AN ANN APPROACHES ON ESTIMATING EARTHQUAKE PERFORMANCES OF EXISTING RC BUILDINGS

M. H. Arslan,[*] *M. Ceylan*,[†] *T. Koyuncu*[‡]

Abstract: This study aims at developing an artificial intelligence-based (ANN based) analytical method to analyze earthquake performances of the reinforced concrete (RC) buildings. In the scope of the present study, 66 real RC buildings with four to ten storeys were subject to performance analysis according to 19 parameters considered effective on the performance of RC buildings. In addition, the level of performance of these buildings in case of an earthquake was determined on the basis of the 4-grade performance levels specified in Turkish Earthquake Code-2007 (TEC-2007). Thus, an output performance data group was created for the analyzed buildings, in accordance with the input data. Thanks to the ANN-based fast evaluation algorithm mentioned above and developed within the scope of the proposed project study, it will be possible to make an economic and rapid evaluation of four to ten-storey RC buildings in Turkey with great accuracy (about 80%). Detection of post-earthquake performances of RC buildings in the scope of the present study will facilitate reaching important results in terms of buildings, which will be beneficial for Civil Engineers of Turkey and similar countries.

Key words: *Earthquake performance, reinforced concrete, artificial neural network*

Received: December 30, 2010
Revised and accepted: September 21, 2012

1. Introduction

In the research published after earthquakes over the past 20 years, the reinforced concrete (RC) buildings damaged by the earthquakes had many common defects, and a large number of the existing RC buildings did not have sufficient strength,

[*]Musa Hakan Arslan – correspondence author
Selcuk University, Engineering Faculty, Department of Civil Engineering, 42075, Konya, Turkey, Phone: + 90 332 223 26 60, Fax: + 90 332 241 06 35, E-Mail: mharslan@selcuk.edu.tr
[†]M. Ceylan
Selcuk University, Engineering Faculty, 42075, Konya, Turkey
[‡]T. Koyuncu
Seydisehir Municipality Konya, Turkey

stiffness or ductility because of these defects. Although the existing RC buildings are weak, Turkey has an earthquake code (TEC-2007) [1] with strict rules in regions with a high earthquake risk, just like other countries. This situation shows that the main reason for the difference between the code and the existing condition is insufficiencies in both the projects and the control mechanism for the construction process.

The earthquake design criteria in the national earthquake codes are constantly upgraded and improved with the increase in knowledge about the real behavior of structures during earthquakes. Performance of the existing RC buildings in Turkey under earthquake effect is determined according to TEC-2007 [1] criteria. By using a series of methods that are developed according to the basic principles of FEMA-356 [2] and ATC-40 [3] and that can be easily adapted to the Turkish building stock; TEC-2007 [1] enables calculation of the performance of existing RC buildings.

The expected earthquakes and current status of particularly the reinforced concrete (RC) building stock in Turkey require RC buildings to be urgently evaluated. Considering the current building stock and the seismicity of Turkey, this is theoretically and practically very difficult. Due to this difficulty, researchers have developed and continue to develop certain rapid evaluation methods and structural scoring systems in the past years [4–11]. The need for a rapid screening of an RC building is first recognized by FEMA [4] in 1988. After that, alternative rapid assessment techniques for the RC frame buildings have been developed by many researchers. For instance, Hassan and Sözen [5] presented an alternative rapid assessment procedure by considering the damage patterns of the low-rise RC frame buildings in Turkey. A similar procedure was introduced by Gülkan and Sözen [6]. Ozcebe et. al [7] and Yakut et al. [8] proposed formulations for rapid assessment for RC buildings. Similarly, Boduroglu, et al. [9] and Pay [10] also introduced slightly different techniques for the seismic and collapse vulnerability assessment of the existing buildings in Turkey. Bal et. al [11] predicted the collapse vulnerability of RC buildings using P25 method. The main objective of these methods was to evaluate an RC building in a very short time and to obtain a result that is close to the real performance. In this way, cost and time-saving will be achieved during detailed evaluation of thousands of buildings. It is obvious that conducting a detailed analysis of an RC building is quite difficult due to financial and time constraints. For this reason, estimating the performance of an RC building within a short time period is very important.

The use of artificial neural network (ANN) models may drastically reduce the computational effort in such cases. The ANN is a type of artificial intelligence application that has been implemented by engineers to carry out specialized design tasks so far. ANNs have been widely used for the prediction of various structural quantities [12–17] structural damage diagnosis and detections [18, 19], evaluation of RC buildings performance [20], active response control of offshore structures [21, 22] and static model identification of an FRP deck [23] etc. ANNs thus have been a powerful tool in solution of various structural engineering problems.

In this study, using the parameters obtained from RC buildings projects in computer media, an ANN based algorithm was developed to evaluate behaviours and performances of RC buildings under earthquake loads. The mentioned algorithms were calibrated for the 4-storey or 10-storey RC buildings, a general type of residence in Turkey, where a significant part of the existing RC building stock of this type is known to be inadequate. Earthquake performances of RC buildings were determined and classified on the basis of the obtained results, and building performances were determined with high accuracy by using the recommended method. Thus, it was shown that this ANN based model, which brings innovations for the fast evaluation of earthquake risks of RC buildings, can be developed on a large number of sample buildings and can be used in areas with a high earthquake risk.

2. Performance Analysis According to TEC-2007 Principles

According to TEC-2007 [1], the performance of RC buildings can be evaluated using two methods: linear or non-linear method. The civil engineer chooses a method to determine the damages and performance of the building, and there is a four-stage performance scale for both of the methods in TEC-2007 [1]. The condition of a damaged building at the time of an anticipated earthquake can be determined with this scale.

The non-linear method is based on plastic hinge hypothesis and performed by carrying out pushover analysis and the capacity curve comprising lateral load – lateral displacement. On the other hand, the linear method is much simpler than the non-linear method and is based on a linear structural analysis approach. In this method, earthquake load reduction coefficient (R), which is an expression of the ductility of the building, and building safety factor (I), are taken as 1. This method can be applied in two ways: a) equivalent static seismic load method (this can be used in the buildings with a coefficient smaller than 8 and a maximum height of 25 meters where torsion is insignificant), and b) mode superposition method (this can be used in all buildings). According to the results of both analyses, an effect capacity ratio for each cross section in the load bearing system is calculated according to Equation 1 provided in TEC-2007 [1] and the damage limit of the section is determined (r). In this formula, R_s refers to the capacity of the related section, E to the elastic earthquake effect which is expected to be accommodated, G and Q refer to the cross section forces produced by the dead and live load.

$$r = \frac{E}{R_s - (G + Q)} \tag{1}$$

Fig. 1 indicates force deformation relationship in a ductile RC section. An identified section damage status gives the storey damage status which then gives the building global damage status. Thus, the global damage and performance level to be recorded in the building in case of an earthquake are determined. The general performance outcomes of RC structures are: withstanding minor earthquakes undamaged; withstanding medium-scale earthquakes with limited damage; and withstanding large-scale earthquakes without total collapse. The critical outcome is the prevention of total structural collapse. This means that the upper level withstands total collapse while the sub-level, for crucial structures, may be slightly damaged but remains fit for immediate occupancy. Between the sub- and

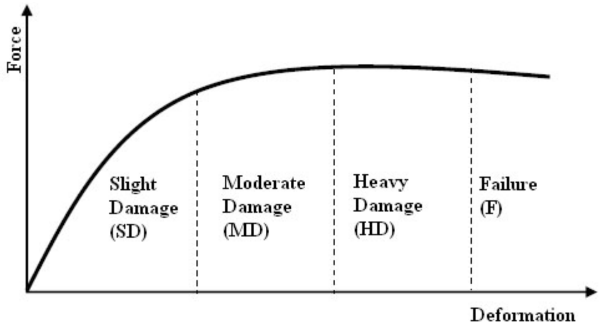


Fig. 1 *Force deformation relationship for ductile members (TEC-2007).*

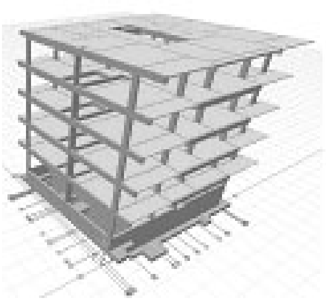
upper-levels, the Life Safety level is required. TEC-2007 [1] divides the building performance level into four categories according to the number of columns, beams and shearwalls. These are Immediate Occupancy (IO), Life Safety (LS), Collapse Prevention (CP) and Collapse (C), respectively. The criteria given in the Code for these performance levels are listed in Tab. I.

Performance Level	Performance Criteria
Immediate occupancy (IO) ***(Class-1, S_1)***	• The ratio of beams in Slight Damage (SD) and Moderate Damage (MD) shall not exceed 10% in any storey. • There must not be any columns beyond Slight Damage (SD). • There must not be any beams beyond Heavy Damage (HD).
Life Safety (LS) ***(Class-2, S_2)***	• The ratio of beams in Moderate Damage (MD) and Heavy Damage (HD) shall not exceed 30% in any storey. • In any storey, the shear force carried by columns in Heavy Damage (HD) shall not exceed 30% of storey shear.
Collapse Prevention (CP) ***(Class-3, S_3)***	• The ratio of beams in Heavy Damage (HD) must not exceed 20% in any storey. • In any storey, the shear force carried by column that passed Slight Damage (SD) must not exceed 30% of storey shear force.
Collapse (C) ***(Class-4, S_4)***	• If the failure cannot be prevented, it is under failure condition.

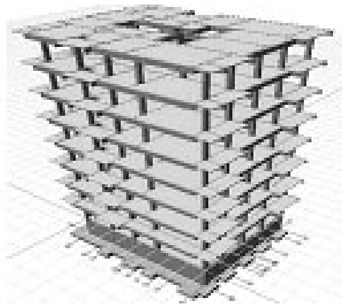
Tab. I *Structure performance based on damage in Turkish Earthquake Code (TEC-2007 [1]).*

3. Formation of Data Set

Most of the residential and commercial buildings in Turkey are constructed with cast-in-situ RC. Again, most of these buildings have 4–10 floors. The total of 66 RC buildings with 4 – 10 storeys, representing the existing RC buildings in Turkey, were selected for the present study [24]. The selected RC buildings were modelled with the commercial program (IDEStatik V.6.0053). The program's models can be easily converted to the SAP2000 [25]. The performance analysis of the RC buildings was performed according to the linear procedure (mode superposition method) specified in TEC-2007 [1]. In the analysis, the earthquake, ground motion with 10% probability of exceedance in 50 years, equivalent to a 475-year return period was chosen. TEC-2007 [1] states that under this earthquake, the residence buildings should provide the Life Safety (LS) performance level (details are given in the Tab. I). The building which provides this performance level will not be severely damaged in the earthquake but retains a margin against onset of partial or total collapse. Two residence building models are shown in Fig. 2 to provide some examples out of 66 residence buildings chosen in the analysis.



Type 1



Type 66

Fig. 2 *Two of the RC buildings analyzed in the study.*

The earthquake performance of an RC building is based on many parameters. These parameters can be divided into two groups: a) parameters related to earthquake and soil type, and b) parameters related to building sectional, material and geometric properties. The parameters considered in the selected RC buildings were as follows: earthquake acceleration (or earthquake zone) (EZ), soil type (Z), building project year (PY), number of storey of the building (NS), average column ratio in a storey, average shear wall ratio in a storey (ρ_{CA}, ρ_{SWA}), average longitudinal bar ratio in columns, average longitudinal bar ratio in shear walls ($\rho_{\ell col}$, $\rho_{\ell SW}$), stirrup (lateral tie or transverse reinforcement) condition in the load bearing system (s_c), basement storey height (B), slab types (ST), concrete compression strength (C), steel tension strength (S), average inertia of beams (I_b) irregularity types (IT), clerestory status (CL), ductility level (R), foundation types (FT), and living load reduction coefficient (n).

TEC-2007 describes different performance levels of RC structures. The performance levels related to the expected damage in a building depend mainly on the storey drift, materials quality, structural system, and construction details of various components and their connections. In the modelling process, in addition to the mentioned input data, the earthquake performance of the buildings was determined by the performance analysis (output data). Four different performance levels of the buildings during an earthquake were grouped as S_1, S_2, S_3 and S_4. Here S_1= IO, S_2= LS, S_3= CP and S_4= C. In the study, the total of 19 different structural parameters described above are used. Arslan [16, 20] and Arslan et al. [17] studied different structural parameters for frame RC and prefabricated industrial buildings. In the mentioned studies, basic parameters were considered as the main reason for damages according to the researchers.

Tab. II indicates variation intervals of some parameters for the selected 66 buildings. For the variation interval of other parameters (PY, s_c, B, S, ST, IT, CL, R, FT, EZ etc.) which are not presented in Tab. II, constants such as 0, 1, 2, 3 etc. were used. For example, value 0 was entered for PY for the buildings built before 1998 and value 1 for the buildings built after 1998. The reason behind this is that TEC went through a radical change in 1998. Therefore, the buildings designed after the year 1998 are safer than the ones designed before 1998. Similarly, for example ST was defined as 1 in hollow-tile floor slab, 2 in plate slab and 3 in beam slab.

Parameter	Minimum Value	Maximum Value
Number of Storey (NS)	4	10
Average Column Ratio (ρ_{CA})	0.008197	0.024721
Average Shear Wall Ratio (ρ_{SWA})	0	0.011725
Average Longitudinal Bar Ratio in Columns ($\rho_{\ell col}$)	0.00843	0.012828
Average Longitudinal Bar Ratio in SW ($\rho_{\ell SW}$)	0	0.010643
Steel Tension Strength (S)	220	420
Concrete Compression Strength (C)	16	20
Average Inertia of Beams (I_B)	0.001092	0.0045
Importance Factor (I)	1	1.5
Soil Type (Z)	1	4
Earthquake Reduction Coefficient (R)	4	7
Living Load Reduction Coefficient (n)	0.3	0.6
Structural Performance (S_1-S_4)	1	4

Tab. II *The used data range.*

4. Artificial Neural Network (ANN)

In this study, a three-layered (input layer, hidden layer and output layer) feed-forward artificial neural network (ANN) stucture was used and trained with the error backpropagation algorithm. In the feed-forward ANNs, the neurons in each layer are only fully interconnected with the neurons in the next layer. Travel of information is processed for a single "forward" direction. Its errors propagate backwards from the output neurons to the inner neurons [26]. The backpropagation algorithm is defined as follows [27]:

1. Initialization: Set all the weights and biases to small real random values.
2. Presentation of input and desired outputs: Present the input vector $x(1), x(2), \ldots, x(N)$ and corresponding desired response $d(1), d(2), \ldots, d(N)$, one pair at a time, where N is the number of training patterns.
3. Calculation of actual outputs: Use Eq. (2) to calculate the output signals $y_1, y_2, \ldots, y_{N_M}$

$$y_i = \varphi\left(\sum_{j=1}^{N_{M-1}} w_{ij}^{(M-1)} x_j^{(M-1)} + b_i^{(M-1)}\right), i = 1, \ldots, N_{M-1} \tag{2}$$

4. Adaptation of weights (w_{ij}) and biases (b_i):

$$\Delta w_{ij}^{(l-1)}(n) = \mu . x_j(n) . \delta_i^{(l-1)}(n) \tag{3}$$

$$\Delta b_i^{(l-1)}(n) = \mu . \delta_i^{(l-1)}(n), \tag{4}$$

where

$$\delta_i^{(l-1)}(n) = \begin{cases} \varphi'(net_i^{(l-1)}) \left[d_i - y_i(n)\right], l = M \\ \varphi'(net_i^{(l-1)}) \sum\limits_k w_{ki} . \delta_k^{(l)}(n), 1 \leq l \leq M \end{cases}, \tag{5}$$

in which $x_j(n)$= output of node j at iteration n, l is the layer, k is the number of output nodes of neural network, M is the output layer, ϕ is the activation function. The learning rate is represented by μ.

After completing the training procedure of the neural network, the weights of MLP are frozen and ready for use in the testing mode. The general structure of ANN is presented in Fig. 3.

5. Application of ANN

In classification of RC buildings under earthquake loads according to their performances, the selection of appropriate ANN architecture is very important for the accuracy of the study. As indicated in the literature [15–16, 20], the optimum number of hidden nodes and learning rate values comprising the architecture of the network were found in the training and testing phase of the ANN via experimentation. Firstly, by keeping the learning rate constant, the number of hidden nodes was increased from 2 to 100. The optimum number of hidden nodes was determined as 80 based on the lowest training and test error. Similarly, 80 hidden nodes which were found as the optimum number of hidden nodes were kept constant. After the stepwise increase of learning rate from 0.001 to 5.0, it was found that the value of 2.0 had the lowest training and testing error. Tab. III indicates the optimum ANN architecture.

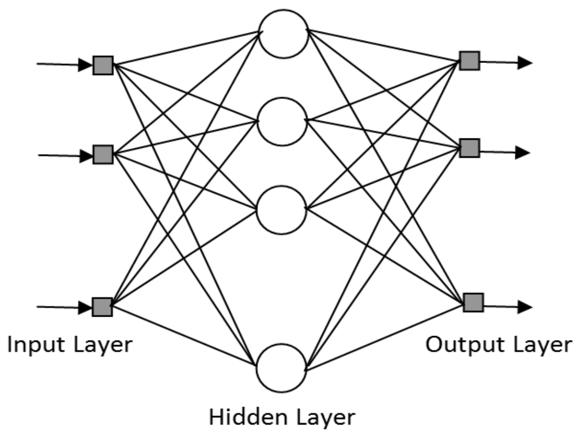


Fig. 3 *The general structure of ANN.*

Number of Hidden Nodes	Learning Rate	Number of Iteration
80	2.0	10,000

Tab. III *Optimum ANN architecture.*

In this study, the ANN was trained with 11 different algorithms which are commonly used in ANN applications in the literature: BFG, CGB, CGF, CGP, GDA, GDM, LM, OSS, RP and SCG algorithms [17]. All training procedures were performed by operating the ANN with 10,000 iterations. 19 different structural parameters (see "Formation of data set" section) were presented to the ANN as inputs. The ANN outputs were labelled as four classes (S_1, S_2, S_3 and S_4) including four different performance levels of the buildings during an earthquake. Fig. 4 shows the used network architecture.

6. Measures for Performance Evaluation

6.1 2-Fold cross-validation

If data is not scarce, then the set of available input-output measurements can be divided into two parts – one part for training and one part for testing. In this way several different models, all trained on the training set, can be compared on the test set. This is the basic form of cross-validation [28].

In this study, 2-fold cross-validation test was performed to confirm the accuracy of the classification procedure and to test generalization capability of the proposed network. The used data set contains the data of 66 buildings comprised of 4 classes (S_1, S_2, S_3 and S_4). Out of these 66 buildings, 7 belong to S_1, 20 belong to S_2, 23 belong to S_3, and 16 belong to S_4. To apply 2-fold cross-validation test, these buildings were divided into 2 data sets. Tab. IV indicates building classes. In line

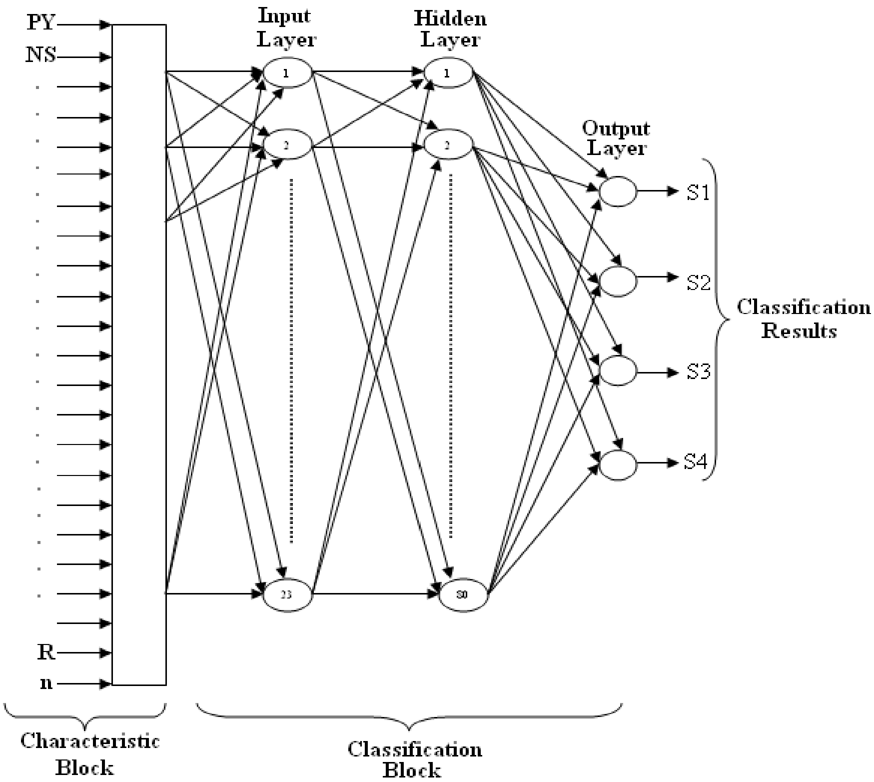


Fig. 4 *ANN Structure.*

with the above mentioned test procedure, the ANN was trained with the 1st data set and tested with the 2nd data set. Then it was trained with the 2nd data set and tested with the 1st data set.

Data Set	Class 1 (S_1)	Class 2 (S_2)	Class 3 (S_3)	Class 4 (S_4)	Total
1	4	11	12	8	35
2	3	9	11	8	31

Tab. IV *Distribution of classified data sets according to groups.*

6.2 Calculation of training and test errors

Training and test errors given in tables were conducted according to Equation 6.

$$\text{Training and test error } (\%) = \left(\frac{\sum\limits_{i=1}^{k} |t(i) - a(i)|}{m * n} \right) * 100, \tag{6}$$

where $t(i)$ is desired outputs, $a(i)$ is outputs of neural network, k is the number of samples in the training or test data, m is the number of segments in the training or test data, and n is the number of outputs of neural network for training or test procedures [29].

6.3 Pre-processing and classification

Classification was made by using four approximations. In three approximations, pre-processing stage was implemented to the original data set. Mean value, standard deviation value and these values together were extracted from data, and the obtained features were presented to the ANN for the classification task. A block representation of these approximations is given in Fig. 5. In other approximation, the original data set was given to the ANN without any pre-processing. The input data (19 different structural parameters) is applied to the ANN directly. The obtained training and test errors for 2-fold validation sets using the proposed approaches are presented in Tab. V, Tab. VI, Tab. VII and Tab. VIII. The accuracy of classification results of ANN with the proposed approximations is indicated in Tab. IX. The classification accuracy was obtained according to Equation 7.

$$\text{Classification Accuracy } (\%) = 100 - \text{ Test Error} \tag{7}$$

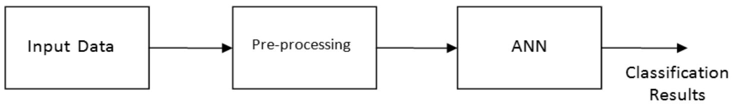


Fig. 5 *Block representation of classification of RC buildings under earthquake loads using ANN with pre-processing.*

Training Algorithm of ANN	Results					
	1. Data Set		2. Data Set		Averaged	
	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)
BFG	4.66	40.15	2.42	35.48	3.54	37.82
CGB	3.23	40.85	0.80	34.23	2.02	37.54
CGF	2.14	40.67	2.44	31.29	2.29	35.98
CGP	1.43	39.61	0.80	34.56	1.12	37.09
GDA	5.50	42.46	1.69	34.28	3.60	38.37
GDM	8.67	39.35	6.45	32.13	7.56	35.74
GDX	4.03	41.13	0.93	34.19	2.48	37.66
LM	4.28	40.53	7.25	33.06	5.77	36.80
OSS	1.89	40.82	0.92	34.27	1.41	37.55
RP	11.33	42.71	5.83	36.13	8.58	39.42
SCG	0.71	43.35	0.80	35.40	0.76	39.38

Tab. V *Training and test errors of ANN with pre-processing using only mean values of data.*

Training Algorithm of ANN	Results					
	1. Data Set		2. Data Set		Averaged	
	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)
BFG	5.71	30.65	6.45	28.35	6.08	29.50
CGB	4.18	32.94	3.48e-09	31.84	2.09	32.39
CGF	7.06	27.91	1.69	34.49	4.38	31.20
CGP	3.63	31.56	1.62e-09	31.08	1.82	31.32
GDA	8.23	32.03	2.84	32.53	5.54	32.28
GDM	11.87	29.92	8.24	32.77	10.06	31.35
GDX	7.85	29.52	3.79	31.73	5.82	30.63
LM	5.71	30.32	4.84	30.65	5.28	30.49
OSS	3.78	31.96	0.01	30.32	1.90	31.14
RP	13.52	31.49	10.22	32.15	11.87	31.82
SCG	6.35	29.13	3.33e-09	31.82	3.18	30.48

Tab. VI *Training and test errors of ANN with pre-processing using only standart deviation values of data.*

Training Algorithm of ANN	Results					
	1. Data Set		2. Data Set		Averaged	
	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)
BFG	2.85	34.11	1.49	28.98	2.17	31.55
CGB	0.71	31.76	0.05	27.89	0.38	29.83
CGF	4.02	31.17	3.55	27.03	3.79	29.10
CGP	0.71	32.04	0.01	28.57	0.36	30.31
GDA	5.38	32.69	0.22	27.01	2.80	29.85
GDM	8.73	32.79	4.85	28.23	6.79	30.51
GDX	3.07	31.13	8.23e-05	27.32	1.54	29.23
LM	3.44e-10	29,41	8.46e-10	26.90	0.00	28.16
OSS	0.66	31.13	0.04	27.09	0.35	29.11
RP	7.83	30.80	2.77	28.13	5.30	29.47
SCG	4.29	30.39	3.47e-09	27.10	2.15	28.75

Tab. VII *Training and test errors of ANN with pre-processing using both mean values and standart deviation values of data.*

7. Results and Discussion

Findings of this study are briefly summarized as follows:

- According to the data used, the performances of RC buildings under earthquake loads were determined with an accuracy of 80.46%.
- The best classification result of ANN using pre-processing is obtained as 71.84 % with extraction of mean and standard deviation values of input data.

Training Algorithm of ANN	Results					
	1. Data Set		2. Data Set		Averaged	
	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)	Training Error (%)	Test Error (%)
BFG*	-	-	-	-	-	-
CGB	0.00	28.20	0.80	21.73	0.40	24.97
CGF	2.70	19.16	0.81	19.91	1.76	19.54
CGP	1.78	28.02	2.52	25.21	2.15	26.62
GDA	0.11	26.99	7.69e-09	23.30	0.06	25.15
GDM	10.16	21.92	4.27	23.48	7.22	22.70
GDX	1.36e-07	26.72	0.81	22.88	0.41	24.80
LM*	-	-	-	-	-	-
OSS	0.03	27.57	0.01	23.07	0.02	25.32
RP	5.81e-04	19.37	0.81	19.94	0.41	19.66
SCG	1.87e-09	26.94	0.81	21.86	0.41	24.40
** Result is not obtained using BFG and LM algorithm*						

Tab. VIII *Training and test errors of ANN without pre-processing.*

	Method	Algorithm	Classification Accuracy (%)
(a)	Mean	GDM	64.22
(b)	Standard deviation	BFG	70.50
(c)	Mean and standard deviation	LM	71.84
(d)	No pre-processing	CGF	80.46

Tab. IX *Accuracy of ANN classification according to four approximations.*

- This classification accuracy is lower than 80.46 % of ANN without pre-processing, but time consumption of network with pre-processing is nearly half of that without pre-processing.

- Using the ANN, the performances of RC buildings could be determined in a very short time like 15 seconds. To determine the performance levels of the buildings, among 11 backpropagation algorithms the best choice is CGF algorithm with a high accuracy ratio. When the previous studies performed with the ANN were analyzed, it was observed that success of the algorithm varies according to the selected data set.

- In evaluation of an RC building, it is known that forming a computer model of the load bearing system takes 1–2 days. In this study, evaluation of a building took only 15 seconds, using the ANN method.

- Procedures such as coring, building survey etc. were not used in this method; rather, building project data were taken into account. It is known that due to insufficient building inspections and other factors, particularly the RC buildings constructed before the 1999 Marmara Earthquake and before TEC-1998 [30] coming into force are very poor according to the building projects. Thus, according to the method presented in this study, the RC buildings which were found to lack sufficient performance levels on the basis of the evaluations made according to their projects will not achieve adequate performance levels also in the on-site measurements. Therefore, the analyzed method can enable fast scanning of all buildings to sort the inadequate ones.

- Especially, when we look at Tab. III, it is seen that the performance levels of the 66 RC buildings are 10.61 % S_1, 30.3 %S_2, 34.85 % S_3, 24.24 % S_4. In TEC-2007 [1], the RC residence buildings have to provide at least S_2 Life Safety (LS) in order to be in the sufficient performance level during the earthquake. According to this statement, 59.09 % of the buildings chosen as examples are the buildings not having sufficient earthquake performance according to the TEC-2007 [1] criteria. These buildings are expected to get moderate and severe damage after the earthquake, therefore they should be evacuated or strengthened. It is obvious that especially the buildings included in the S_4 group are at great risk and the complete collapse risk of these buildings under a probable earthquake in the region is very high.

- In all of the studies [5–11] carried out on the evaluation of the present RC buildings, the probability of collapse of the sample buildings under a possible earthquake was detected with different proportions. Here, the variability of the parameters used in the studies, the sample structure group, the analysis methods chosen and the approaches can be seen as the main reason. In addition, TEC-2007 [1] performance criteria have not been taken as the basis in any of these methods so far.

- In other studies conducted by Arslan [16, 20], the performance analysis of modeled simple RC frames was carried out according to some basic factors (stirrup spacing, reinforcement ratio, concrete compressive strength, column axial load level etc.) which were thought to have effect in the earthquake damage. These studies examined the proportions in which the ANN predicted the structure performance. In this study, however, the authors worked on the samples taken from the real structure stock, evaluated the sample structures according to TEC-2007 [1] norms and categorized the structures into four different groups according to these analyses. As a result of the ANN analysis carried out, a method which predicted the performance level of the building after the earthquake (S_1, S_2, S_3, S_4) has been achieved. Thus, based on the created model, the performance of an RC residence, whose 19 structural parameters were known, as a result of a possible earthquake can be predicted with a ratio of 80.46%.

- Since the study was carried out on the basis of TEC-2007 [1] norms, the structure performance after the earthquake was determined according to the related code criteria. There are not any other studies taken TEC-2007 [1] as the basis and using the ANN in the literature.

- In this study, for the training and test phase, two-fold cross-validation method was used for the generalization ability of ANN. The test phase was realized ten times, separately. Thus, the test results of ANN were generalized for estimating earthquake performances. The accuracy of 80.46 % is enough for the ANN application because of pioneering work in the civil engineering area.
- The present study has demonstrated that all of these selected parameters directly affect the seismic performance of building, which is a function of lateral load carrying capacity and earthquake performance.
- The analysis has also indicated that a considerable portion of existing RC building stock in Turkey may not meet the safety standards of the Turkish Earthquake Code (TEC-2007).
- It should be noted that the selected ANN models presented above are valid only for the ranges of database given in Tab. II. Therefore, the estimation capacity and estimation duration of each algorithm is expected to be lower than those calculated in this study in case of increasing the selected buildings.

8. Summary and Conclusions

The residence RC buildings, comprising an important part of the structural stock in Turkey, prepared according to the former regulations and having the numbers of floors between 4 and 10 are at great risk in possible earthquakes. The huge number of these buildings makes the analysis of the buildings one by one and in detail impossible. Considering these problems, quick evaluation of these present buildings and their categorization by determining their earthquake performances according to TEC–2007 [1] criteria are very important and popular issues.

With this study, an ANN based algorithm which determines the earthquake performance of residence buildings according to the conditions of the code and which can make categorization was achieved. Thus, the earthquake performance of an RC building, whose quick evaluation is made, can be determined in a short period of time. In addition, it should not be forgotten that the accuracy of the study depends on the sample buildings chosen, the calculation methods and the parameters which are present during the instruction and test processes of ANN.

References

[1] TEC-2007. Turkish Earthquake Code. Regulations on structures constructed in disaster regions. Ministry of Public Works and Settlement. Ankara, 2007 (In Turkish).

[2] Federal Emergency Management Agency. FEMA-356. Prestandard and commentary for seismic rehabilitation of buildings. Washington (DC), 2000.

[3] ATC-40: Seismic evaluation and retrofit of concrete buildings, Redwood City (CA), Applied Technology Council, 1996.

[4] FEMA 155, Rapid Visual Screening of Buildings for Potential Seismic Hazards: Supporting Documentation, Federal Emergency Management Agency, FEMA 500 C Street, SW Washington, D.C. 20472, USA [http://www.fema.gov], 1988.

[5] Hassan A. F., Sözen M. A.: Seismic Vulnerability Assessment of Low-Rise Buildings in Regions with Infrequent Earthquakes, ACI Structural Journal, USA, **94**, 1, January-February 1997, pp 31-9..

[6] Gülkan P., Sözen M. A.: Procedure for Determining Seismic Vulnerability of Building Structures, ACI Structural Journal, USA, **96**, 3, May-June 1999, pp. 336-342.

[7] Yakut A., Ozcebe G., Yucemen M. S.: A Statistical Procedure for the Assessment of Seismic Performance of Existing Reinforced Concrete Buildings in Turkey 13th World Conference on Earthquake Engineering, 13 WCEE, Vancouver, BC, Canada, Paper No: 687, 2004.

[8] Yakut A., Gülkan P., Bakır B. S., Yılmaz M. T.: Re-examination of Damage Distribution in Adapazari: Structural Considerations, Engineering Structures, Elsevier Publications, **27**, 2005, pp. 990-1001.

[9] Boduroglu H., Özdemir P., Ilki A., Sirin S., Demir C., Baysan F.: Towards a Modified Rapid Screening Method for Existing Medium Rise RC Buildings in Turkey, 13th World Conference on Earthquake Engineering, 13 WCEE August 1-6, Vancouver, B.C., Canada, 2004.

[10] Pay A. C.: New Methodology for the Seismic Vulnerability Assessment of Existing Buildings in Turkey, Master Thesis, METU, Middle East Technical University, Department of Civil Engineering, August, Ankara, Turkey, 2001.

[11] Bal I. E., Tezcan S. S., Gülay F. G.: Advanced applications of the P25 – scoring method for the rapid assessment of RC buildings, Proceedings of the 1st ECEES, Geneva, 3-8 September 2006.

[12] Mo Y. L., Hung H. Y., Zhong J.: Investigation of stress-strain relationship of confined concrete in hollow bridge columns using neural networks, Journal of Testing and Evaluation, ASTM, **30**, 4, 2002, pp. 330-339.

[13] Jeng C. H., Mo Y. L.: Quick seismic response estimation of prestressed concrete bridges using artificial neural networks, Journal of Computing in Civil Engineering, ASCE, **118**, 4, 2004, pp. 360-369.

[14] Giri V., Upadhyay A.: ANN based prediction of moment coefficients in slabs subjected to patch load, Structural Engineering and Mechanics, **29**, 1, 2006, pp. 77-89.

[15] Arslan M. H.: Prediction of torsional strength of RC beams by using different articial neural network algorithms and building codes, Advances in Engineering Software, **41**, 7-8, 2010, pp. 946-955.

[16] Arslan M. H.: An evaluation of effective design parameters on earthquake performance of RC buildings using neural networks, Engineering Structures, **32**, 2010, pp. 1888-1898.

[17] Arslan M. H., Ceylan M., Kaltakcı M. Y., Özbay Y., Gülay F. G.: Prediction of force reduction factor (R) of prefabricated Industrial Buildings Using Neural Networks, Structural Engineering and Mechanics, **27**, 2, 2007, pp. 117-134.

[18] Cho H. N., Cho Y. M., Lee S. C., Hur C. K.: Damage assessment of cable stayed bridges using probabilistic neural network, Structural Engineering and Mechanics, **17**, 3, 2004, pp. 483-492.

[19] Lee J. J., Lee J. W., Yi J. H., Yun C. B., Jung H. Y.: Neural network-based damage detection for bridges considering errors in baseline finite element models, Journal of Sound and Vibration, **280**, 3-5, 2005, pp. 555-578.

[20] Arslan M. H.: Determination of effective parameteres on failure load and displacement of existing RC buildings using ANN, Natural Hazards and Earth Systems Journal, **9**, 2009, pp. 967-977.

[21] Chang S., Kim D., Chang C., Cho S. G.: Active response control of an offshore structure under wave loads using the modified probabilistic neural network, Journal of Marine Science and Technology, **14**, 2, 2009, p. 240.

[22] Kim D. H., Kim D., Chang S. K.: Application of lattice probabilistic neural network for active response control of offshore structures, Structural Engineering and18 Mechanics, **31**, 2, 2009a, pp. 153-162.

[23] Kim D., Kim D. H., Cui J., Seo H. Y., Lee Y. H.: Iterative neural network strategy for static model identification of an FRP deck, Steel and Composite Structures, **9**, 5, 2009b, pp. 445-455.

[24] Koyuncu T.: A New Method for Rapid Assesment of Performances of Existing RC Buildings Under Earthquake Loading, MSc Thesis, Selcuk University, (In Turkish), 2009.

[25] CSI. SAP2000 V-7.4. Integrated finite element analysis and design of structures basic analysis reference manual, Berkeley (CA, USA): Computersand Structures Inc., 2000.

[26] Ripley B. D.: Pattern Recognition and Neural Networks, Cambridge, Cambridge University Press, 1996.

[27] Haykin S.: Neural Networks: A Comprehensive Foundation, New York, Macmillan, 1994.

[28] Allen D. M.: The relationship between variable selection and data augmentation and a method for prediction, Technometrics, **16**, 1974, pp. 125-127.

[29] Özbay Y., Ceylan R., Karlik B.: A fuzzy clustering neural network architecture for classification of ECG arrhytmias, Computers in Biology and Medicine, **36**, 2006, pp. 376-388.

[30] TEC-1998. Turkish Earthquake Code. Regulations on structures constructed in disaster regions. Ministry of Public Works and Settlement. Ankara (In Turkish), 1998.