functions are shown in Table 2.

Testing the Network

The next step is to test the performance of the developed model. At this stage unseen data are exposed to the model. In order to evaluate the performance of the developed ANN models quantitatively and verify whether there is any underlying trend in performance of ANN models, statistical analysis involving the coefficient of determination (R2), the root mean square error (RMSE), and the mean bias error (MBE) were conducted. RMSE provides information on the short term performance which is a measure of the variation of predicated values around the measured data.

4.2. Programming the Neural Network Model

MATLAB is a numerical computing environment and also a programming language. It allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creating user interfaces and interfacing with programs in other languages. The Neural Network Toolbox contains the MATLAB tools for designing, implementing, visualizing and simulating neural networks. It also provides comprehensive support for many proven network paradigms, as well as graphical user interfaces (GUIs) that enable the user to design and manage neural networks in a very simple way.

Various network architectures were investigated in order to determine the optimal MLP architecture (i.e. the highest coefficient of determination, the lowest root mean square error and the lowest mean bias error) for each combination of input variables. Different training algorithms were used with changes in the number of neurons and hidden layers. In addition, different transfer functions including the tangent sigmoid, log sigmoid and linear functions in the hidden layer were also investigated.
The following observations have been made for the neural nets:

The best net contains four and two nodes in the first and the second layers respectively, and the activation function is hyperbolic tangent. The net with hyperbolic tangent performed better than the net with sigmoid, because the domain for mapping the training data in hyperbolic tangent case has been wider and the input was more recognizable for the net. The training time for the net that uses the hyperbolic tangent has been faster than the one employing sigmoid as activation function.

5. RESULTS AND DISCUSSIONS

5.1.Fundamental Natural Period and Lateral Displacement

The analytical (ETABS) fundamental natural periods and lateral displacements of the various building models along the longitudinal and transverse direction are tabulated in the table. The variation of the fundamental natural period and lateral displacement of all the models for the seismic design are shown in the figures below.
From the table it is very clear that, the natural period is increasing with story height so stiffness of the building is directly proportional to its natural frequency and hence inversely proportional to the natural period. From above results for building with infill walls the lateral displacement for the response spectrum method is greater than the lateral displacement for the equivalent static method along both longitudinal and transverse direction. So earthquake resistant design of building gives the best performance.

Table 3 : Fundamental Natural Period

Model No	Equivalent Static Method		Response Spectrum Method		Analytical (sec)
	Longitudinal direction (m)	Transverse direction (m)	Longitudinal direction (m)	Transverse direction (m)	
1	0.0020	0.0021	0.0030	0.0030	0.28
2	0.0031	0.0032	0.0046	0.0046	0.35
3	0.0034	0.0035	0.0048	0.0049	0.34
4	0.0040	0.0043	0.0053	0.0055	0.36
5	0.0056	0.0060	0.0072	0.0075	0.41
6	0.0065	0.0071	0.0079	0.0084	0.43
7	0.0087	0.0096	0.0104	0.0112	0.49
8	0.0109	0.0124	0.0128	0.0144	0.54
9	0.0137	0.0148	0.0161	0.0172	0.62

5.2. Performance Point and Location of Hinges

The base force of the building depends on its lateral strength, as the stiffness of walls is considered in soft storey buildings. The plastic hinges at the performance point, along transverse direction, for all the models with infill walls of seismic designed buildings, are located in the range IO-LS are formed in the columns and beams of ground storey, where as along longitudinal direction plastic hinges are in IO-LS range are formed in the columns and beams of ground storey. In general the plastic hinges of all the models of seismic designed buildings lie in between the range of immediate occupancy and life safety. Hence the performance of these building models is considered as life safety, at this post-earthquake damage state, significant damage to the structure may have occurred but in which some margin against either total or partial structural collapse remains. The level of damage is lower than that of collapse-prevention level. Major structural components have not dislodged and fallen, threatening life safety either within or outside the building.

Table 4 : Performance Point And Location Of Hinges

Model No	Performance Point		Location of Hinges								
	Base Force (ton)	Displacement(mm)	A-B	B-IO	IO-LS	LS-CP	CP-C	C-D	D-E	>E	Total
1	590	18	30	4	22	-	-	-	-	-	56
2	770	28	36	13	20	-	-	-	-	-	69
3	1060	30	38	14	23	-	-	-	-	-	75
4	1310	33	46	16	23	-	-	-	-	-	85
5	1480	43	60	4	34	-	-	-	-	-	98
6	1530	44	74	2	36	-	-	-	-	-	112
7	1660	53	100	17	18	-	-	-	-	-	135
8	1740	61	125	10	10	-	-	-	-	-	145
9	1850	73	133	8	10	-	-	-	-	-	151

5.3. Neural Networks for Prediction of Seismic Behaviour

MATLAB software is used to create neural network. For creating the network, totally 42 data sets are used which are listed in the table. These data were generated analytically using structures with infill walls. The network was trained and then tested by 7 and 7 data sets for displacement and base shear (respectively), at performance point which are tabulated in table. And for trial model with ten and eleven storey buildings input data are used in table. Displacement and base shear at performance point predicted for building for trial models using ANN is compared with actual values of ETABS output as shown in table. The results clearly show that predicted values using neural network at displacement and base shear on the performance point are close to actual values. It can be observed that overall prediction is good.

Table 5 : Input Parameters For Trial Models

Models/ Input Parameters	1	2	3	4	5	6	7
No. of storeys	3	4	5	6	7	8	9
Storey Height (m)	9	12	15	18	21	24	27
Area of beam (m^2)	35.28	47.04	58.80	70.56	82.32	94.08	105.84
Area of column (m^2)	25.92	34.56	54.675	65.61	76.545	108	121.5
Total Weight of Building (ton)	640	905	1200	1475	1750	2070	2350

Table 6 : Output Values For Trial Models Using Neural Networks

Models/ Target	1	2	3	4	5	6	7
Displacement (mm)	3.3353	3.6832	4.5601	5.698	6.7811	8.6225	11.1945
Base shear (ton)	590	770	1060	1310	1480	1530	1660

Table 7 : Input Parameters For Testing Models

Input Parameters	Model 8	Model 9
No. of storeys	10	11
Storey Height (m)	30	33
Area of beam (m^2)	117.26	129.36
Area of column (m^2)	135	148.5
Total Weight of Building (ton)	2515	2910

Table 8 : Predicted Values For Testing Models

Predicted Values	Model 8	Model 9
Displacement (mm)	13.8561	15.9511
Base shear (ton)	1746.773	1839.663

Table 9 : Comparision Of Actual Values With Predicted Values For Testing Models

	Model 8	Model 9
Displacement (ETABS) (mm)	14.4	17.2
Displacement (ANN) (mm)	13.8561	15.9511
Base Shear (ETABS) (ton)	1740	1850
Base Shear (ANN) (ton)	1746.773	1839.663

The values predicted by ANN is approximately equal to the actual values tabulated by ETABS analysis. So the results obtained by the ANN is satisfactory. The predicted values for displacement and base shear at performance point using ANN vary only marginally from the actual values.

5.4. Comparision Between Measured Data And Predicted Values Of ANN:

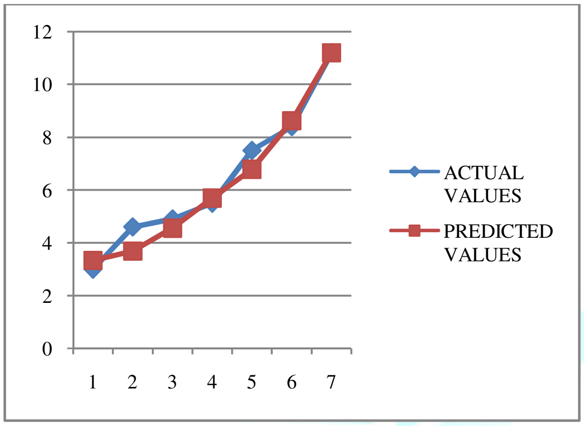

Figure 6: Comparision Between Actual Output Values With Predicted Output Values For Displacement Trial Models

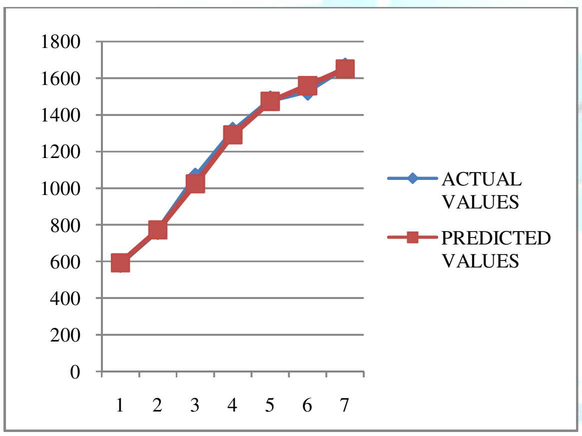

Figure 7: Comparision Between Actual Output Values With Predicted Output Values For Base Shear Trial Models

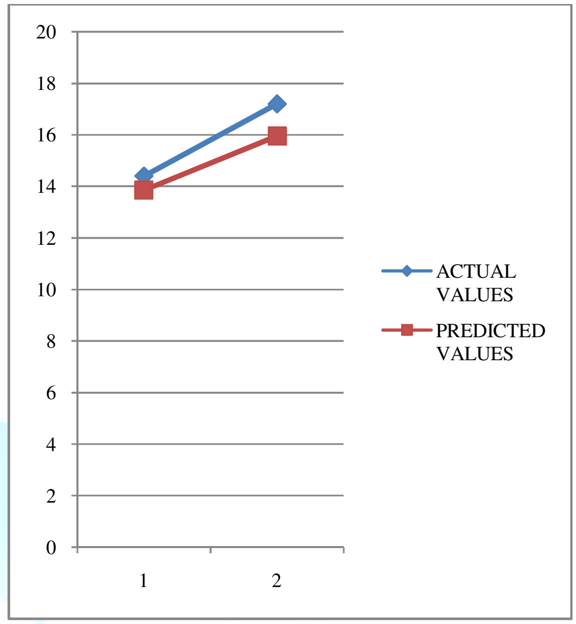

Figure 8: Comparision Between Actual Output Values With Predicted Output Values For Displacement Test Models

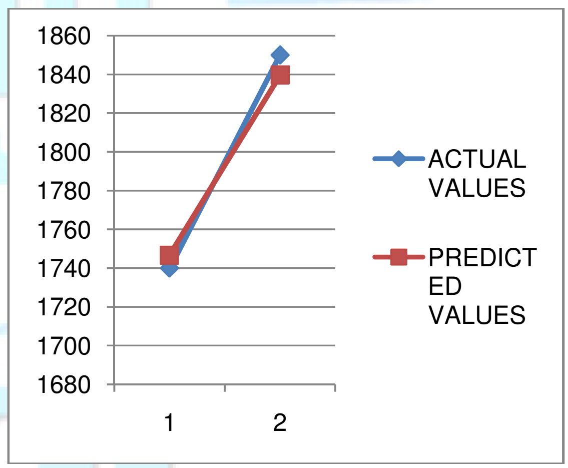

Figure 9: Comparision Between Actual Output Values With Predicted Output Values For Base Shear Test Models

6. CONCLUSIONS AND SCOPE FOR FUTURE WORK

On the basis of present study following conclusions are drawn:

It is observed that performance of all structures in elastic range have definite values for model with infill walls at immediate occupancy and performance of the structures with low rise building in plastic range have clear point at life safety in comparison with ulti storey buildings that have unclear point at life safety. It can be seen that the performance of all the models lies in between life safety and collapse prevention. Overall the performances of these models are satisfactory and some of the elements in some models require retrofitting. The predicted values in displacement and base shear at performance point for testing model building using artificial neural network vary only marginally from the actual values. The values show that prediction by artificial neural network is satisfactory. The networks trained can efficiently be used in the analysis of structure within the bounds being considered. These bounds can easily be extended to cover a wider range of analysis. The methods presented in here can also be employed for training networks for other types of space structures such as barrel vaults, domes, and antenna type of structures.

Scope for Future Work

In this thesis, the dynamic behaviour of the RC buildings are studied using artificial neural network. For further work, we can try to optimize the structures using genetic algorithms. We can also try to use artificial neural networks for studying the behaviour of other structures such as domes, antenna type of structures. Neural networks are generally used to generate the earthquake magnitudes using past records.

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