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Neural network based model for seismic assessment of existing RC buildings

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Abstract. The objective of this study is to reveal the sufficiency of neural networks (NN) as a securer, quicker, more robust and reliable method to be used in seismic assessment of existing reinforced concrete buildings. The NN based approach is applied as an alternative method to determine the seismic performance of each existing RC buildings, in terms of damage level. In the application of the NN, a multilayer perceptron (MLP) with a back-propagation (BP) algorithm is employed using a scaled conjugate gradient. NN based model wasd eveloped, trained and tested through a based MATLAB program. The database of this model was developed by using a statistical procedure called P25 method. The NN based model was also proved by verification set constituting of real existing RC buildings exposed to 2003 Bingol earthquake. It is demonstrated that the NN based approach is highly successful and can be used as an alternative method to determine the seismic performance of each existing RC buildings.

Keywords: neural networks; scaled conjugate gradient algorithm; rapid assessment; P25 method; existing RC buildings

1. Introduction

The seismic assessment of existing reinforced concrete buildings is one of the most important matters being investigated by the researchers (Askan and Yucemen 2010, Gulay *et al*., 2011, Ozcebe *et al*. 2004, Ozcebe *et al*. 2003a, Ozcebe *et al*. 2003b, Ozcebe *et al*. 2003c, Sen 2010, Verderame *et al*. 2010, Yakut 2004, Yakut *et al*. 2003a, Yakut *et al*. 2003b, Yakut *et al*. 2003c, Yucemen *et al*. 2004). The seismic assessment studies generally focused on the reinforced concrete buildings, since they compose the majority of the building stocks throughout the world, especially in developing countries. Recent earthquakes, resulting in serious damage and casualties, have revealed the insufficiencies of existing reinforced concrete buildings in terms of some parameters such as design, materials to be used and labour (Yakut 2004).

Therefore, significant number of researches have been conducted to assess existing reinforced concrete building stocks and to provide means of improving the expected seismic performance of the vulnerable buildings. Yakut (2004) presented a preliminary assessment procedure to determine seismic performance of low- to mid-rise reinforced concrete buildings. In this procedure, a capacity index is calculated by taking into account the size, orientation and material properties of

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lateral load resisting structural system and type of underlying soil. Then architectural features, workmanship and material quality are reflected to this index by using various coefficients. Testing and calibration of this procedure is based on the compiled data from the damage surveys of Erzincan, Afyon, Bingöl earthquakes. He considered the implementation of the proposed assessment procedure for moderate or low ductility buildings. The method classifies the buildings either as safe or as unsafe and does not guarantee accurate results.

In the developing countries, there is a huge amount of the reinforced concrete buildings to be seismically assessed. When the seismic assessment time and the amount of the RC structures stocks are taken into consideration, it is obvious that faster, more robust, simple and reliable alternative seismic assessment method urgently need to be developed.

Fuzzy logic and inference systems are used in civil engineering. Sen (2010) presented a method that based on Fuzzy Logic Model to classify the existing buildings in terms of fuzzy sets as ‘‘without”, ‘‘slight”, ‘‘moderate”, ‘‘heavy”, and ‘‘complete” hazard categories. Fuzzy Logic Model is presented for the screening stage and using eight input variable data provided from storey number, soft storey, cantilever extension, visible building quality, weak storey, pounding effect, hill-slope effect and peak ground velocity (PGV) factors with one hazard categorization as output. He applied the proposed model to the 1249 existing reinforced buildings in Zeytinburnu quarter of Istanbul City. He found that about majority of the buildings falls in the “moderate” hazard category.

Neural network (NN) is an alternative method as a tool for modelling complex phenomena in different areas of research and engineering applications. In recent years, the NN was effectively applied in many engineering applications (Al-Salloum *et al*. 2012, Arjun and Kumar 2011, Arslan 2010, Badaoui *et al*. 2012, Caglar 2009, Caglar *et al*. 2008) and it seems to be very promising. NN is artificial intelligence tools able to generate meaningful solutions to problems through learning and generalizing from examples and experiences. Learning can occur even when the input data contain errors, incompleteness or fuzziness often typical of the design process. NNs are also advantageous because of their special features, such as low sensitivity to error, the structure of massive parallel processing, distribution of stored information and their generalization capability and adaptability to new data.

The aim of this study is to reveal the sufficiency of NN as a securer, quicker, more robust and reliable method to be used in seismic assessment of existing reinforced concrete buildings. The NN based approach is applied as an alternative method to determine the seismic performance of each existing RC buildings, in terms of damage level. Damage level of buildings can be grouped into five different levels as “none” for undamaged, “light”, “moderate”, “severe” and “collapsed”. The data were used to train, test and verify the NN based seismic assessment model. The data of training and testing sets are developed by using of a statistical procedure called P25 method (Gulay *et al*. 2011). The verification set is constituted of real existing RC buildings affected by Bingol earthquake to determine the performance of NN based seismic assessment model. Bingol database, existing 27 RC buildings, is gathered from literature (http://www.seru.metu.edu.tr/archives.html). The consistency between the results of real buildings and the estimations of the NN based model supports the effectiveness of the model.

2. Neural Networks (NN)

NN is a computational tool, which attempts to simulate the architecture and internal operational features of the human brain and nervous system. NN 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 adjustable weighted interconnections. The NN architecture is commonly referred to as a fully interconnected feed forward 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 most widely used training algorithm for multi-layered feed forward 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 adjust the weights and bias values. The inputs and the outputs of training and testing sets must be initialized before training a feed work network. In the forward phase, the weighted sum of input components is calculated as

$$net_j = \sum_{i=1}^{n} w_{ij} X_i + bias_j \tag{1}$$

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

$$out_j = f(net_j) = \frac{1}{1+e^{-(net_j)}} \tag{2}$$

The training of the network is achieved by adjusting the weights and 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 result in the right output for any input. Training the weights of the network is iteratively adjusted to capture the relationship between the input and output patterns.

The most classic training algorithm for the multi-layer feed-forward neural network is back-propagation algorithm. Two back-propagation training algorithms, which are gradient descent and gradient descent with momentum, are slow. Therefore, several adaptive training algorithms for NN have recently been put forward such as Conjugate Gradient Algorithm (CG) and Scaled Conjugate Gradient Algorithm (SCG). In this study, SCG is used as optimization algorithm, suggested in Moller (1993).

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

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

$$R^2 = 1 - \frac{\sum_i (T_i - out_i)^2}{\sum_i (out_i)^2} \tag{4}$$

where T_i and out_i *are* the target outputs and output of neural network values respectively for i_{th}

output neuron, and m is the number of neurons in the output layer. R^2 is for the absolute fraction of variance.

3. P25 method

In this study, P25 method is used to determine the seismic performance of buildings in database, consisting of training, testing and verification sets. P25 method is a statistical analysis based on the observed damage and significant building attributes. This method calibrates the results produced by using the characteristic parameters of the structure such as the cross sectional dimensions and stiffness of the existing columns, shear walls and filling walls, structural system layout, building height, structural irregularities, materials and soil properties.

In this method, a "K" factor is calculated by using effective shear area index and bending rigidity of the critical floor along with building height parameter calculated by using the characteristic features of each building. In addition, 25 correction factors are determined. The building performance score, hence finally, is obtained by multiplying the calculated value of "K" and correction factors.

The resulting performance score is assessed by bandwidths showing the building's risk area. The reliability of the structure is determined by the risk area of performance score classified as "low risk area", "medium risk area" and "high risk area". The basic structure of P25 method can be found at the reference (Gulay *et al*. 2011). As this article explains the essential perspectives of the P25 method in detail, there was no need to give detailed information about how the method works. However, the required discussion regarding P25 method was included in this paper as far as the proposed NN method is interested in the method.

4. Numerical studies

In this study, the NN was applied to estimate the damage level of existing reinforced concrete buildings subjected to potential earthquakes (Fig. 1). 9750 different types of buildings were generated by using of the real buildings plan and used for training and testing sets. 27 of real existing RC buildings are additionally used for verification set. The performance of all these buildings was determined through P25 method.

The data was divided into three parts as the training, testing and verification sets. 9150 data are selected as training set and employed to train NN based model. 600 data, not used in the training process, are selected as the testing set and used to validate the generalization capability of trained NN based model. Furthermore, the verification set is used to check the performance of this model. The verification set is consisted of 27 real RC buildings affected in the 1 May 2003 Bingol earthquake (http://www.seru.metu.edu.tr/archives.html).

Inputs of NN based model were consisted of 25 data sets of the most important structural parameters affecting the seismic response of existing RC building. These parameters are selected as number of storeys, heights of storeys, typical beam dimensions, soil conditions, soil profile and other observational or measurable parameters like material quality, soft storey irregularity, short column irregularity and frame discontinuity, etc. Total moment of inertia for each storey is also defined in order to avoid limitation to describe the structure due to the number of columns, shear-walls and number of bays (Table 1). The output of NN based model is selected as performance

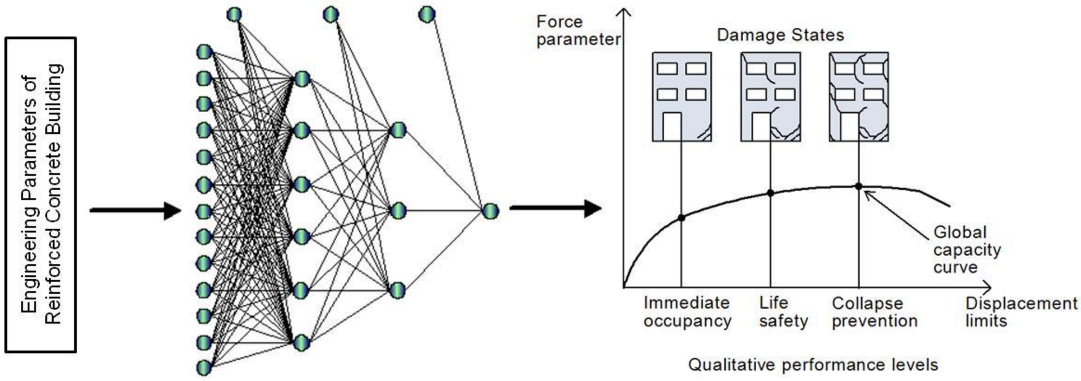


Fig. 1 The general structure of NN based seismic assessment model

Table 1 Physical properties and chemical compositions of raw materials

Input parameters	Notations
Number of stories	N
Ground storey height	h_z
Storey height	h_n
Area of ground floor	A_e
Total moment of inertia (in x-direction)	I_x
Total moment of inertia (in y-direction)	I_y
Shear-wall (in x-direction)	P_x
Shear-wall (in y-direction)	P_y
Spacing of confinement reinforcement	E
Concrete quality	BS
Total area of the infill wall in ground floor (in x-direction)	D_x
Total area of the infill wall in ground floor (in y-direction)	D_y
x-side dimension of the smallest rectangle for ground floor plan	L_x
y-side dimension of the smallest rectangle for ground floor plan	L_y
Soil profile	Z
Torsion irregularity	A_1
Floor discontinuity	A_2
Vertical structural element discontinuity	B_3
Short Column	K_k
Total area of overhang portion	A_c
Strong beam and weak column	ZG
Basement floor	t_d
Pounding potential	C_0
The level difference of each floor	S_k
Soil conditions	t

score of the existing RC building.

Inputs and outputs are normalized in the (0-1) range by using simple normalization methods. The numbers of neurons in input and output layers are based on the geometry of the problem. But, there is no general rule for the selection of the number of neurons in a hidden layer and the number of the hidden layers. Hence, they were determined by trial and error method in this study.

In order to determine most appropriate NN model, a lot of different NN models with various numbers of hidden layers and neurons in hidden layers are trained and tested for 5000 epochs. The criterion to establish the most appropriate NN model was selected as the determination coefficient (R^2). The most appropriate NN models were chosen considering to the performance of both training and testing sets in terms of R^2. The R^2's of the NN models were determined for both one

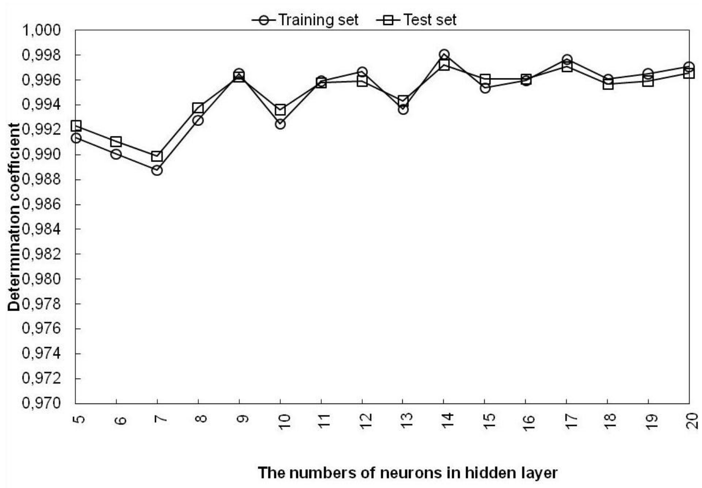


Fig. 2 The determination coefficient of NN models with number of neurons in one hidden layer

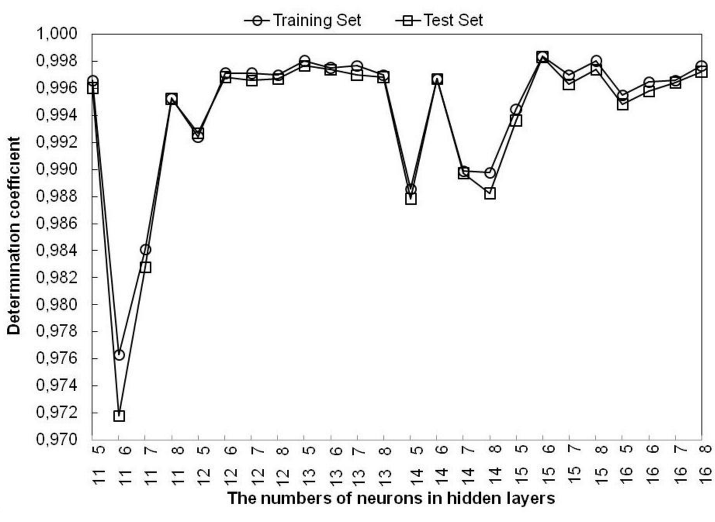


Fig. 3 The determination coefficient of NN models with number of neurons in two hidden layer

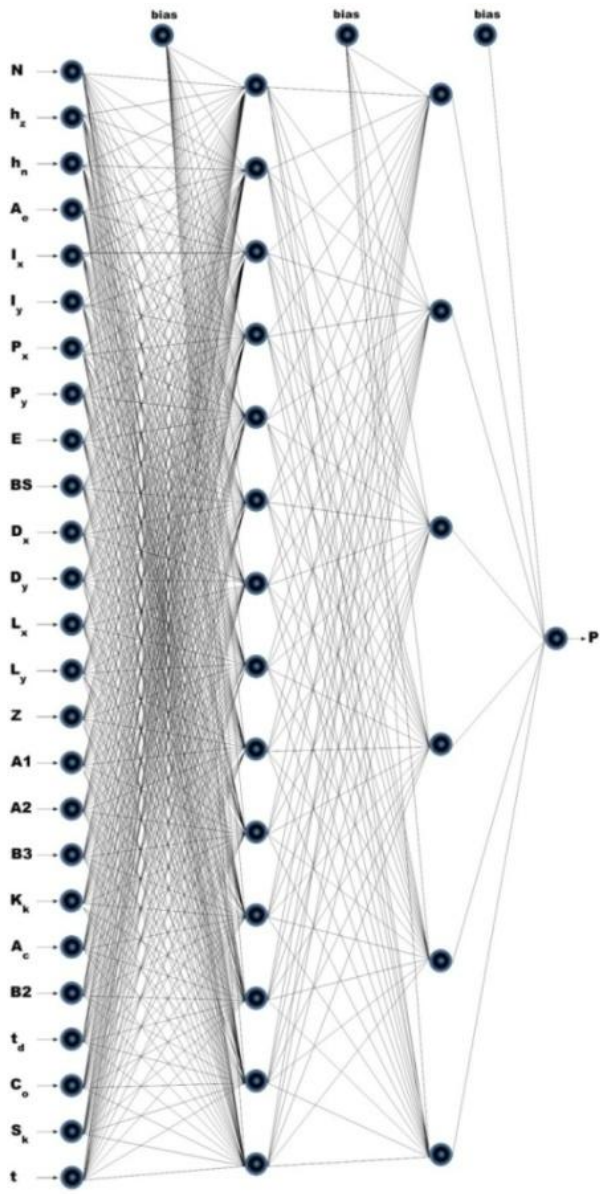


Fig. 4 Architecture of NN based seismic assessment model

and two hidden layers with various numbers of neurons. While Fig. 2 illustrates the obtained results of R^2 values for one hidden layers, Fig. 3 indicates the case where the combinations of two hidden layers were used to get the NN model with the best performance.

Figs. 2 and 3 show the effect of the number of hidden layers and neurons in the hidden layers on the NN model accuracy. As can be seen from Figs. 2 and 3, the comparison of the performance of the NN models with both one and two hidden layers revealed the fact that the two layers model resulted in better model accuracy. Consequently, the NN based seismic assessment model was selected with 25 neurons in input layer, 14 neurons in first hidden layer, 6 neurons in second hidden layer and 1 neuron in output layer to define the performance score (P) of the existing RC building (Fig. 4).

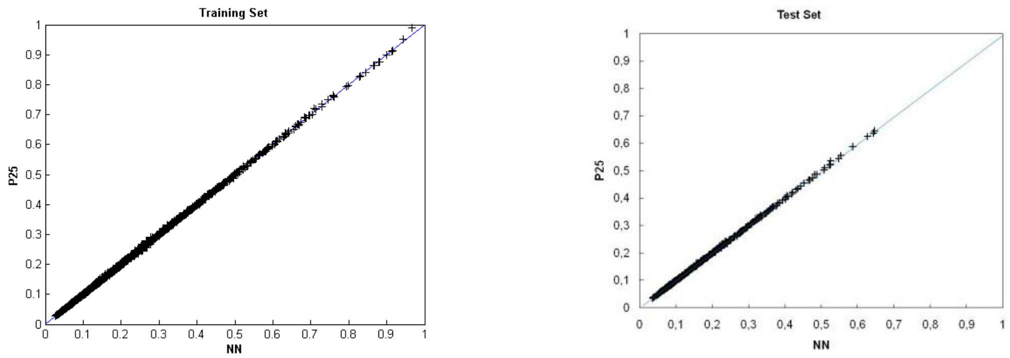
A Matlab based program with a graphical user interface (GUI) was developed to train and test the NN based model (Caglar 2009). In the NN based seismic assessment model, type of back-propagation is scaled conjugate gradient algorithm (SCGA), activation function is sigmoidal function, and number of epochs (learning cycle) are 100000.

The values of parameters used in this research are summarized as follow

• Number of input layer unit = 25.
• Number of hidden layers = 2.
• Number of first hidden layer units = 14.
• Number of second hidden layer units = 6.
• Number of output layer units = 1.
• Learning algorithm = scaled conjugate gradients algorithm (SCGA).
• Learning cycle = 100,000.

Table 2 The comparison of performance scores of NN based model with P25 method

No	ID	Performance Score		$\frac{NN}{P25}$	P25	YSA	Existing status
		*P*25	NN				
1	BNG-3-4-1	38.08	25.32	0.66	Moderate	Moderate	Light
2	BNG-3-4-2	45.88	40.47	0.88	None	None	None
3	BNG-3-4-4	44.11	42.71	0.97	None	None	None
4	BNG-5-5-1	41.11	29.74	0.72	Light	Moderate	Light
5	BNG-6-2-8	48.88	49.74	1.02	None	None	Severe
6	BNG-6-3-1	34.56	39.42	1.14	Moderate	Moderate	Moderate
7	BNG-6-3-4	57.75	47.42	0.82	Light	Light	Light
8	BNG-6-3-10	45.86	38.86	0.85	None	Moderate	None
9	BNG-6-3-11	49.23	48.06	0.98	None	None	None
10	BNG-6-3-12	43.82	40.82	0.93	None	None	None/Light
11	BNG-6-4-2	14.34	14.32	1.00	Severe	Severe	Severe
12	BNG-6-4-3	32.19	22.96	0.71	Moderate	Moderate	Collapsed
13	BNG-6-4-5	65.91	65.01	0.99	None	None	None
14	BNG-6-4-7	33.55	32.11	0.96	Moderate	Moderate	Moderate
15	BNG-10-3-3	35.30	22.93	0.65	Moderate	Moderate	Moderate
16	BNG-10-3-10	18.03	7.53	0.42	Moderate	Severe	Severe
17	BNG-10-4-4	17.71	17.06	0.96	Moderate	Moderate	Moderate
18	BNG-10-4-6	29.29	31.03	1.06	Moderate	Moderate	Light
19	BNG-10-4-9	46.36	46.46	1.00	None	None	None
20	BNG-10-5-1	35.85	29.79	0.83	Moderate	Moderate	Moderate
21	BNG-10-5-2	26.47	26.88	1.02	Moderate	Moderate	Light
22	BNG-10-5-11	52.81	47.19	0.89	Light	Light	Light
23	BNG-11-2-3	26.94	28.61	1.06	Moderate	Moderate	Moderate
24	BNG-11-4-1	29.09	29.17	1.00	Moderate	Moderate	Severe
25	BNG-11-4-2	32.59	27.67	0.85	Moderate	Moderate	Severe
26	BNG-11-4-4	35.63	33.73	0.95	Moderate	Moderate	Moderate
27	BNG-11-4-5	54.35	50.95	0.94	None	None	None



(a) training set (b) testing set

Fig. 5 Performance of NN based seismic assessment model

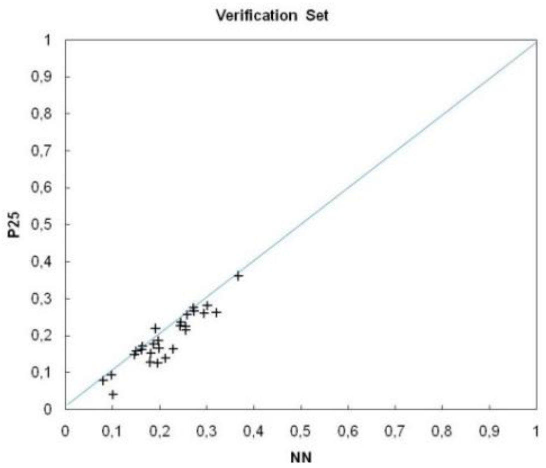


Fig. 6 Performance of NN based performance assessment model for reference set

5. Results and discussions

The performance of the NN based seismic assessment model showed that the correlations between targets and outputs are consistent as shown in Figs. 5(a) and 5(b) for training and testing sets, respectively. The results of Fig. 5(a) indicate that the NN based seismic assessment model is successful in learning the relationship between the input parameters and outputs. The results of testing phase in Fig. 5(b) show that the NN based seismic assessment model is capable of generalizing this relationship. Performance of verification set of NN based seismic assessment model were presented in Table 2 and Figs. 6-7.

The results of verification set determined through P25 method and NN based seismic assessment model are given in Table 2. The normalized results of NN based seismic assessment model with P25 results were compared to assess the convergence of this model. As can be seen from the results of verification set, NN based model results agree well with the P25 method results.

The performance of verification set for NN based model and P25 method were compared with

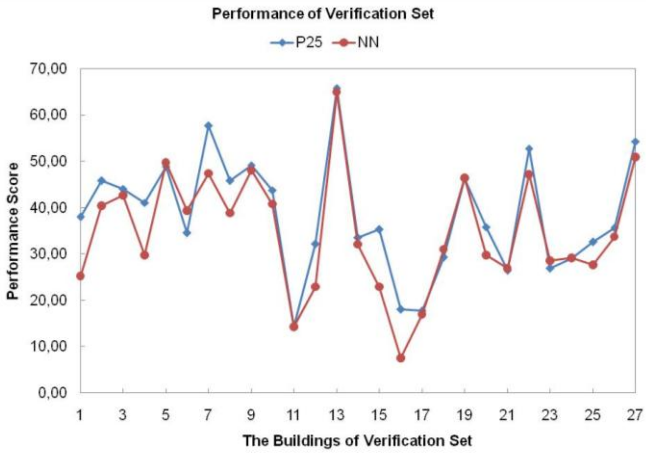


Fig. 7 Performance of NN based performance assessment model for reference set

the existing status of real RC buildings and tabulated in Table 2. P25 method and NN based seismic assessment model capture 19 and 18 out of 27 existing building status, respectively. It should be pointed out that this minor difference due to the training necessity of the NN based seismic assessment model by using the database of training and testing sets developed by P25 method. The critical point to show the success of the NN based model, however, is the closeness of the ratio of performance score values resulted from P25 and NN based model.

6. Conclusions

NN based seismic assessment model was developed to determine the seismic performance of existing reinforced concrete buildings. NN based model was tested with the testing set which is not used in the training process. NN based model was also confirmed with verification set, which is constituted of real 27 of existing RC buildings affected by earthquake. Results obtained by the NN based model were truly competent and showed good generalization. A careful study of the results leads to the observations of excellent agreement between NN based model predictions and P25 method outcomes.

The performance of NN based model is presented for training, testing and verification sets. The results of training set indicate that the NN based model is successful in learning the relationship between the input parameters and outputs. The results of testing and verification sets also show that the NN based model is capable of generalizing between input and output variables. It was proven that the NN based approach applied in this study is highly successful for the determination of the seismic performance of existing reinforced concrete buildings.

Although a careful examination of Table 2 discloses the fact that the damage level of 3 buildings out of 27 have been estimated incorrectly, the results obtained by the NN based model were truly competent and showed good generalization. As NN based model was trained by using P25 method, the outcomes were compared with both P25 method and the existing status of real RC buildings. The comparisons revealed that there were only 3 buildings out of 27 not having the same level of damage. If compared to the existing results of real RC buildings, these two methods indicate variations. The proposed neural network approach has demonstrated to have a high capacity of generalization and NN based model can be used as an alternative method to determine the seismic performance of existing RC buildings. It is proven that the NN based model can successfully determine the damage level of existing RC buildings.

The seismic assessment of existing reinforced concrete buildings is one of the most important matters in order to minimise the adverse effects of earthquakes. There is a great challenge and responsibility for engineers to determine the earthquake safety of huge building stock rapidly and take the required quick countermeasures to minimise the possible death toll. The model proposed in this study is a rapid assessment model to determine the earthquake performance of existing stocks in a quicker, simpler and more reliable way. Accordingly, NN based model has a great potential to make significant contribution to the determination of earthquake performance of this huge building stocks.

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Appendix A

Table A1 Input parameters of reference set buildings

ID	N	h_z (m)	h_n (m)	A_s (m^2)	I_x (m^4)	I_y (m^4)	P_x	P_y	E (mm)	BS	D_x (m^2)	D_y (m^2)	L_x (m)	L_y (m)	Z	$A1$	$A2$	$B3$	K_k	A_c	ZG	t_d	C_o	S_k	t
BNG-3-4-1	4	2.80	2.80	488.58	0.19	0.20	0.00	0.00	250.00	1.00	2.12	5.48	21.05	22.45	1.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00
BNG-3-4-2	4	2.80	2.80	467.23	0.27	0.11	1.00	0.00	250.00	2.00	6.08	8.14	20.55	21.35	1.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00
BNG-3-4-4	4	2.80	2.80	477.50	0.36	0.28	0.00	1.00	250.00	2.00	3.72	1.76	23.70	20.55	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
BNG-5-5-1	5	3.80	3.00	370.51	0.10	0.20	0.00	0.00	100.00	2.00	2.54	7.62	15.80	23.45	1.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00
BNG-6-2-8	2	3.20	2.70	102.40	0.05	0.01	0.00	0.00	500.00	1.00	0.00	2.95	16.00	6.40	0.30	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	0.00
BNG-6-3-1	3	3.30	2.80	218.90	0.08	0.08	0.00	0.00	400.00	3.00	5.20	3.40	22.00	9.95	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00
BNG-6-3-4	3	3.00	2.90	106.95	0.02	0.04	0.00	0.00	300.00	3.00	3.10	0.00	8.00	11.50	1.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
BNG-6-3-10	3	3.50	3.00	112.84	0.03	0.02	0.00	0.00	250.00	3.00	1.22	4.59	10.40	10.85	1.00	1.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00
BNG-6-3-11	3	3.15	2.80	212.95	0.07	0.07	0.00	0.00	200.00	2.00	1.61	2.97	14.15	15.05	1.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
BNG-6-3-12	3	3.65	2.80	128.26	0.09	0.03	0.00	0.00	250.00	3.00	0.00	6.18	11.35	12.60	1.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
BNG-6-4-2	4	3.40	2.80	505.15	0.08	0.14	0.00	0.00	400.00	1.00	3.31	14.92	21.45	23.55	1.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
BNG-6-4-3	4	2.80	2.80	134.36	0.02	0.05	0.00	0.00	500.00	1.00	1.25	3.48	11.15	12.05	1.00	1.00	0.00	0.00	0.00	1.00	1.00	1.00	0.00	1.00	0.00
BNG-6-4-5	4	2.80	2.80	90.59	0.02	0.06	0.00	0.00	300.00	4.00	0.58	4.16	9.15	9.90	1.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
BNG-6-4-7	4	2.75	2.75	218.75	0.60	0.11	1.00	0.00	500.00	1.00	2.08	2.07	17.50	12.50	1.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
BNG-10-3-3	4	3.40	3.40	306.06	0.21	0.15	0.00	0.00	500.00	2.00	0.00	1.76	20.75	14.75	1.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00
BNG-10-3-10	3	3.50	2.80	652.66	0.30	0.07	0.00	0.00	500.00	1.00	1.23	11.58	29.65	23.70	1.00	1.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00
BNG-10-4-4	4	5.40	3.00	787.20	0.41	0.17	0.00	0.00	100.00	2.00	4.89	16.67	25.15	31.30	1.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
BNG-10-4-6	4	3.30	2.70	602.00	0.18	0.70	0.00	0.00	100.00	4.00	8.72	0.00	28.00	21.50	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00
BNG-10-4-9	4	5.00	3.20	550.20	9.73	10.73	1.00	1.00	100.00	4.00	3.63	12.52	21.00	26.20	1.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	1.00
BNG-10-5-1	5	2.80	2.80	583.67	3.62	0.27	1.00	1.00	500.00	3.00	6.87	8.19	23.30	25.05	1.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
BNG-10-5-2	5	3.85	3.40	627.00	0.43	0.47	1.00	1.00	100.00	4.00	0.00	8.04	38.00	16.50	1.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00
BNG-10-5-11	5	3.00	2.75	91.98	0.08	0.03	0.00	0.00	500.00	3.00	1.42	4.01	8.40	10.95	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
BNG-11-2-3	2	2.90	2.80	121.00	0.03	0.04	0.00	0.00	400.00	1.00	1.32	0.00	13.75	10.10	0.30	0.00	0.00	0.00	1.00	1.00	1.00	0.00	0.00	1.00	1.00
BNG-11-4-1	4	3.15	2.80	224.85	0.08	0.51	0.00	1.00	500.00	1.00	3.57	1.00	19.30	11.65	1.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
BNG-11-4-2	4	3.50	3.00	125.62	0.04	0.02	0.00	0.00	500.00	1.00	1.68	3.80	12.95	9.70	1.00	1.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00
BNG-11-4-4	4	3.05	2.80	121.46	0.04	0.04	0.00	0.00	500.00	1.00	1.10	1.71	11.85	10.25	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00
BNG-11-4-5	4	2.80	2.80	145.78	0.05	0.05	0.00	0.00	500.00	3.00	1.83	2.42	8.55	17.05	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00