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Neural networks in 3-dimensional dynamic analysis of reinforced concrete buildings

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Abstract

The objective of this study is to investigate the adequacy of Artificial Neural Networks (ANN) as a securer, quicker and more robust method to determine the dynamic response of buildings in 3D. For this purpose, two ANN models were proposed to estimate the fundamental periods, base shear force, base bending moments and top-floor displacement of buildings in two directions. Total moment of inertia for each storey was defined in order to avoid limitation to describe the structure due to the number of columns, shear-walls and number of bays. The same input layer was submitted to different types of ANN models for various outcomes. In the ANN models, a multilayer perceptron (MLP) with a back-propagation (BP) algorithm was employed using a scaled conjugate gradient. ANN models were developed, trained and tested in a based MATLAB program. A training set of 150 and a validation set of 15 buildings were produced from dynamic response of different buildings. Finite Element Analysis (FEA) was used to generate training and testing set of ANN models. It was demonstrated that the neural network based approach is highly successful to determine response of buildings subjected to earthquake.

Keywords: Dynamic analysis; Response of buildings; Neural networks; Scaled conjugate gradient algorithm

1. Introduction

The prediction and evaluation of seismic responses of structures subjected to earthquake is one of the major concerns in the field of civil engineering. Seismic responses of reinforced concrete structures has been investigated using different methodologies, and it appears a great complexity in the analysis of real building due to lack of incomplete data related to excitation, creating an idealized model, modelling the dynamic load, performing an analysis and extrapolating the predictions to real system. Although, these problems require reasoning and interpretative experience from the analyst, the new generation of programs tends to capture the knowledge or experience of expert analysts. Therefore, the prediction and evaluation of seismic responses of structures requires extensive knowledge of conceptual design, structural details, mathematical models and analysis assumptions. In spite of extensive development of computational methods, the dynamic analysis of structures in 3D is away from a satisfactory level in the structural engineering point of view. Therefore, a new methodology is necessary to overcome these problems.

Artificial neural network (ANN) has been applied as an alternative method for more realistic estimation of seismic behaviour of reinforced concrete (RC) plane frame structures. ANN is a powerful data-modelling tool that is able to capture and represent complex relationships between inputs and outputs. It appears to offer a means of dealing with many multi-variety problems in which was exact analytical model does not exist or at least was very difficult and time consuming to develop. ANN is also an alternative method and a tool for modelling complex phenomena in different areas of research and engineering practice.

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In recent years, the ANN was effectively applied in many engineering applications [1–4] and ANN seems to be very promising. Ghaboussi and Lin [5] proposed a new method based on neural networks of generating artificial earthquake accelerograms. Wu et al. [6] applied the neural networks to recognize the locations and the extent of individual member damage of a simple 3-storey frame. Yun et al. [7] reported a method to estimate the joint damages of a steel structure from modal data using a neural networks technique. Numerical simulation-based study is carried out on a 2-bay and 10-storey steel frame and also the method is verified with an experimental study on a 2-storey frame. The results found look very reliable. Lee and Han [8] developed efficient five artificial neural network-based models for the generation of artificial earthquake and response spectra. In order to verify the developed models, several numerical examples were used in this study, suggesting that that the procedure using neural network-based models are applicable to generate artificial earthquakes and response spectra. Zapico et al. [9] presented a method of damage assessment based on neural networks and applied to the Steelquake structure. The neural network was used to calibrate the initial undamaged structure, and another one to predict the damage. Natural frequencies of the structure were used as inputs of the neural networks. The data used to train the neural networks through a finite element model. The neural network was demonstrated to possess a high capacity of generalizing and displaying damage levels of the structure.

The objective of this study is to discuss the sufficiency of NN as a securer, quicker and more robust method to be used in prediction of dynamic responses of RC buildings. The NN based models were employed as an alternative method to determine the dynamic response of buildings in 3D, in terms of fundamental periods in two directions, maximum values of base shear-forces, base bending moments and top-floor displacements time histories in two directions. They also enable the designer to rapidly compute the response of buildings in 3D during the preliminary design stage. In these models the goal is to drastically reduce the computational work.

2. Artificial neural network

ANN is a computational tool, which attempts to simulate the architecture and internal operational features of the human brain and nervous system. ANN architectures are formed by three or more layers, including an input layer, an output layer and a number of hidden layers in which neurons are connected to each other with modifiable weighted interconnections. The ANN architecture is commonly referred to as a fully interconnected feedforward multilayer perceptron. In addition, there is a bias, which is only connected to neurons in the hidden and output layers with modifiable weighted connections. The number of neurons in each layer may vary depending on the problem.

The most widely used training algorithm for multi-layered feedforward networks is the back-propagation (BP) algorithm. The BP algorithm basically involves two phases. The first one is the forward phase where the activations are propagated from the input to the output layer. The second one is the backward phase where the error between the observed actual value and the desired nominal value in the output layer is propagated backwards in order to modify the weights and bias values. The inputs and the outputs of training and testing sets must be initialized before then the training a feed work network. In the forward phase, the weighted sum of input components is calculated as

$$\mathrm{net}_j = \sum_{i=1}^{n} w_{ij}x_i + \mathrm{bias}_j \tag{1}$$

where net_j is the weighted sum of the jth neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the jth neuron and the ith neuron in the preceding layer, x_i is the output of the ith neuron in the preceding layer. The output of the jth neuron out_j is calculated with a sigmoid function as follows:

$$\mathrm{out}_j = f(\mathrm{net}_j) = \frac{1}{1 + \mathrm{e}^{-(\mathrm{net}_j)}} \tag{2}$$

The training of the network is achieved by adjusting the weights and is carried out through a large number of training sets and training cycles. The goal of the training procedure is to find the optimal set of weights, which would produce the right output for any input in the ideal case. Training the weights of the network is iteratively adjusted to capture the relationship between the input and output patterns.

The BP training algorithm with gradient descent and gradient descent with momentum are slow. Therefore, several adaptive training algorithms for ANN have recently been discovered such as Conjugate Gradient Algorithm (CG) and Scaled Conjugate Gradient Algorithm (SCG). In this study, SCG is used as optimization algorithm, which is all set to standard values suggested in Moller [10].

The output of the network is compared with a desired response to produce an error. The performance function for feed forward networks is the sum of the squares error (SSE). The process of feed forward and back-propagation continue until the required sum of the squares error is reached. The SSE is defined as

$$\mathrm{SSE} = \sum_{i=1}^{m} (T_i - \mathrm{out}_i)^2 \tag{3}$$

where T_i and out_i are the target outputs and output of neural network values respectively for ith output neuron, and m is the number of neurons in the output layer.

3. Architecture of ANN models

The ANN based models were applied to predict the 3D response of buildings in terms of fundamental periods,

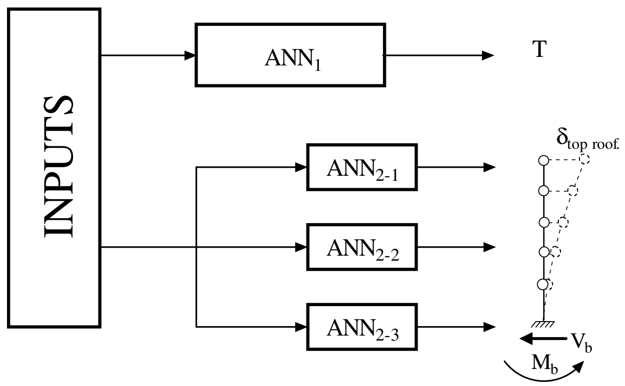

Fig. 1. ANN models with the same inputs.

maximum values of top displacements, base shear forces and base moments in the time domain. Two different ANN models, which used the same input layer, were developed as shown in Fig. 1.

Fundamental periods of the building in two directions were simulated with the ANN_1 model (Fig. 4). The maximum of base shear forces, base moments and top displacements time histories in two directions were simulated with the ANN_2 model (Fig. 5). The ANN_2 model had 3 subs ANN models numbered as ANN_{2-1} to define the displacements in output layer, ANN_{2-2} to define the base shear force in output layer, and ANN_{2-3} to define the base moments in output layer. Therefore, the same input layer was used for three different outcomes in the ANN_2 model.

Dynamic analyses of two dimensional 165 RC buildings subjected to earthquake were carried out SAP2000 software packet program. The response of buildings is summarized in terms of fundamental periods, maximum top displacements, base shear forces and base moments time histories. Dynamic analyses of these buildings were selected and used as a database for this research. Data were divided into three sections: (1) the training set, (2) testing set and (3) verification set.150 of these data were employed as the training set, 10 data were employed as the testing set and 5 data were employed as the testing set. Therefore, 15 of these data, which were not used in the training process, were used to validate the generalization capability of NN model.

In time history dynamic analysis of buildings, 1999 Marmara earthquake in Turkey records from Yarımca-Petkim station (Fig. 2), were used. The acceleration peak of earthquake records was normalized between 0.20 and 0.60 g in N–S and E–S to simulate the *x*-direction and *y*-direction of buildings, respectively. The same values of acceleration peak were applied to buildings along the both N–S and E–W directions (Fig. 3).

The buildings are assumed to be fixed base (without soil–structure interaction), with damping ratio of 5% in all modes, and the floors as rigid diaphragms with infinite in-plane stiffness. The sections of structural elements are rectangular and their dimensions are kept constant for all stories. The slab thickness is 10 cm, the beam dimensions are 25×70 cm and the storey heights of buildings are assumed to be constant with the exception of ground storey. The modulus of elasticity (Young's module) $E = 30\ \mathrm{kN/mm^2}$, Poisson's ratio $\upsilon = 0.20$ and the mass density $\rho = 24\ \mathrm{kN/m^3}$ are assumed for all models.

Inputs of ANN models were consist of 11 data in terms of general properties of buildings and earthquake (Table 1). Although all inputs were used in the ANN_2 model, only acceleration peak was not used in input layer of the ANN_1 model. Total moment of inertia for each storey is defined in order to avoid limitation to describe the structure due to the number of columns, shear-walls and number of bays.

The number of neurons in input and output layers is based on the geometry of the problem. But, there is no general rule for selection of the number of neurons in a hidden layer and the number of the hidden layers. Hence, they are determined by trial and error in this study. Numbers of different NN models with various hidden neurons are trained and tested for only 3000 epochs. Each NN model is initialized with different random weights. The most appropriate NN models are chosen corresponding to performance of training and testing sets. Therefore, the ANN_1 model is selected as 11 neurons in input layer, 15 neurons in hidden layer and 2 neurons in output layer to define the fundamental periods (Fig. 4). The ANN_2 model is selected as 10 neu-

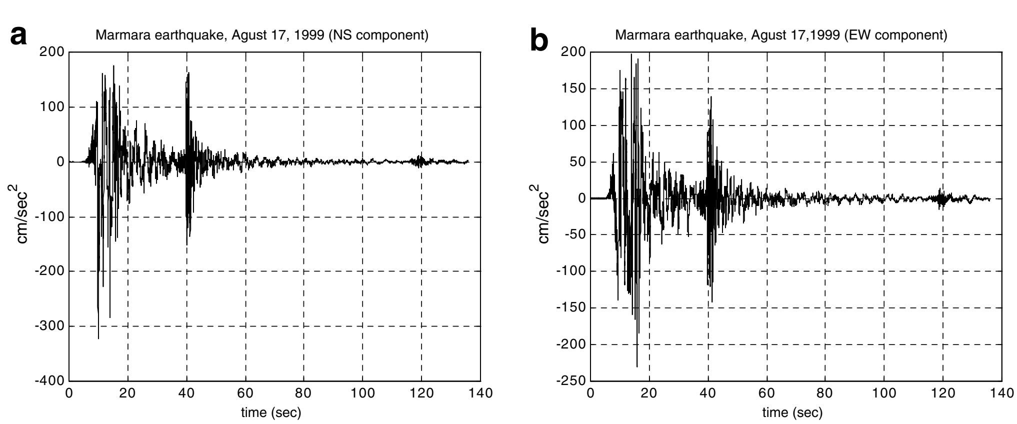

Fig. 2. The Marmara earthquake records: (a) N–S direction and (b) E–W direction.

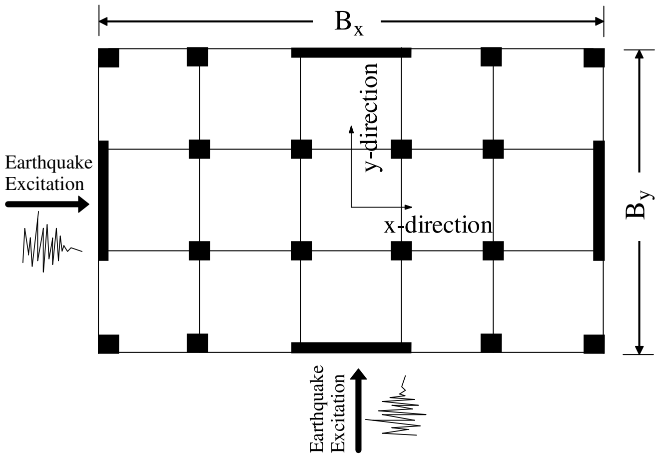

Fig. 3. The general typical floor plan and notations of buildings.

Table 1
Inputs for ANN models

Notations	Inputs
A_p	Acceleration peak
S_w	Shear-wall
I_x	Total moment of inertia (in direction x)
I_y	Total moment of inertia (in direction y)
H_n	Storey height
H_b	Storey height of base floor
L_x	Max bay widths (in direction x)
L_y	Max bay widths (in direction y)
B_x	Widths of building in plan (in direction x)
B_y	Widths of building in plan (in direction x)
N	Number of storey

rons in input layer, 15 neurons in hidden layer and 2 neurons in output layer, to define the displacements (Fig. 5a), the base shear force (Fig. 5b), the base moments (Fig. 5c) using ANN_{2-1}, ANN_{2-2}, ANN_{2-3} sub models respectively. Inputs and outputs are normalized in the (0–1) range by using normalization values given in Table 2.

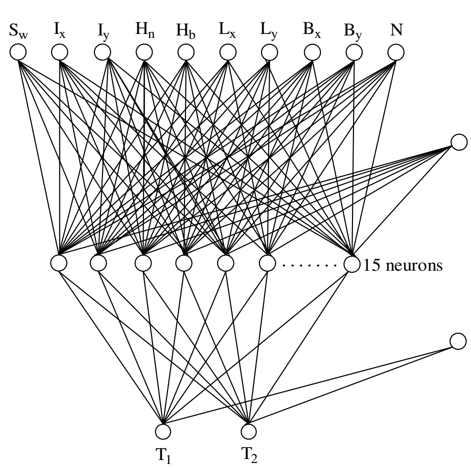

Fig. 4. Architecture of proposed ANN_1 model.

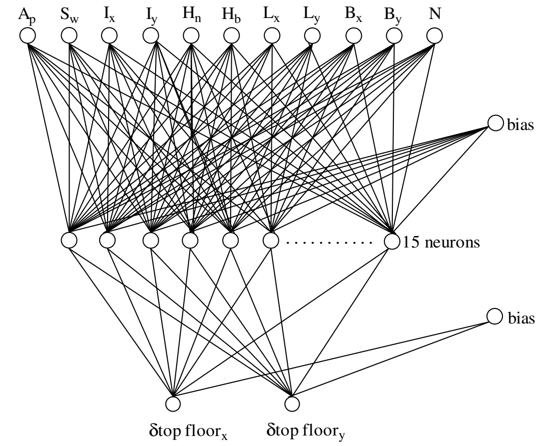

Fig. 5a. Architecture of proposed ANN_{2-1} model.

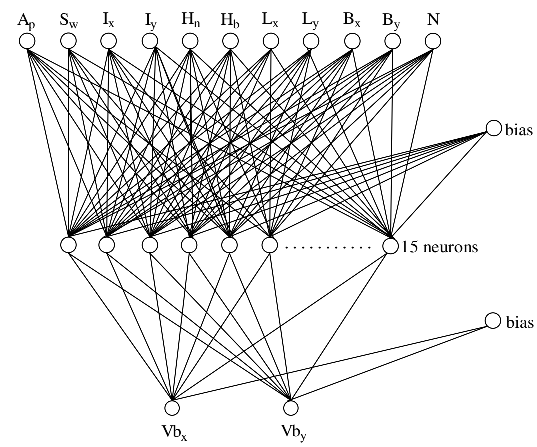

Fig. 5b. Architecture of proposed ANN_{2-2} model.

MATLAB based computer program was developed to train and test the ANN models, which consist of database determined from Finite Element Analysis (FEA) outcomes. In the ANN models, type of back-propagation is scaled conjugate gradient algorithm, activation function is

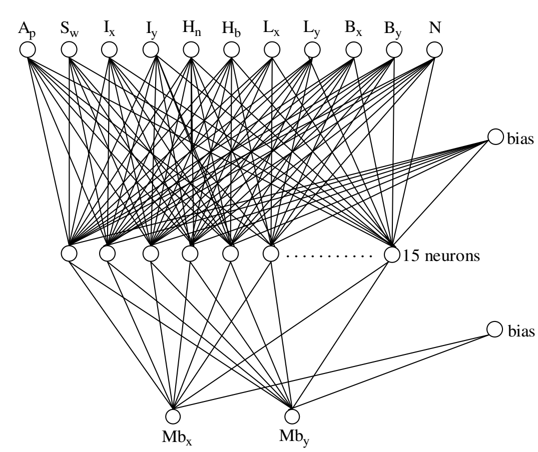

Fig. 5c. Architecture of proposed ANN_{2-3} model.

Table 2
Range of parameters in the database and normalization values

Parameter	Minimum	Maximum	Normalization value
$A_{p\ (g)}$	0.20	0.60	1
S_w	0.00	1.00	1
I_x (m^4)	0.020	10.00	10
I_y (m^4)	0.020	10.00	10
H_n (m)	2.80	4.00	10
H_b (m)	2.80	4.00	10
L_x (m)	2.50	6.00	10
L_y (m)	2.50	6.00	10
B_x (m)	10.00	50.00	100
B_y (m)	10.00	50.00	100
N	3.00	15.00	100
T (s)	0.20	2.50	5.00
δ_{top} (m)	0.002	1.30	1.50
V_b (10^4 kN)	0.20	5.00	10
M_b (10^5 kN m)	0.50	8,00	10

Sigmoidal Function, and number of epochs (learning cycle) is about 25000.

4. Results and discussion

In this study, training set, 150 different buildings, and validation set, 15 different buildings, for ANN models were generated using FEA. The ANN based approach was applied to determine the response of buildings, in terms of fundamental periods, maximum top displacements, base shear forces and base moments time histories. In order to test the capability of the proposed ANN model, the results were compared with the FEA outcomes. The performance of the ANN models showed that the correlations between targets and outputs are consistent as shown in Figs. 6 and 7.

The results of training sets, as shown in Figs. 6a and 7a, indicate that the neural network was successful in learning the relationship between the different input and outputs parameters. The results of testing sets, as shown in Fig. 6b and 7b, that the neural network was capable of generalizing between input and the output variables.

All values in validation set for ANN_1 models have good correlation with FEA outcomes (Fig. 6b). Although, some values in validation set for ANN_2 models showed some scattered, the most of the results are in good correlation with FEA outcomes (Fig. 7b).

4.1. Testing sets: model A buildings

The typical floor plan of model A buildings with different number of stories as 3–5–7–9 and 11, is shown in Fig. 8. The inter-storey height is 3.60 m for the ground and subsequent stories. The column dimensions are selected as 30 cm × 50 cm in outer axes in x-direction and the rest

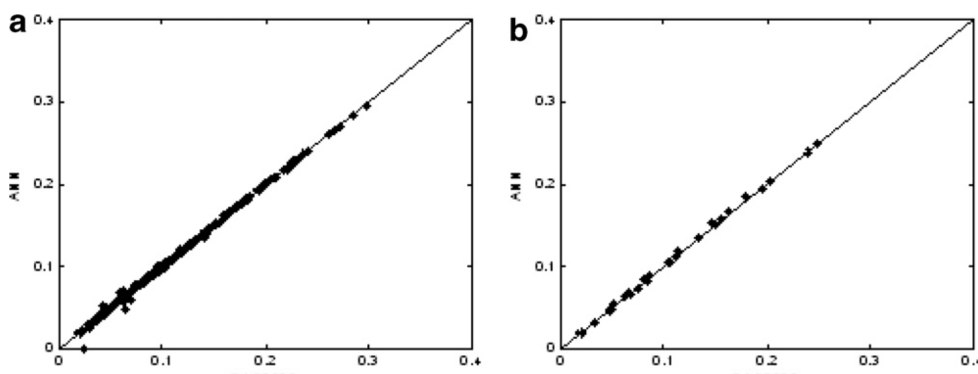

Fig. 6. Performance of proposed ANN_1 model: (a) training set and (b) testing set.

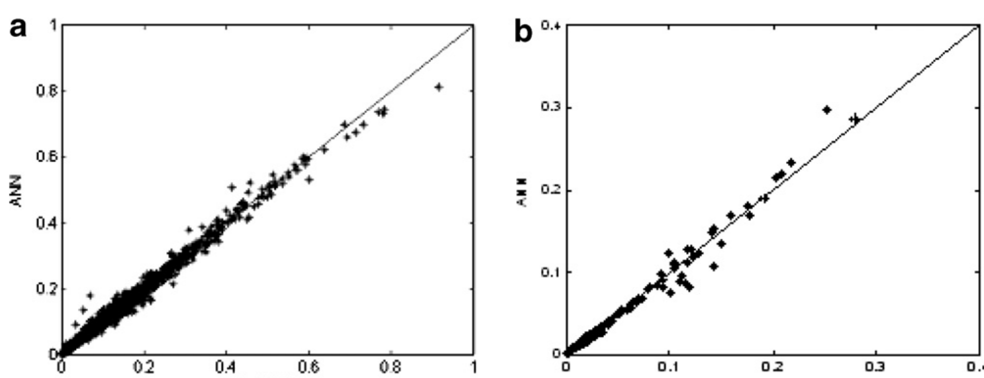

Fig. 7. Performance of proposed ANN_2 model: (a) training set and (b) testing set.

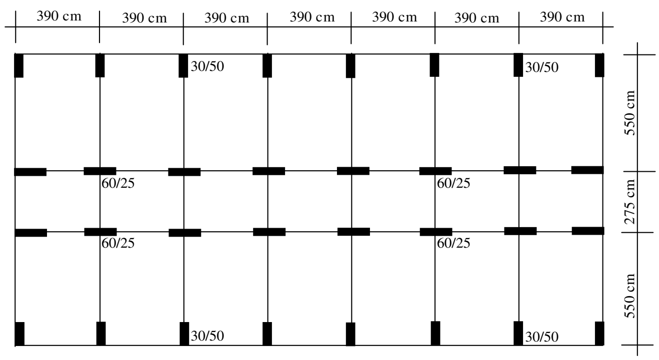

Fig. 8. The typical floor plan of model A buildings.

are 60 cm × 25 cm. The width of the building along x-axes is $B_x = 27.30$ m and along y-axes $B_y = 13.75$ m. The peak acceleration was selected as 0.39 g. The input data and general characteristics of Model A buildings are given in Table 6.

The fundamental periods of the building in two directions were computed and compared with the ANN_1 model and the FEA. The results are given in Fig. 9 graphically.

The top-floor displacements (Fig. 10a), base shear-forces (Fig. 10b) and base moments (Fig. 10c) along the two directions of model A buildings were computed and compared with ANN_2 model and the FEA. The sum of the squares error (SSE), the root-mean-squared (RMS) and the absolute fraction of variance (R^2) for testing set of ANN models were tabulated in Table 3. All of these statistical values proved that the proposed ANN model is appropriate and it predicts the dynamic response of buildings, in terms of the fundamental periods, top-floor displacement, base shear-forces and base bending moments, accurately when compared with the results of FEA.

The outcomes of R^2 are 0.999197, 0.988616 and 0.941560 for periods, displacements and base moments respectively. So, they demonstrate the good correlation. The outcome of R^2 is 0.853312 for base shear forces and it showed some scatter. This is because the base shear forces in x-direction were not good correlated. But in y-direction the base shear forces mutually correlated as seen in Fig. 10b.

4.2. Testing sets: model B buildings

The typical floor plan of model B buildings with different number of stories as 5–7–9 11 and 13, is shown in Fig. 11. The inter-storey height is 3.00 m for the ground and subsequent stories. The column dimensions are selected as 60 cm × 60 cm in both axes and shear-wall dimension selected as 500 cm × 25 cm. The width of the building along x-axes $B_x = 15.00$ m along y-axes

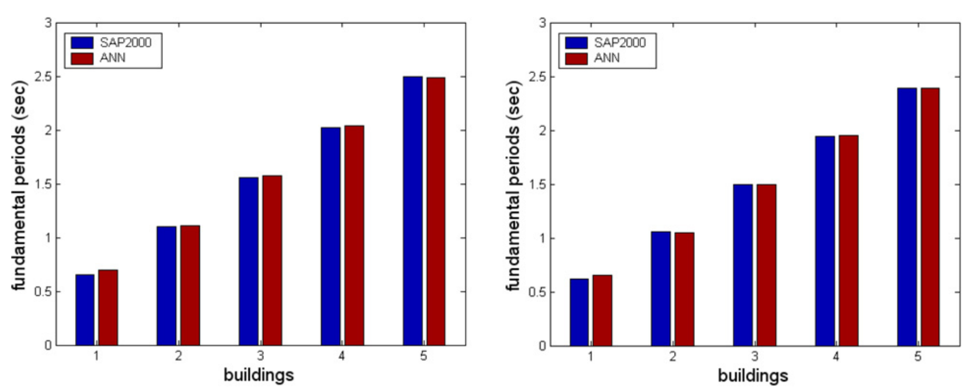

Fig. 9. Fundamental periods in two directions.

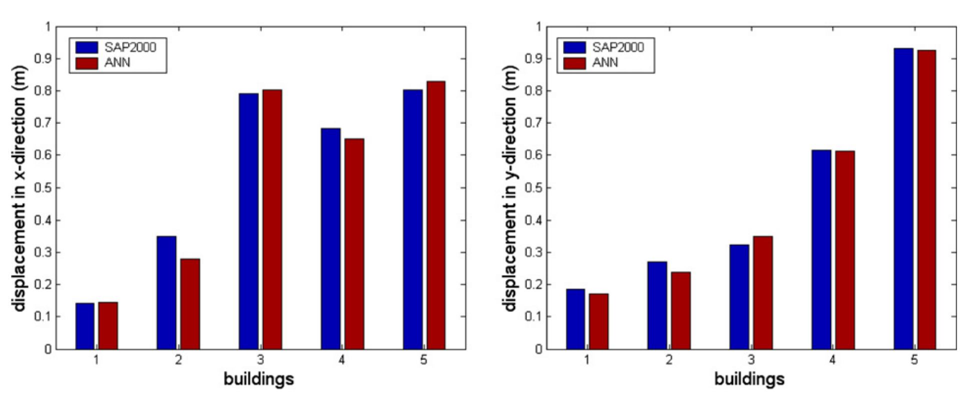

Fig. 10a. Maximum values of top-floor displacement time histories in two directions.

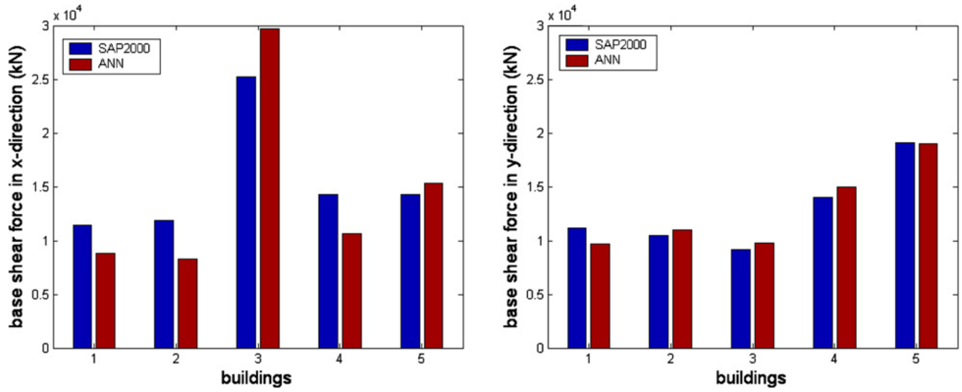

Fig. 10b. Maximum values of base shear-forces time histories in two directions.

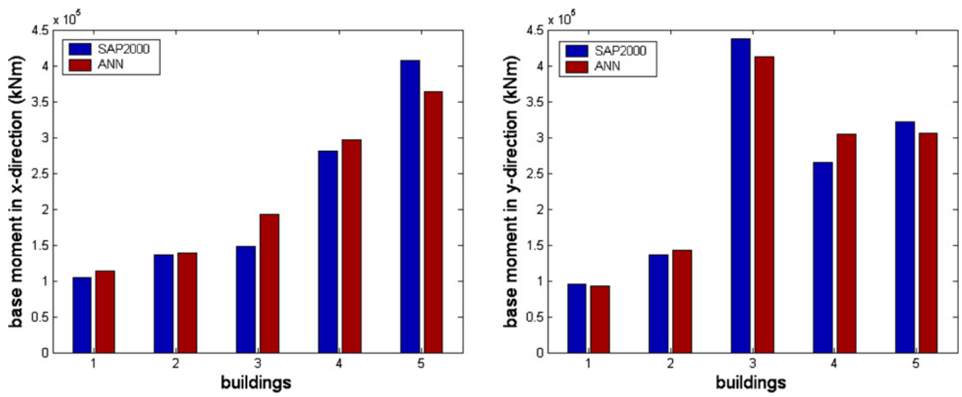

Fig. 10c. Maximum values of base bending moment time histories in two directions.

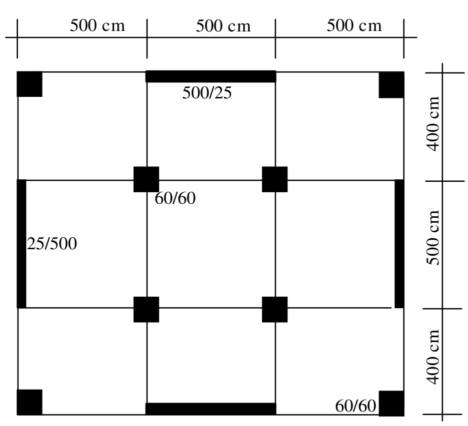

Fig. 11. The typical floor plan of model B buildings.

$B_y = 13.00$ m and the peak acceleration selected as 0.45 g. The input data and general characteristics of model B buildings are given in Table 6.

The fundamental periods of the building in two directions were computed and compared with the ANN_1 model and the FEA. The results are given in Fig. 12 graphically.

The top-floor displacements (Fig. 13a), base shear-forces (Fig. 13b) and base moments (Fig. 13c) along the two directions of model B buildings were computed and compared with ANN_2 model and the FEA. The sum of the squares error (SSE), the root-mean-squared (RMS) and the absolute fraction of variance (R^2) for testing set of ANN models were tabulated in Table 4. All of these statistical values proved that the proposed ANN model is appropriate and it predicts the dynamic response of buildings, in terms of the fundamental periods, top-floor displacement, base shear-forces and base bending moments, accurately when compared with the results of FEA.

Table 3
The statistical values in testing for model A buildings

Statistical values	Period (ANN_1)	Displacement (ANN_{2-1})	Base shear force (ANN_{2-2})	Base moments (ANN_{2-3})
SSE	0.003193	0.009010	0.571167	0.677701
RMS	0.017868	0.030017	0.238991	0.260327
R^2	0.999197	0.988616	0.853312	0.941560

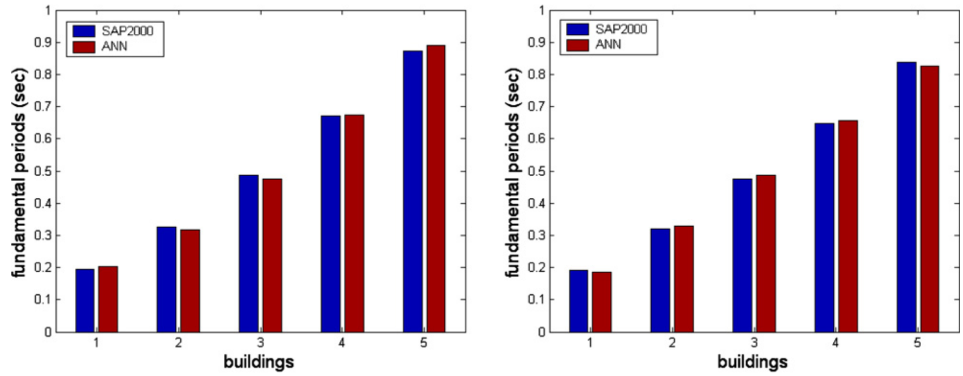

Fig. 12. Fundamental periods in two directions.

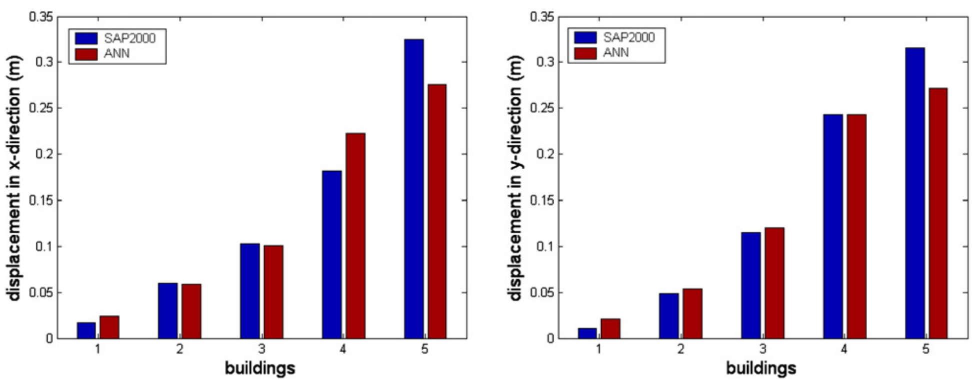

Fig. 13a. Maximum values of top-floor displacement time histories in two directions.

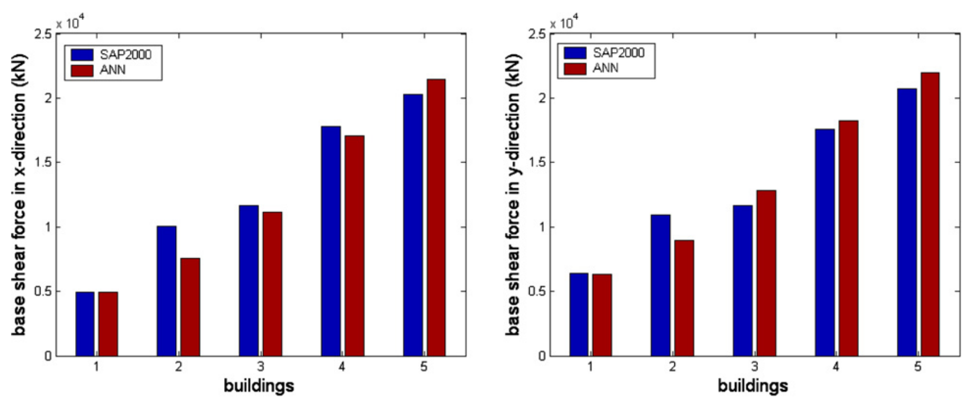

Fig. 13b. Maximum values of base shear-forces time histories in two directions.

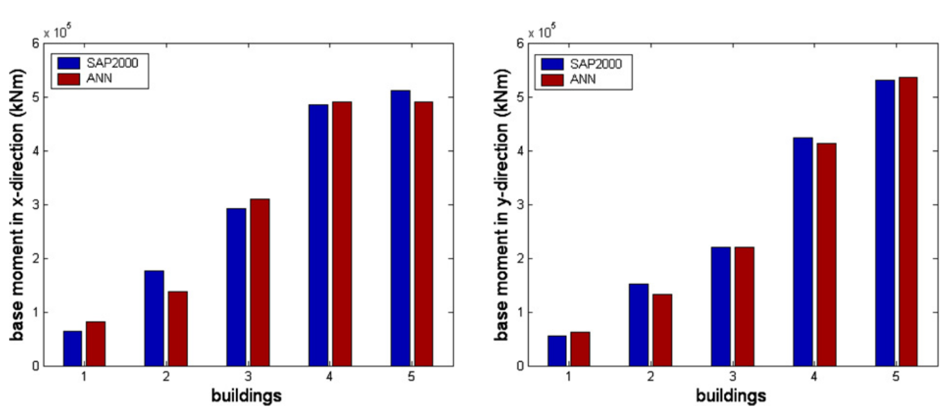

Fig. 13c. Maximum values of base bending moment time histories in two directions.

Table 4
The statistical values in testing for model B buildings

Statistical values	Period (ANN_1)	Displacement (ANN_{2-1})	Base shear force (ANN_{2-2})	Base moments (ANN_{2-3})
SSE	0.001068	0.006104	0.156905	0.307185
RMS	0.010333	0.024707	0.125262	0.175267
R^2	0.998110	0.936905	0.955843	0.989930

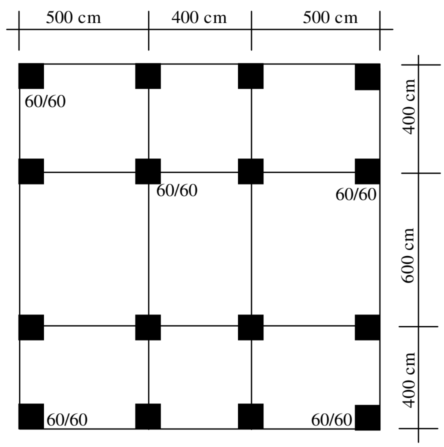

Fig. 14. The typical floor plan of model C buildings.

Table 5
The statistical values in testing for model C buildings

Statistical values	Period (ANN_1)	Displacement (ANN_{2-1})	Base shear force (ANN_{2-2})	Base moments (ANN_{2-3})
SSE	0.018239	0.007705	0.147199	0.554960
RMS	0.042707	0.027758	0.121326	0.235576
R^2	0.991137	0.993125	0.961671	0.982517

The outcomes of R^2 are 0.998110. 0.936905, 0.955843 and 0.989930 for periods, displacements, base shear forces and base moments respectively. So, they demonstrate the good correlation as seen Figs. 13a–13c.

4.3. Verification sets: model C building

The typical floor plan of model C buildings with different number of stories as 4–6–8–10 and 12, is shown in

Table 6
General characteristics of buildings

Notations	Testing sets		Verification sets
	Model A buildings	Model B buildings	Model C buildings
A_p	0.39 g	0.45 g	0.60 g
S_w	0	1	0
I_x	0.0900 m^4	5.3078 m^4	0.2160 m^4
I_y	0.0625 m^4	5.3078 m^4	0.2160 m^4
H_n	3.60 m	4.00 m	3.60 m
H_b	3.60 m	3.00 m	3.60 m
L_x	3.90 m	5.00 m	3.60 m
L_y	5.50 m	5.00 m	3.60 m
Bx	27.30 m	15.00 m	15.00 m
By	13.75 m	13.00 m	13.00 m
N	3 5 7 9 11	5 7 9 11 13	5 7 9 11 13

Fig. 14. The inter-storey height is 3.60 m for the ground and subsequent stories. The column dimensions are selected as 60 cm $\times$ 60 cm in both axes and shear-wall dimension selected as 500 cm $\times$ 25 cm. The width of the building along x-axes is $B_x = 15.60$ m along y-axes $B_y = 13.50$ m and the peak acceleration selected as 0.60 g. The input data and general characteristics of Model C buildings are given in Table 6.

The fundamental periods of the building in two directions were computed and compared with the ANN_1 model and the FEA. The results are given in Fig. 15 graphically.

The top-floor displacements (Fig. 16a), base shear-forces (Fig. 16b) and base moments (Fig. 16c) along the two directions of model A buildings were computed and compared with ANN_2 model and the FEA. The sum of the squares error (SSE), the root-mean-squared (RMS) and the absolute fraction of variance (R^2) for testing set of ANN models were tabulated in Table 5. All of these statistical values proved that the proposed ANN model

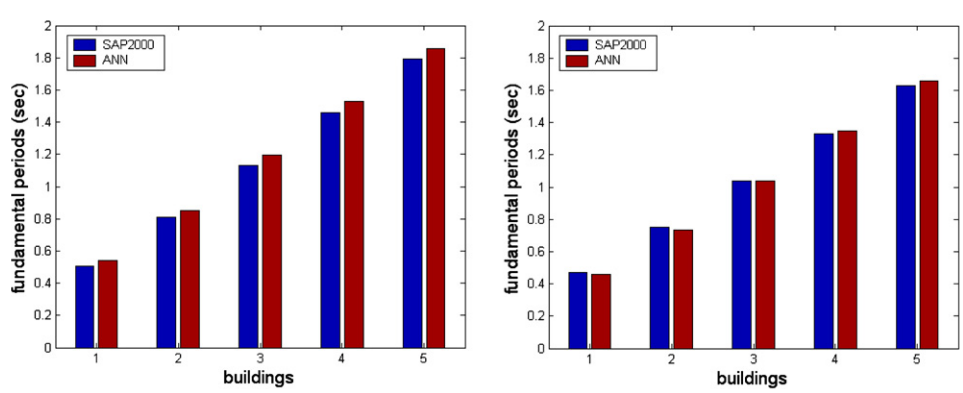

Fig. 15. Fundamental periods in two directions.

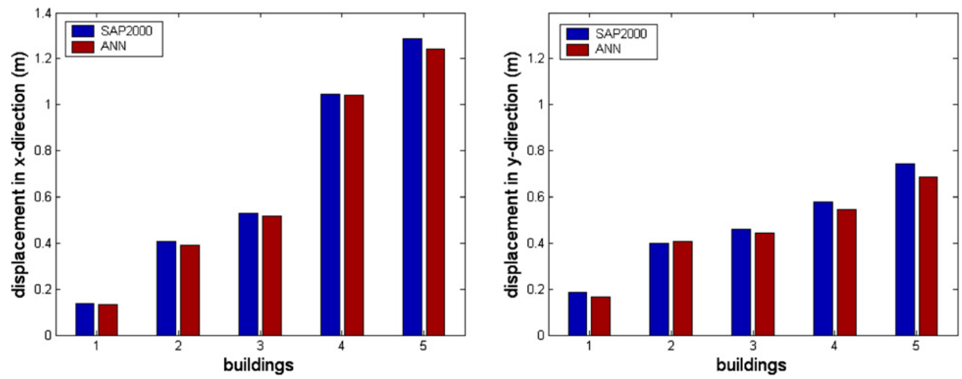

Fig. 16a. Maximum values of top-floor displacement time histories in two directions.

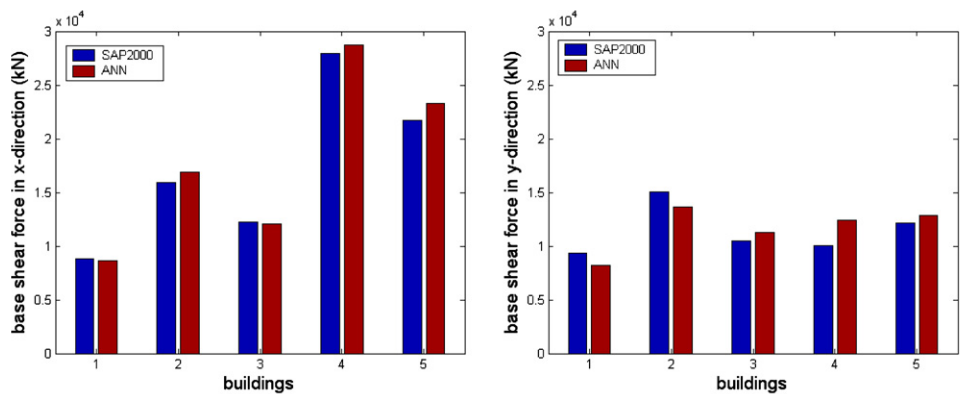

Fig. 16b. Maximum values of base shear-forces time histories in two directions.

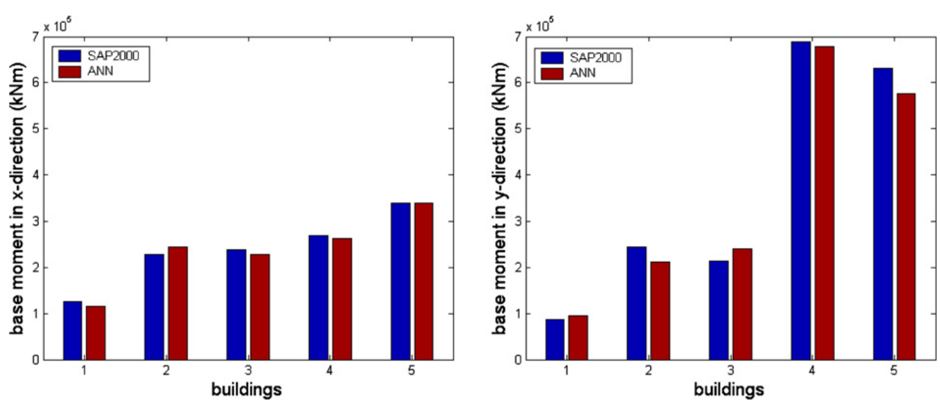

Fig. 16c. Maximum values of base bending moment time histories in two directions.

is appropriate and it predicts the dynamic response of buildings, in terms of the fundamental periods, top-floor displacement, base shear-forces and base bending moments, accurately when compared with the results of FEA.

The outcomes of R2 are 0.991137, 0.993125, 0.961671 and 0.982517 for periods, displacements, base shear forces and base moments respectively. So, they demonstrate the good correlation as seen Figs. 16a–16c.

5. Conclusions

In this study, the ANN based model was developed and compared with the results obtained from numerical analysis. The dynamic response of 165 different buildings were selected and used as a database. 150 of these data were employed as the training set and 15 data were employed as the validation set. The ANN model was tested with the testing set which was not used in the training process.

It was proven that the ANN-based model can successfully determine the 3D response of buildings in terms of the fundamental periods, maximum values of base shear-forces, base bending moments and top-floor displacement time histories.

Results obtained by the ANN model were truly competent and showed good generalization. A careful study of the results leads to observations of excellent agreement between ANN predictions and FEA outcomes. These indicated that the ANN is a powerful and user friendly computational tool to determine the 3D response of buildings subjected to earthquake. The based ANN models also enable the designer to rapidly compute the response of buildings in 3D during the preliminary design stage. The proposed model drastically reduced the computational work.

Appendix A. Validation results of ANN_1 model

See Tables A1, A2 and A3.

Table A1
Results of model A buildings for testing sets

Number of stories		SAP2000 (s)	NN	NN/SAP2000
3	x-axes	0.6553	0.6961	1.06226
	y-axes	0.6194	0.6498	1.04908
5	x-axes	1.1042	1.1090	1.00434
	y-axes	1.0531	1.0517	0.99867
7	x-axes	1.5603	1.5751	1.00948
	y-axes	1.4991	1.4993	1.00013
9	x-axes	2.0230	2.0399	1.00835
	y-axes	1.9460	1.9523	1.00323
11	x-axes	2.4933	2.4875	0.99767
	y-axes	2.3941	2.3931	0.99958

Table A2
Results of model B buildings for testing sets

Number of stories		SAP2000 (s)	NN	NN/SAP2000
5	x-axes	0.1931	0.2021	1.04661
	y-axes	0.1909	0.1845	0.96647
7	x-axes	0.3268	0.3170	0.97001
	y-axes	0.3202	0.3291	1.02780
9	x-axes	0.4881	0.4751	0.97337
	y-axes	0.4745	0.4858	1.02381
11	x-axes	0.6714	0.6730	1.00238
	y-axes	0.6482	0.6566	1.01296
13	x-axes	0.8721	0.8895	1.01995
	y-axes	0.8373	0.8274	0.98818

Table A3
Results of model C buildings for verification sets

Number of stories		SAP2000 (s)	NN	NN/SAP2000
5	x-axes	0.5040	0.5423	1.07599
	y-axes	0.4704	0.4588	0.97534
7	x-axes	0.8124	0.8512	1.04776
	y-axes	0.7513	0.7350	0.97830
9	x-axes	1.1316	1.1942	1.05532
	y-axes	1.0394	1.0395	1.00010
11	x-axes	1.4579	1.5316	1.05055
	y-axes	1.3318	1.3491	1.01299
13	x-axes	1.7906	1.8554	1.03619
	y-axes	1.6283	1.6602	1.01959

Appendix B. Validation results of ANN_{2-1} model

See Tables B1, B2 and B3.

Table B1
Results of model A buildings for testing sets

Number of stories		SAP2000 (m)	NN	NN/SAP2000
3	x-axes	0.1422	0.1441	1.01336
	y-axes	0.1846	0.1722	0.93282
5	x-axes	0.3501	0.2784	0.79520
	y-axes	0.2692	0.2384	0.88558
7	x-axes	0.7904	0.8032	1.01619
	y-axes	0.3219	0.3499	1.08698
9	x-axes	0.6842	0.6508	0.95118
	y-axes	0.6144	0.6114	0.99511
11	x-axes	0.8025	0.8286	1.03252
	y-axes	0.9300	0.9269	0.99666

Table B2
Results of model B buildings for testing sets

Number of stories		SAP2000 (m)	NN	NN/SAP2000
5	x-axes	0.0167	0.0239	1.43114
	y-axes	0.0108	0.0208	1.92593
7	x-axes	0.0598	0.0591	0.98829
	y-axes	0.0484	0.054	1.11570
9	x-axes	0.1031	0.1013	0.98254
	y-axes	0.1147	0.1206	1.05144
11	x-axes	0.1818	0.2222	1.22222
	y-axes	0.2430	0.2427	0.99877
13	x-axes	0.3245	0.2763	0.85146
	y-axes	0.3157	0.2718	0.86094

Table B3
Results of model C buildings for verification sets

Number of stories		SAP2000 (m)	NN	NN/SAP2000
5	x-axes	0.1365	0.1331	0.97509
	y-axes	0.1863	0.1659	0.89050
7	x-axes	0.4089	0.3891	0.95158
	y-axes	0.4011	0.4082	1.01770
9	x-axes	0.5292	0.5192	0.98110
	y-axes	0.4623	0.4424	0.95695
11	x-axes	1.0461	1.0418	0.99589
	y-axes	0.5799	0.5456	0.94085
13	x-axes	1.2873	1.2439	0.96629
	y-axes	0.7416	0.6845	0.92300

Appendix C. Validation results of ANN_{2-2} model

See Tables C1, C2 and C3.

Table C1
Results of model A buildings for testing sets

Number of stories		SAP2000 (10^4 kN)	NN	NN/SAP2000
3	x-axes	1.1410	0.8827	0.77362
	y-axes	1.1180	0.9659	0.86395
5	x-axes	1.1870	0.8265	0.69629
	y-axes	1.0490	1.0975	1.04623
7	x-axes	2.5240	2.9689	1.17627
	y-axes	0.9157	0.9776	1.06760
9	x-axes	1.4260	1.0681	0.74902
	y-axes	1.4010	1.4954	1.06738
11	x-axes	1.4260	1.5265	1.07048
	y-axes	1.9120	1.9006	0.99404

Table C2
Results of model B buildings for testing sets

Number of stories		SAP2000 (10^4 kN)	NN	NN/SAP2000
5	x-axes	0.4901	0.4931	1.00612
	y-axes	0.6419	0.6302	0.98177
7	x-axes	1.0071	0.7555	0.75017
	y-axes	1.0904	0.8935	0.81942
9	x-axes	1.1630	1.113	0.95701
	y-axes	1.1637	1.2835	1.10295
11	x-axes	1.7780	1.7057	0.95934
	y-axes	1.7615	1.8206	1.03355
13	x-axes	2.0270	2.1467	1.05905
	y-axes	2.0752	2.1968	1.05860

Table C3
Results of model C buildings for verification sets

Number of stories		SAP2000 (10^4 kN)	NN	NN/SAP2000
5	x-axes	0.8829	0.8602	0.97429
	y-axes	0.9381	0.8165	0.87038
7	x-axes	1.5936	1.6896	1.06024
	y-axes	1.5045	1.3631	0.90602
9	x-axes	1.2267	1.2018	0.97970
	y-axes	1.0443	1.1245	1.07680
11	x-axes	2.7900	2.8703	1.02878
	y-axes	1.0005	1.2392	1.23858
13	x-axes	2.1670	2.3317	1.07600
	y-axes	1.2129	1.2842	1.05878

Appendix D. Validation results of ANN_{2-3} model

See Tables D1, D2 and D3.

Table D1
Results of model A buildings for testing sets

Number of stories		SAP2000 (10^5 kN)	NN	NN/SAP2000
3	x-axes	1.0480	1.1410	1.08874
	y-axes	0.9541	0.9320	0.97684
5	x-axes	1.3680	1.3940	1.01901
	y-axes	1.3610	1.4220	1.04482
7	x-axes	1.4760	1.9320	1.30894
	y-axes	4,3710	4,1290	0.94464
9	x-axes	2.8130	2.9690	1.05546
	y-axes	2.6510	3,0440	1.14825
11	x-axes	4,0750	3,6350	0.89202
	y-axes	3,2130	3,0540	0.95051

Table D2
Results of model C buildings for testing sets

Number of stories		SAP2000 (10^5 kN)	NN	NN/SAP2000
5	x-axes	0.6320	0.8130	1.28639
	y-axes	0.5480	0.6220	1.13504
7	x-axes	1.7590	1.3830	0.78624
	y-axes	1.5210	1.3330	0.87640
9	x-axes	2.9250	3,0980	1.05915
	y-axes	2.1980	2.2000	1.00091
11	x-axes	4,8550	4,9060	1.01050
	y-axes	4,2370	4,1400	0.97711
13	x-axes	5,1210	4,9070	0.95821
	y-axes	5,3010	5,3680	1.01264

Table D3
Results of model C buildings for verification sets

Number of stories		SAP2000 (10^5 kN)	NN	NN/SAP2000
5	x-axes	1.2670	1.1610	0.91634
	y-axes	0.8760	0.9430	1.07648
7	x-axes	2.2760	2.4440	1.07381
	y-axes	2.4390	2.1220	0.87003
9	x-axes	2.3880	2.2900	0.95896
	y-axes	2.1300	2.4100	1.13146
11	x-axes	2.7010	2.6320	0.97445
	y-axes	6,8850	6,7810	0.98489
13	x-axes	3.3840	3.3790	0.99852
	y-axes	6.3150	5.7610	0.91227

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