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Application of artificial neural networks for dynamic analysis of building frames

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Abstract. Many building codes use the empirical equation to determine fundamental period of vibration where in effect of length, width and the stiffness of the building is not explicitly accounted for. In the present study, ANN models are developed in three categories, varying the number of input parameters in each category. Input parameters are chosen to represent mass, stiffness and geometry of the buildings indirectly. Total numbers of 206 buildings are analyzed out of which, data set of 142 buildings is used to develop these models. It is demonstrated through developed ANN models that geometry of the building and the sizes of the columns are significant parameters in the dynamic analysis of building frames. The testing dataset of these three models is used to obtain the empirical relationship between the height of the building and fundamental period of vibration and compared with the similar equations proposed by other researchers. Experiments are conducted on Mild Steel frames using uniaxial shake table. It is seen that the values obtained through the ANN models are close to the experimental values. The validity of ANN technique is verified by experimental values.

Keywords: dynamic analysis; artificial neural network; data driven tools

1. Introduction

The purpose of carrying out dynamic analysis is to obtain earthquake induced lateral forces on the buildings. Response Spectrum Method and Time History Method are the two approaches by which such analysis can be performed. Time History analysis of structures for problems with large number of degrees of freedom is time consuming.

1.1 Fundamental period of vibration

The fundamental period has a primary role in seismic design and assessment as it is the main feature of the structure that allows one to determine the elastic demand, and indirectly, the required inelastic performance in static procedures. In the majority of cases, the assessment of the period is considered as a function of the structural system classification and number of storeys or height. (Verderame *et al*. 2010). Structural dynamics principles indicate that the fundamental period plays

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a prominent role in anticipating the forces to which a structure will be subjected during earthquake ground motions. (Gilles and McClure 2008). The seismic response of a structural building system depends on several factors including its configuration, dynamic characteristics and the characteristics of the applied ground motion. It is imperative to simulate these factors as close to reality as possible in order to correctly predict seismic performance or vulnerability of a given structural system using experimental and/or analytical techniques. (Annan *et al*. 2009). Seismic responses of reinforced concrete structures have been investigated using different methodologies which involve a great complexity particularly in the analysis of real building due to lack of complete data related to excitation, creation of an idealized model, modeling the dynamic loads, performing an analysis and extrapolating the predictions to the real system. (Caglar *et al*. 2008). The fundamental vibration period of a building appears in the equation specified in building codes to calculate the design base shear and lateral forces. It is seen that although the code formulas provide periods that are generally shorter than the measured periods, these formulas can be improved to provide better correlation with the measured data. An improved empirical formula is obtained for RC moment resisting frames based on available dataset of 27 RC moment resisting buildings. The dataset is actual recorded observations taken during several California earthquakes (Goel and Chopra 1997). Sameh S.F. Mehanny (2011) quantified the error in the calculated period of single-mode dominant structures due to the error propagated through variation and uncertainty in the values of both mass and stiffness parameters. According to achieved results, a relative error in the period of vibration in the order of 19% for new designs/constructions and of about 25% for existing structures for assessment purposes is acknowledged. Verderame Gerardo M. *et al*. (2010) determined relationships of elastic period of sub-standard reinforced concrete moment resisting frame buildings for the three populations (with seismic coefficient 0.05g, 0.07g and 0.1g.) of seismic building. Crowley Helen and Pinho Rui (2006) proposed simplified equation to relate the yield period of vibration of existing buildings to their height for use in large-scale vulnerability assessment applications.

1.2 Artificial neural network

Since last two decades or so Artificial Neural Networks (or ANNs) are employed effectively for simplification of complex problems with large number of computations in the field of Civil and Structural Engineering (Flood and Kartam 1994a and b). In Artificial neural network the transmission and the processing of the input data are assigned to a network of simple computing units, called neurons. Each neuron returns an output signal when the weighed sum of the inputs exceeds an activation value. The output value is computed by defining a transfer or activation function. The principal advantage of a properly trained neural network is that it requires a trivial computational burden to produce an approximate solution. Such approximations appear to be valuable in situations where the actual response computations are intensive in terms of computing time and a quick estimation is required. For each problem a neural network is trained utilizing information generated from a number of properly selected analyses. The data from these analyses are processed in order to obtain the necessary input and output pairs, which are subsequently used to produce a trained neural network. One of the most important characteristics of neural networks is learning. Learning may be supervised or unsupervised depending on the topology of networks. Therefore, topology, training or learning method and kind of activation function of neurons are its basic characteristics. Neural networks have two operation modes, training mode and normal mode. In the training mode, adjustable parameters of the networks are modified. In the normal mode, the trained networks are applied for simulating of outputs (Ahamadi *et al*. 2008).

1.3 Use of artificial neural network in the dynamic analysis

In recent years, ANN was successfully applied in many structural engineering applicati- ons including seismic analysis (Adeli and Hojjat 2001). Ghaboussi and Lin (1998) proposed a method based on neural networks for generating artificial earthquake accelerograms. Lee and Han (2002) developed five artificial neural network-based models for the generation of artificial earthquake and response spectra. Caglar *et al*. (2008) proposed two ANN models to estimate the fundamental period of vibration, base shear forces, base bending moments and top floor displacement. In all eleven Input parameters were chosen for developing the models which were easy to obtain from the drawings except Moment of Inertia values. Chakraverty S. *et al*. (2006) developed ANN based models to compute response of structural system subject to Indian Earthquakes for Chamoli and Uttarkashi ground motion data. Ahmadi *et al*. (2008) employed Generalized Regression (GR) Neural Network and Back Propagation wavelet Neural Network (BPW) for approximating the dynamic time history responses of eight storey steel frame structure. Results of BPW were compared with those of GR which indicated that the accuracy of BPW was better than that of GR. Kamyab Moghadas and Gholizadeh (2008) introduced a parallel wavelet back propagation neural network model. Heidari *et al*. (2006) used Fast Wavelet Transform (FWT) and Discrete Wavelet Neural Network (DWN) to approximate the dynamic responses of the structures. The numerical results showed that the time of dynamic analyses is reduced to about 0.1 of the time required for the time history dynamic analysis using the original earthquake. Arslan M. Hakan (2009) developed ANN based models for estimating the failure load and failure displacement of R.C. structures. Seven input parameters were chosen to predict the failure load and failure displacement. It has been demonstrated that all these input parameters directly affected the seismic performance of the building. Alireza Mortezaei and Kimia Mortezaei (2012) investigated the adequacy of Artificial Neural Networks to determine the three dimensional dynamic response of FRP strengthened RC buildings under the near-fault ground motions. For this purpose, one ANN model was proposed to estimate the base shear force, base bending moments and roof displacement of buildings in two directions. It was demonstrated that the neural network based approach is highly successful in determining the response. Joghataie A. and Farrokh M. (2008) developed a new type of activation function based on the use of the Prandtl–Ishlinskii operator and used in the feed forward neural networks in order to improve capabilities in learning to identify and analyze nonlinear structures subject to dynamic loading. Lagaros Nikos D. and Papadrakakis Manolis (2012) proposed a new adaptive scheme in order to predict the structural non-linear behavior when earthquake actions of increased severity are considered. The predicted structural response by ANNs can be used in the performance based design framework when dynamic analyses are performed, aiming at reducing the excessive computational cost. Kameli Iman *et al*. (2011) have applied artificial neural network to predict the structural response of reinforced concrete frames with masonry infilled walls.

In view of the above discussions, it is felt necessary to apply data driven technique in the form of Artificial Neural Networks as it learns from the examples and empirical equations for fundamental period of vibration are suggested along X and Y directions. Even analytical methods are also based on certain assumptions which may introduce the errors in the actual value and analytical value. These data driven techniques extract the information from the data presented to them. Even though the ANN models are developed from the analytical values, it is seen that ANN technique estimates the values closer to experimental values than the analytical values. Data-driven modeling can be considered as an approach to modeling that focuses on using the Machine Learning methods in building models that would complement or replace the “knowledge-driven” models describing physical behavior. (Solomatine 2002). Hence the applicability of this technique is judged by developing the models in different categories with an aim to know whether ANN technique understands the theory of structural dynamics or not. Article 2 describes the details of the application of ANN technique for dynamic analysis along with the results and discussions. The results obtained through the ANN models are further reduced to the equation of different forms as suggested by building code and different researchers. The ANN results are also verified through the tests conducted on mild steel frames. These details are covered in article 3.

2. Application of ANN in the dynamic analysis

In the present work, ANN models are developed under three categories varying number of input parameters. It is seen that the ANN models developed with five input parameters also gives results with acceptable accuracy. It indicates that geometry, mass and stiffness of the building are the significant parameters in the dynamic analysis. Concept of Hinton Diagram is used to identify appropriate input parameters to some extent.

2.1 Geometry and material properties

The buildings are assumed to be fixed at the base without soil structure interaction and the floors as rigid diaphragm. The sections of the structural elements are rectangular and square for the beams as well as the columns. The thickness of slab is 150 mm and the height of the floor as 3m or 3.5m. The beam sections are considered in the size range of 230 mm × 450 mm to 450 mm × 750 mm. The column sections for square shapes are assumed in the size range of 300 mm × 300 mm to 750 mm × 750 mm and that for rectangular shapes are considered in the range of 230 mm × 300 mm to 230 mm × 600 mm. The modulus of elasticity is considered as $5000\sqrt{f_{ck}}$ and the mass density as 25 KN/m^3. Three grades of concrete assumed in the analysis are M20, M25 and M30. Live load intensity is considered as either 2 KN/m^2 or 3KN/m^2. A typical floor plan of building is shown in Fig. 1

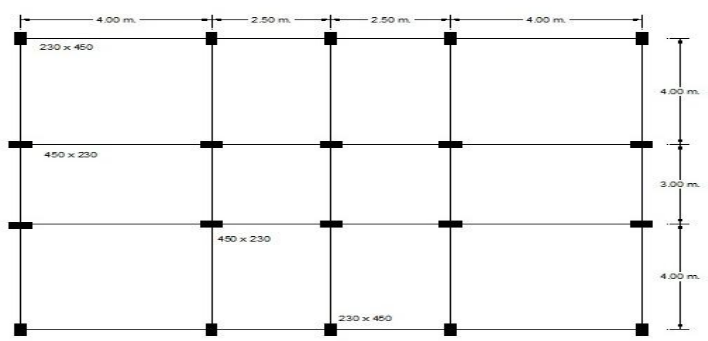

Fig. 1 Typical floor plan of building

2.2 Generation of data

Total numbers of 206 buildings with height range between 4 storeys to 15 storeys are analyzed for natural periods of vibration along X as well as Y directions. The structures are assumed to be located in the seismic zone number III on the medium soil. Importance Factor (I) as 1 and Response Reduction factor (R) as 5 are considered for all buildings. Base shear force and top floor displacement are also obtained through this analysis. Authors have developed MATLAB codes to perform the analysis. Effect of first three modes is considered for the dynamic analysis.

2.3 Methodology

Out of the data for 206 buildings, the data set of 142 buildings is used to train the model and that of remaining 64 buildings is used to test the model. This division of the data is arrived at after the several trials. In order to avoid over fitting of the data, validation check is applied. So the division of the data is approximately 70 % for training, approximately 15% for validation and remaining about 15% for testing the model. The statistic measures used to assess the accuracy of the developed models are Root Mean Squared Error (RMSE), Correlation Coefficient (R) and Coefficient of Efficiency (CE). Levenberg-Marquardt algorithm is used to train the model. CE and R are the correlation measures that measure the “goodness of the fit” of modeled data with respect to the observed data. The CE statistic provides a measure of the ability of a model to predict values which are different from the mean. CE ranges from $-\infty$ at the worst case to +1 for a perfect correlation; R ranges from -1(perfect negative correlation), through 0 (no correlation), to +1 (perfect positive correlation). CE of 0.9 and above is very satisfactory, 0.8 to 0.9 represents a fairly good model, and below 0.8 is deemed unsatisfactory. RMSE is an absolute error measure. Goodness of fit and absolute error measures is to be used in combination to assess model performance. Scatter plots also provide a useful visual aid to assess a model’s accuracy. (Dawson and Wilby 2001).

2.4 Model formulation

In the present study, ANN models are developed under three categories, namely category A, category B and category C as shown in Table 1. Each category mentioned here consists of four subcategories as mentioned in Table 2. The basic aim of arriving at the optimum ANN architecture is to decide the significant parameters of the building required for dynamic analysis of the buildings.

Category A comprises all ANN models developed with 9 input parameters. These input parameters are chosen considering the effect of geometry, mass distribution and the stiffness characteristics of the building frames in the dynamic analysis. Effect of geometry is incorporated

Table 1 Details of the categories of ANN models

Category of ANN model	Number of input parameters	Sub- categories
A	9	4
B	8	4
C	5	4

Table 2 Output parameters of subcategories of ANN models

Model	Direction of Analysis	Output parameters		
		Output 1	Output 2	Output 3
ANN 1	X	Natural period of vibration for first mode (T_1)	Natural period of vibration for second mode (T_2)	Natural period of vibration for third mode (T_3)
ANN 2	Y	Natural period of vibration for first mode (T_1)	Natural period of vibration for second mode (T_2)	Natural period of vibration for third mode (T_3)
ANN 3-1	X	Base shear force	------	------
ANN 3-2	Y	Base shear force	------	------
ANN 4-1	X	Top floor displacement	-------	-------
ANN 4-2	Y	Top floor displacement	------	------

Table 3 Input parameters for X direction

Sr. No.	Parameter	Notation used
1	Length of building	L
2	Width of building	W
3	Number of columns	N_c
4	Number of beams	N_B
5	Minimum dimension of column along X direction	W_{cmin}
6	Maximum dimension of column along X direction	W_{cmax}
7	Height of the building	H
8	Height of the storey	h
9	Number of floors	n

Table 4 Input parameters for Y direction

Sr. No.	Parameter	Notation used
1	Length of building	L
2	Width of building	W
3	Number of columns	N_c
4	Number of beams	N_B
5	Minimum dimension of column along Y direction	D_{cmin}
6	Maximum dimension of column along Y direction	D_{cmax}
7	Height of the building	H
8	Height of the storey	h
9	Number of floors	n

in terms of L, W and H whereas the effect of the mass of the building is incorporated in terms of N_c, N_B, W_{cmin}, W_{cmax}, D_{cmin}, D_{cmax} and n. The stiffness characteristic of the building frames is assumed in terms of W_{cmin}, W_{cmax}, D_{cmin}, D_{cmax} and h.

Category B comprises all ANN models developed with eight input parameters. The perimeter of the building (P) is introduced as a substitute for two input parameters viz. Length and Width of building. New set of ANN models are developed using eight input parameters instead of nine.

Category C comprises all ANN models developed with five input parameters. With an aim of minimizing the number of input parameters to avoid duplication of inputs to the model, an attempt is made to develop these models using only five input parameters as a trial. Perimeter (P) and height of the building (H) can represent the geometry to the model, sizes of the columns and height of the storey (W_{cmin}, W_{cmax}, D_{cmin}, D_{cmax} and h) can be referred for the stiffness calculations and the effect of the other input parameters like number of beams and columns per floor and number of floors (N_c, N_B and n) may be taken indirectly into account through the perimeter of the building, height of the building and other input parameters chosen. So five input parameters becomes: Perimeter of the building (P), Minimum Width of the Column (W_{cmin}), maximum width of Column (W_{cmax}), Height of the building (H) and Height of the storey (h) along X direction and Perimeter of the building (P), Minimum depth of the column (D_{cmin}), and maximum depth of column (D_{cmax}), Height of the building (H) and height of the storey (h) along Y direction.

All these input parameters are easy to obtain from the drawings. Table 3 and 4 given below shows the input parameters used along X and Y directions respectively for category A models.

The concept of Hinton diagram is used to understand the influence of each input over the output parameter. The Hinton diagram provides a qualitative display of the values in a data matrix (normally a weight matrix). Each value is represented by a square whose size is associated with the magnitude and whose color indicates the sign. Hinton Diagram used here represent weight matrix between the Input layer and Hidden layer of ANN model graphically.

2.5 Results and discussions

As per the discussions in previous paragraphs, comparison of the results is discussed

here in this article. Architecture of ANN model describes number of neurons in input layer, hidden layer and output layer sequentially. Epochs is number of iterations at the end of which error between predicted and target values are reduced as low as possible.

2.5.1 Results of category A models

ANN models are developed and the results are shown in Table 5 and Table 6.

2.5.2 Results of category B models

The results of these models are shown in Table 7 and Table 8. Also are shown the scatter plots of ANN models of category B in Figs. 2-5.

Table 5 Results of ANN models (Category A)

Model	Architecture	Performance parameters	T_1	T_2	T_3	Epochs
ANN1	9:9:3	R	0.97	0.97	0.97	12
		RMSE	0.100	0.039	0.022	
		CE	0.92	0.93	0.92	
ANN2	9:8:3	R	0.98	0.98	0.98	21
		RMSE	0.056	0.016	0.0088	
		CE	0.95	0.96	0.98	

Table 6 Results of ANN models (Category A)

Model	Architecture	Performance parameters	Base shear	Epochs
ANN3-1	9:30:1	R	0.99	43
		RMSE	107.21	
		CE	0.975	
ANN3-2	9:25:1	R	0.98	25
		RMSE	150.24	
		CE	0.953	

Table 7 Results of ANN models (Category B)

Model	Architecture	Performance parameters	T_1	T_2	T_3	Epochs
ANN1	8:8:3	R	0.97	0.97	0.97	12
		RMSE	0.099	0.033	0.0022	
		CE	0.93	0.93	0.92	
ANN2	8:5:3	R	0.98	0.98	0.98	20
		RMSE	0.059	0.017	0.010	
		CE	0.95	0.96	0.97	

Table 8 Results of ANN models (Category B)

Model	Architecture	Performance parameters	Base shear	Epochs
ANN3-1	8:30:1	R	0.98	14
		RMSE	106.53	
		CE	0.975	
ANN3-2	8:40:1	R	0.98	62
		RMSE	136.60	
		CE	0.961	
Model	Architecture	Performance parameters	Top floor displacement	Epochs
ANN4-1	8:27:1	R	0.96	24
		RMSE	0.000458	
		CE	0.90	
ANN4-2	8:22:1	R	0.98	31

Table 9 Results of ANN models (Category C)

Model	Architecture	Performance parameters	T_1	T_2	T_3	Epochs
ANN1	5:4:3	R	0.96	0.96	0.97	19
		RMSE	0.105	0.0354	0.0218	
		CE	0.90	0.91	0.93	
ANN2	5:6:3	R	0.97	0.97	0.98	23
		RMSE	0.061	0.019	0.012	
		CE	0.94	0.95	0.96	

Table 10 Results of ANN models (Category C)

Model	Architecture	Performance parameters	Base shear	Epochs
ANN3-1	5:12:1	R RMSE CE	0.97 177.288 0.930	39
ANN3-2	5:30:1	R RMSE CE	0.98 133 0.963	21
Model	Architecture	Performance Parameters	Top Floor Displacement	Epochs
ANN4-1	5:3:1	R RMSE CE	0.95 0.000508 0.885	11
ANN4-2	5:4:1	R RMSE CE	0.98 0.000582 0.955	25

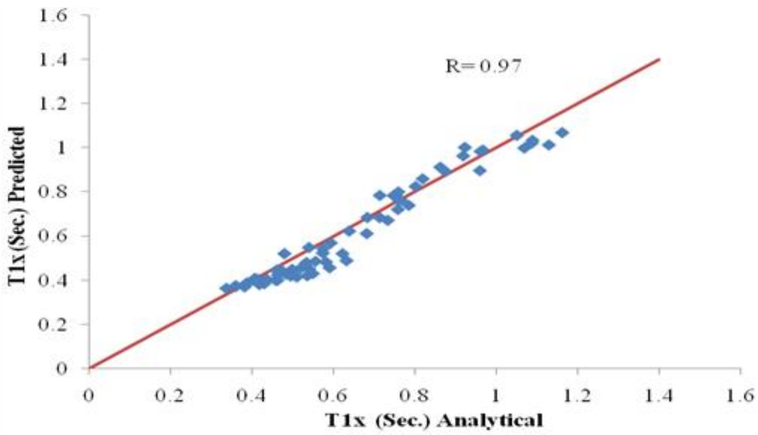

Fig. 2 Scatter plot of fundamental period of vibration along X direction. (ANN1 Model)

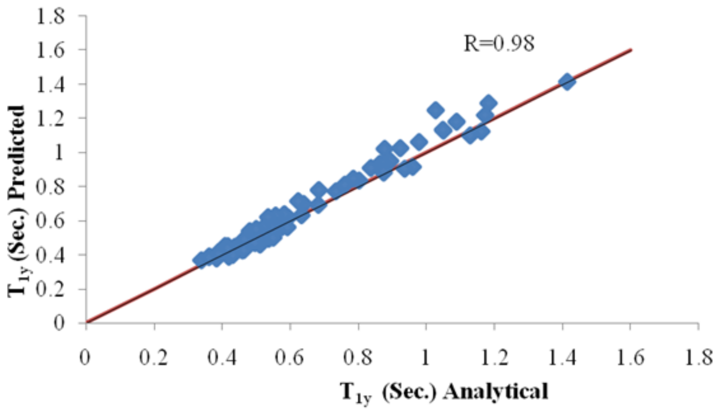

Fig. 3 Scatter plot of fundamental period of vibration along Y direction (ANN2 Model)

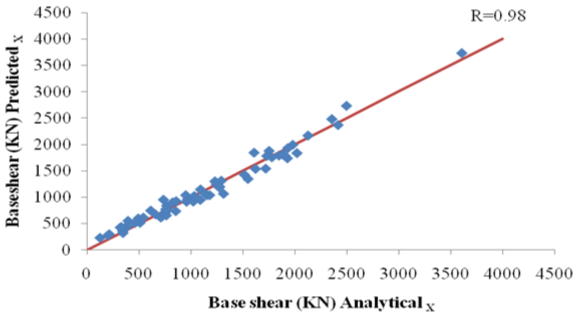

Fig. 4 Scatter plot of base shear force along X direction (ANN3-1 Model)

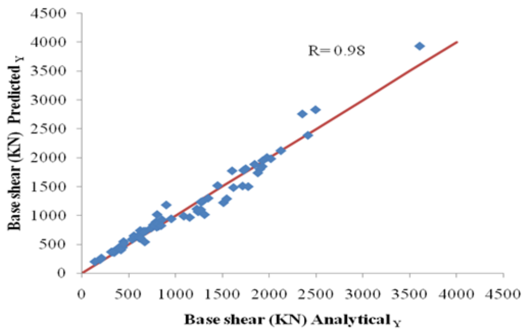

Fig. 5 Scatter plot of base shear force along Y direction (ANN3-2 Model)

2.5.3 Results of category C models

The results of these models are shown in table 9 and table 10.

2.5.4 Hinton diagram and its significance in the study

A typical Hinton Diagram is shown in Fig. 6 for ANN 2 model developed under category B. The Hinton Diagram for ANN1and ANN2 models in category A and Category B has shown more influence from N_c, N_B and W_{cmin}, W_{cmax}(along X direction) or D_{cmin}, D_{cmax} (along Y direction) and n. Hinton Diagram thus indirectly shows the influence of mass and stiffness over the natural periods of vibrations.

Fig. 7 shows the Hinton Diagram for ANN 2 model developed under category C. In case of ANN1 and ANN2 models developed under category C, the influence of W_{cmin}, W_{cmax} (along X direction) or D_{cmin}, D_{cmax} (along Y direction) and H is seen in the Hinton Diagram. Here also the effect of stiffness of the building is well understood by the model indirectly through D_{cmin} and D_{cmax} and h. It is evident from fig. 6 that the input parameters D_{cmin}, D_{cmax} and N_c have opposite influence on the values of T when compared with the influence of other input parameters like perimeter (P), height of the building (H), height of storey (h), and number of floors (n). The buildings are analyzed as multi degree of freedom systems. However for the sake of understanding the meaning of Hinton diagrams only, the equation of T is used in the single degree of freedom system in the following paragraph.

From the theory of structural dynamics, for single degree of freedom systems fundamental period of vibration (T) is found out as,

$$T = 2\pi\,(m/k)^{1/2} \tag{1}$$

$$k = N_c\,(12\,E\,I\,/\,h^3) \tag{2}$$

$$k = N_c\,[12\,E\,(w\,D^3/12)\,/\,h^3] \tag{3}$$

where w = width of column, D is the depth of column, E is Modulus of Elasticity, I is moment of Inertia, N_c is number of columns and h is height of storey.

$$T = 2\pi\,(m\,h^3/N_c\,E\,w\,D^3)^{1/2} \tag{4}$$

Further mass (m) of the system may be worked out using perimeter (P) and height of the building (H). This influence can be seen in the Hinton diagram shown in figure number 6 and

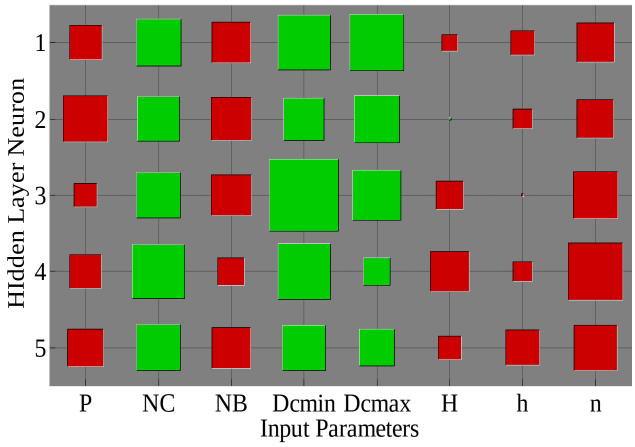

Fig. 6 Hinton diagram of ANN 2 model (category B)

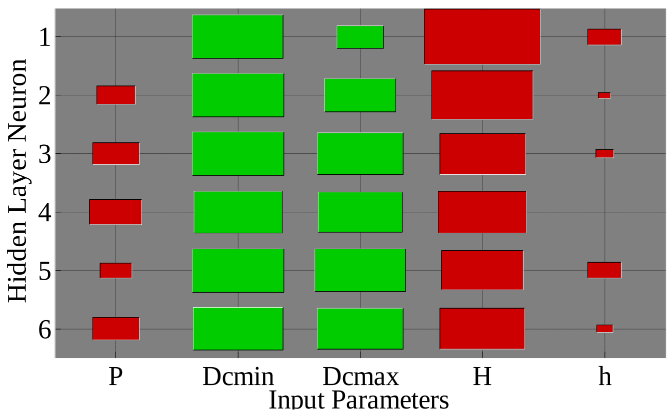

Fig. 7 Hinton diagram of ANN 2 model (category C)

figure number 7. It indicates that ANN assigns weight values to every input parameter considering its positive or negative influence on the output parameters. This article has shown that ANN technique understand the theory of structural dynamics reasonably well and may be used to derive the empirical equation of fundamental period of vibration (T_1) as discussed in the next article.

3. Comparison of ANN results with the other equations

The empirical equations are obtained from the testing dataset of the ANN models and ANN estimated values are compared with the experimental values as discussed in the following paragraphs.

3.1 *Fundamental period of vibration (T_1)*

The developed models are used to obtain the relationship between the height of the building and fundamental period of vibration along X and Y directions. Table 11 shows the comparison of the equations suggested by different researchers or building code and those obtained through developed ANN models. The empirical equations are derived from the developed models under category B. These equations are obtained for the buildings up to 40 m in height.

This table shows that the equations derived from ANN technique along X direction agrees good with the recommended equations by IS 1893 (Part1): 2002, lower bound of Goel and Chopra (1997) and in filled frames with openings by Crowley and Pinho (2006). ANN equation along Y direction is close to the equation recommended as best fit by Goel and Chopra (1997). Also the Table 11 indicates that even though the forms of the empirical equations suggested by different researchers are different, their estimate comes closer to each other for the buildings up to 40 m in

Table 11 Comparison of ANN equations and other recommended equations

Source of the equation	Suggested Equation	ANN equation along X direction	ANN equation along Y direction
IS 1893(Part1): 2002	$T = 0.075\ H^{0.75}$	$T = 0.0703\ H^{0.75}$	$T = 0.0811\ H^{0.75}$
Goel and Chopra (1997)			
Lower bound	$T = 0.0466\ H^{0.9}$	$T = 0.0457\ H^{0.9}$	$T = 0.053\ H^{0.9}$
Best fit	$T = 0.052\ H^{0.9}$		
Upper bound	$T = 0.065\ H^{0.9}$		
Crowley and Pinho (2006)			
Bare frames	$T = 0.054\ H$	$T = 0.0344\ H$	$T = 0.040\ H$
In filled frames with openings	$T = 0.034\ H$		
Fully in filled frames	$T = 0.025\ H$		

Fig. 8 Photograph of mild steel frame

height. It may be perhaps for the same reason IS 1893 (Part1):2002 has recommended actual dynamic analysis for the buildings more than 40 m in height in zone IV and zone V.

The equation of T_1 along X and Y directions are obtained as below for the buildings up to the height of 20 m.

$$T_X=0.127\ H^{0.75} \tag{5}$$

$$T_Y=0.143\ H^{0.75} \tag{6}$$

The equations given in Table 11 are obtained for buildings up to 40 m in height. It indicates that for the buildings more than 20 m height and less than 40 m height, the coefficient of H in Eqs. (5) and (6) is less than 0.075 and hence average value of the coefficient is 0.0703 along X direction and 0.0811 along Y direction. Further as the stiffness of all the buildings along X direction is more than that along Y direction, in the dataset used, T_X is less than T_Y.

3.2 Experimental validation

Mild steel frames are tested on Uni-axial shake table to determine the fundamental period of vibration (T_1) along Y direction. Table 12 shows the details of the frames tested and the experimental results. Fig. 8 is the photograph of the frame, taken during the experimentation.

The results obtained for mild steel frames are transferred to reinforced concrete buildings following the similitude laws given by Rogerio and Carlos (2000) as shown in Table 13.

Table 14 shows that the experimental values are reasonably closer to the ANN values.

It is worth noting that even though ANN models are developed from the analytical values, estimated values are closer to the experimental values than the analytical values.

However Table 15 shows the error estimated between the ANN predicted values of T_1 and experimental values of T_1.

Table 12 Details of mild steel frames

Frame No.	Column size in mm	Beam size in mm	Floor size in mm	Fundamental period of vibration (M.S.Frames) T_1(sec)	Fundamental period of vibration (RCC Building) T_1 (sec.)
1	25×12×250	25×12×200	200 ×200 × 8	0.0293	0.484
2	25×12×350	25×12×200	200 ×200 × 8	0.0498	0.704
3	12×12×250	25×12×200	200 ×200 × 8	0.0396	0.806
4	12×12×300	25×12×200	200 ×200 × 8	0.0469	0.717

Table 13 Scale ratio for frequency of vibration

Building No.	$\lambda = L_p/L_M$ (Scale ratio for length)	$e = E_p/E_M$ (Scale ratio for modulus of elasticity)	$\rho = \rho_p/\rho_M$ (Scale ratio for specific mass)	$f = (e/\rho)^{1/2}/\lambda$ (Scale Ratio for frequency)
1	12	0.11	0.318	0.049
2	10	0.11	0.318	0.0588
3	15	0.11	0.318	0.0396
4	10	0.11	0.318	0.0588

Table 14 Comparison of experimental values and ANN predicted values

Building No.	Height (H) (m)	T_1 Analytical (sec.)	T_1 Experimental (sec.)	T_1 by ANN (sec.)
1	9	0.484	0.598	0.743
2	10.5	0.704	0.846	0.834
3	11.25	0.806	1.000	0.878
4	9	0.717	0.797	0.743

Table 15 Error estimate for the experimental (T_1) and ANN (T_1)

Building No.	Height (H) (m)	T_1 Experimental (sec.)	T_1 by ANN (sec.)	Percentage error
1	9	0.598	0.743	-24.24
2	10.5	0.846	0.834	1.42
3	11.25	1.000	0.878	13.89
4	9	0.797	0.743	6.77

Code formulas are calibrated intentionally to underestimate the period by approximately 10-20% at first yield of the building (Goel and Chopra 1997). Table 15 has shown that the ANN values are under estimated from 1% to 14% except for the first building frame.

4. Conclusions

The present study shows that ANN technique understands theory of structural dynamics reasonably well as seen from Table number 5 to Table number 10. The empirical equations obtained through ANN technique agrees good with the equations proposed by other researchers and building code as it is evident from Table 11. ANN predicted values of T_1 are underestimated from 1 to 14% as seen in Table 15. Thus base shear and top floor displacement values obtained through ANN technique may be considered for approximate analysis and during preliminary structural design of the buildings.

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