INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2011; 3:433-448

ESTIMATING THE VULNERABILITY OF THE CONCRETE MOMENT RESISTING FRAME STRUCTURES USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Heavy economic losses and human casualties caused by destructive earthquakes around the world clearly show the need for a systematic approach for large scale damage detection of various types of existing structures. That could provide the proper means for the decision makers for any rehabilitation plans. The aim of this study is to present an innovative method for investigating the seismic vulnerability of the existing concrete structures with moment resisting frames (MRF). For this purpose, a number of 2-D structural models with varying number of bays and stories are designed based on the previous Iranian seismic design code, Standard 2800 (First Edition). The seismically–induced damages to these structural models are determined by performing extensive nonlinear dynamic analyses under a number of earthquake records. Using the IDARC program for dynamic analyses, the Park and Ang damage index is considered for damage evaluation of the structural models. A database is generated using the level of induced damages versus different parameters such as PGA, the ratio of number of stories to number of bays, the dynamic properties of the structures models such as natural frequencies and earthquakes. Finally, in order to estimate the vulnerability of any typical reinforced MRF concrete structures, a number of artificial neural networks are trained for estimation of the probable seismic damage index.

Received: 10 July 2011; Accepted: 20 November 2011

KEY WORDS: Seismic vulnerability; concrete structures; damage index; nonlinear dynamic analysis; artificial neural networks

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1. INTRODUCTION

Our knowledge from the earthquakes and their destructive effects on structures has been improved greatly during the last few decades. Accordingly, the seismic design provisions necessary for the design of new buildings and rehabilitation of the existing structures have been witnessing rapid changes. The concept of performance based design now is present in many seismic design codes and guidelines. However, determining the vulnerability of the existing structures that have been designed and built using the previous Codes remains a great challenge.

In the current state of the practice, the structures are designed to withstand the minor to moderate earthquakes by remaining within their elastic range. For larger earthquakes, the inelastic response of the structural elements provides a mechanism for dissipation of the input energy. Therefore, it is important to identify the level of damage for the structures undergoing inelastic deformation during an earthquake episode. A large body of literature is available on evaluating the amount of the seismic damage imposed to the structures, using different measures[1-4]. Not surprisingly, numerous local and global damage indices have been introduced ever since, to determine the remaining capacity of the system after the earthquake event[1-4]. Depending on the number of damage states considered, the vulnerability of the existing structures can be evaluated accordingly. These damage states can be used for post earthquake damage evaluation of the structures, performance prediction of the newly designed buildings, and reliability analysis of existing buildings and facilities.

In his method, Rytter[5] distinguishes four levels of damage detections as the following; Level 1 (Detection), that provides a qualitative indication that damage might be present in the structure; Level 2 (Localization), which gives information about the probable position of the damage; Level 3 (Assessment), that provides an estimate of the extent of the damage; Level 4 (Consequence), which offers information about the safety of the structure. Doebling and Farrar[3] classified the structural damages into linear and nonlinear categories. Linear damage indicates that a structure with elastic behavior keeps its linear-elastic behavior after the damage. However, nonlinear damage indicate that a structure with linear elastic behavior shows nonlinear behavior after the damage.

Marvala and Hunt [6] presented a number of neural network techniques, which employs frequency response function and modal data simultaneously to identify faults in the building structures. They tested their proposed method on simulated data from a cantilevers beam. Worden [7] applied neural network to diagnose damage in a simple simulated lumped-parameter mechanical system. It was shown that the system transmissibility provides a sensitive feature for the detection of small stiffness changes. Xia et al. [4] proposed a statistical method with combined uncertain frequency and mode shape data for structural damage identification. They updated a finite element model by comparing the measured vibration data before damage, or the same analytical finite element model of the undamaged structure with those measured after damage. Thus, the changes in vibration characteristics the finite element model becomes equal to the changes in the measured data as closely as possible. They applied the proposed method to a laboratory tested steel cantilever beam and frame structure.

Hung and Kao [8] presented a two steps approach for damage detection in building structures. The system identification, as the first step, involves using neural system identification networks (NSIN) to identify the undamaged and damaged states of a structural system. The partial derivatives of the outputs with respect to the inputs of the NSIN which identify the system in a certain undamaged or damaged state, have a negligible variation with different system errors. Then in the second step, structural damage detection involves using the neural damage detection network (NDDN) to detect the location and the extent of the structural damage. The input to the NDDN is taken as the aforementioned partial derivatives of NSIN, and the output of the NDDN identifies the damage level for each member in the structural system.

Huang et al. [9] tried to identify the dynamic characteristics of a building to diagnose any earthquakes induced damages to the building, using a back-propagation neural network approach. The dynamic characteristics of the system were directly evaluated using the weighting matrices of the neural network trained by the observed acceleration responses and input base excitation. The level of the damage to the building under a large earthquake is assessed by comparing the modal properties and response parameters of the structural system under the target earthquake with those for small earthquakes without causing any damage to the buildings. They demonstrated the feasibility of the proposed approach by processing the dynamic response of a five-storey steel frame subjected to the Kobe earthquake with different intensities through shaking table tests. Tsai and Hsu [2] employed displacement time histories of the existing structures and back-propagation neural network technique to assess the severity and location of the defects for reinforced concrete structures. They used the results of finite-element analysis of a simply-supported reinforced concrete beam with the assumed defects, for training the neural networks and also controlling their performance in identifying the assumed damages.

Kirkegaard and Rytter [10] considered the potential of using back-propagation neural network for damage assessment of a free-free cracked straight steel beam based on vibration measurements. Zieminaski and Piatkowski [11] applied the neural networks for damage detection in rod structures. The identification method was based on the analysis of propagation of waves in solids. Zang and Imregun [12] used the measured frequency response functions (FRF) as input data to train artificial neural networks for structural damage detection. Harpula and Ziemianski [13] applied the neural networks for damage detection in bar structures based on changes in their dynamic characteristics.

In this work, the Park and Ang [1] damage index is considered to assess the seismic damage imposed to different reinforced concrete MRF structural models. Extensive nonlinear time history analyses performed using a number of earthquake records with different intensities. Then, the generated data base is used to train a number of artificial neural networks for prediction of the damage index. Also, numerical examples presented to demonstrate the performance of the proposed method.

2. DAMAGE INDEX

In order to quantitatively estimate the seismic damage of the structural buildings, an appropriate damage assessment method is needed. Among different existing damage indices that have been proposed by researchers, the Park and Ang [13] damage index is selected due to its frequent use in the literature, for evaluating the seismic damage imparted to the concrete MRF structures. The Park and Ang damage index is defined as:

$$D.I._{PA} = \frac{d_m}{d_u} + \frac{b}{d_u F_y} \int dE \tag{1}$$

in which:

$D.I._{PA}$ = The Park & Ang Damage Index

d_m = Maximum deformation of structure during an earthquake

d_u =Ultimate deformation capacity of building structure under monotonic loading

b = Dimensionless strength reduction parameter

$\int dE$ = Hysteretic energy absorbed by building structure during time story analysis

Also, the following damage states are used;

$0 \le D.I._{PA} < 0.4$ Representing repairable damage

$0.4 \le D.I._{PA} < 1.0$ Representing damage beyond repair

$1.0 \le D.I._{PA}$ Representing total collapse of structure

As it was mentioned earlier, the IDARC program was used to perform the time history dynamic analyses. The program is able to calculate the Park & Ang damage index for different elements of the building structures. The damage index can be obtained for a structural element (local damage index), for different stories, and for the whole of the building (global damage index). In this research, the global damage indices are calculated for structural damage assessment purposes. In that regard, 24 planar reinforced concrete structures are designed according to the first edition of Iranian seismic design Code, Standard 2800 [14]. The natural periods of vibration of the first few modes of the structural models are shown in Table 1.

The designed structural models were dynamically analyzed using six earthquake components recorded on stiff soil shown in Table 2, with different intensities. As the Table 1 shows, the dominant frequencies of the earthquake records is an indication that they have been recorded on stiff soil (Soil type 2 based on Iranian seismic Code, Standard 2800). Figures 1 and 2 show the acceleration time histories and the Fourier amplitudes of these records. The earthquake records have been scaled such that their PGA be equal to 10, 20, 30, 40, 50, and 60 percent of the acceleration of gravity (g). The damage indices are calculated for all combination of structural models and earthquake records. The resulting data base is used for training a number of artificial neural networks.

As an example, the damage indices computed for a 3 story-1 bay structural model (3s-1b) under different scaled Tabas earthquake record with PGA from 0.1g to 1.0g are shown in Figure 3. The obtained results indicate that for PGA’s up to 0.3g, no plastic hinges are formed in the structural models. However, due to the first term in the right hand side of Eq. (1), one still could have a nonezero value for the damage index.

Table 1. The Natural Periods of the First 5 Modes of the Structural Models

Structural model	Period (sec)				
	Number of mode				
	1	2	3	4	5
3s1b	0.66	0.17	0.07	*	*
3s2b	0.68	0.18	0.08	*	*
3s3b	0.69	0.19	0.09	*	*
4s1b	0.75	0.21	0.09	0.05	*
4s2b	0.77	0.22	0.10	0.06	*
4s3b	0.77	0.22	0.11	0.06	*
5s1b	0.84	0.28	0.13	0.07	0.04
5s2b	0.84	0.29	0.13	0.08	0.05
5s3b	0.85	0.29	0.14	0.08	0.05
6s1b	1.01	0.32	0.16	0.09	0.06
6s2b	1.02	0.33	0.17	0.10	0.07
6s3b	1.02	0.34	0.17	0.10	0.07
7s1b	1.06	0.34	0.17	0.10	0.07
7s2b	1.07	0.35	0.18	0.11	0.07
7s3b	1.07	0.35	0.19	0.11	0.08
8s1b	1.12	0.36	0.19	0.11	0.07
8s2b	1.11	0.36	0.19	0.12	0.08
8s3b	1.11	0.36	0.20	0.12	0.08
9s1b	1.26	0.42	0.22	0.13	0.09
9s2b	1.25	0.42	0.23	0.14	0.10
9s3b	1.25	0.42	0.23	0.14	0.10
10s1b	1.33	0.47	0.25	0.16	0.11
10s2b	1.31	0.47	0.26	0.17	0.11
10s3b	1.30	0.47	0.26	0.17	0.12

Table 2. Characteristics of the earthquake records used in this study

Earthquake record	Date	PGA (g)	Soil dominant frequency (Hz)
Tabas	09/16/1978	0.93	2.42
Manjil	06/20/1990	0.514	2.94
Naqan	04/06/1977	0.714	3.293
Bam	12/26/2003	0.793	5.54
El Centro	05/18/1940	0.348	2.56
Taft	07/21/1952	0.179	4.81

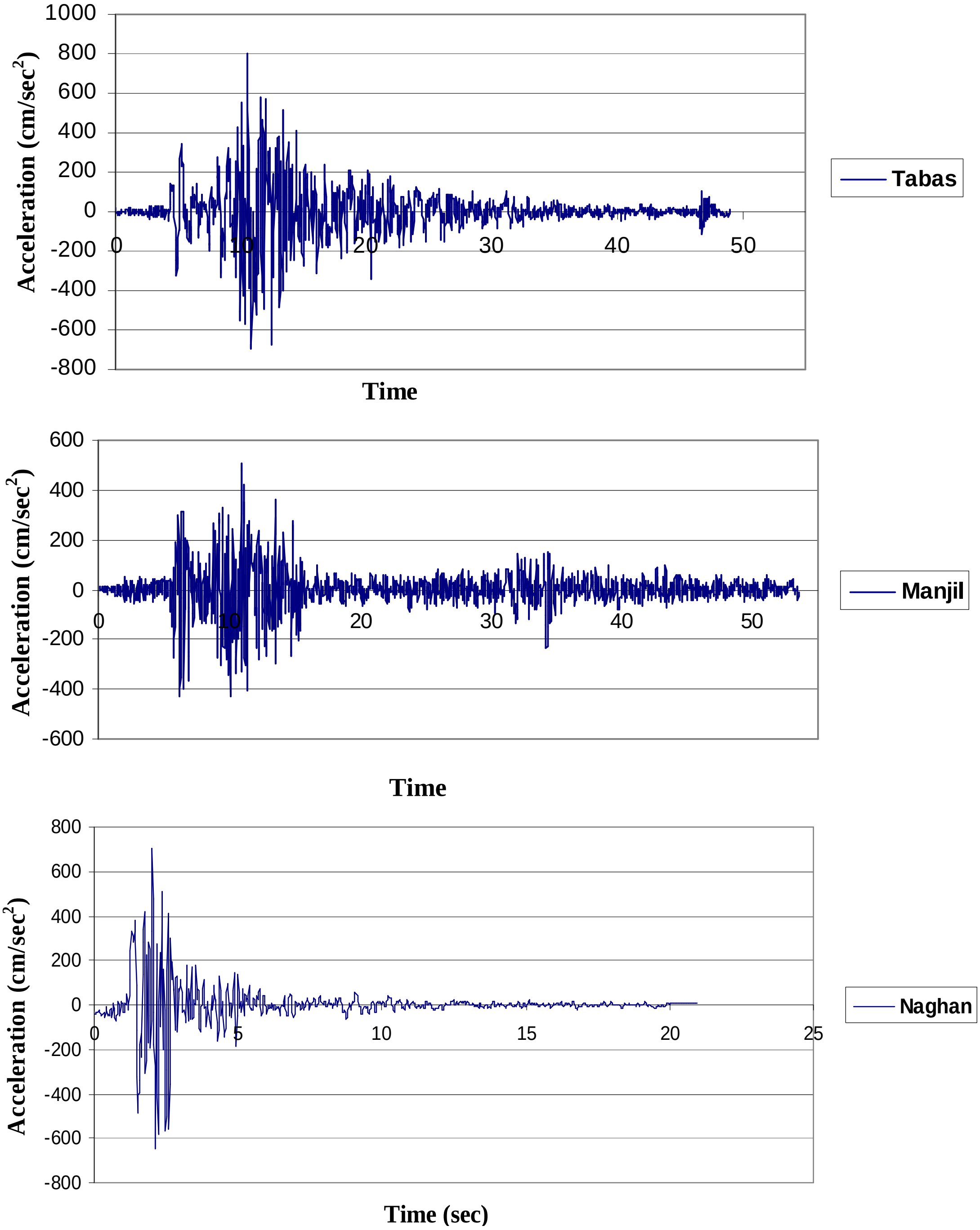


Figure 1. Earthquake records acceleration time histories

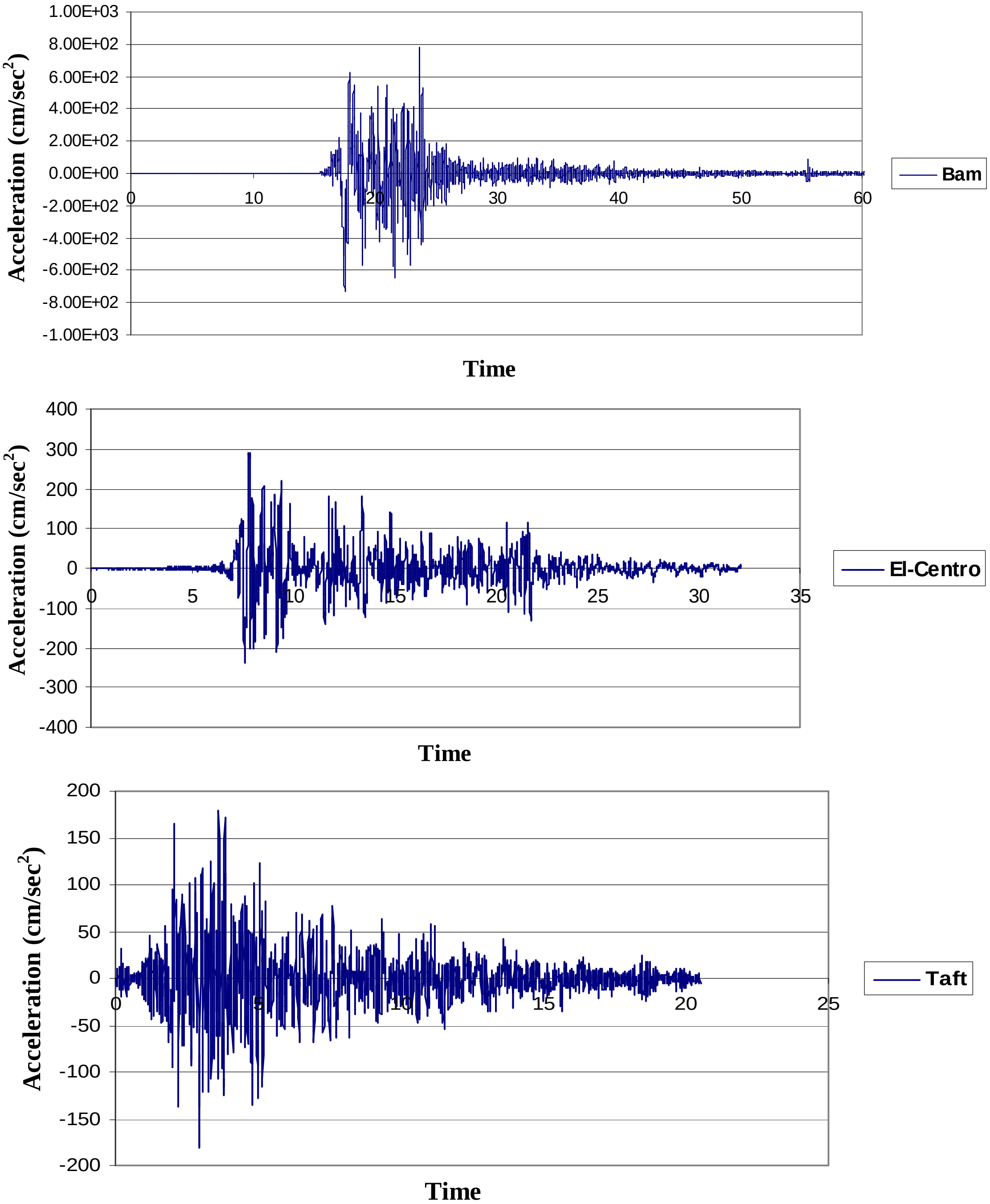
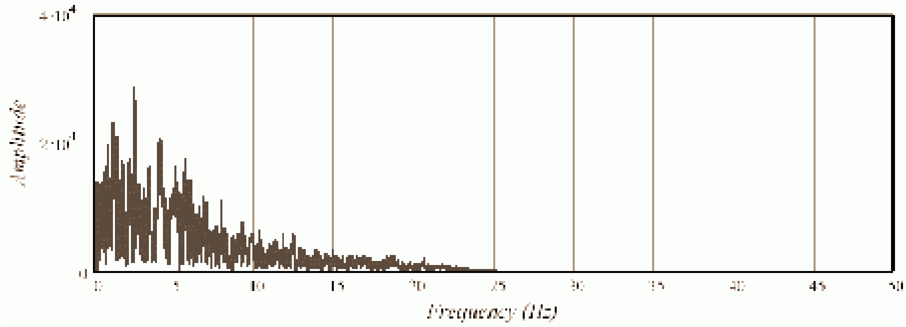
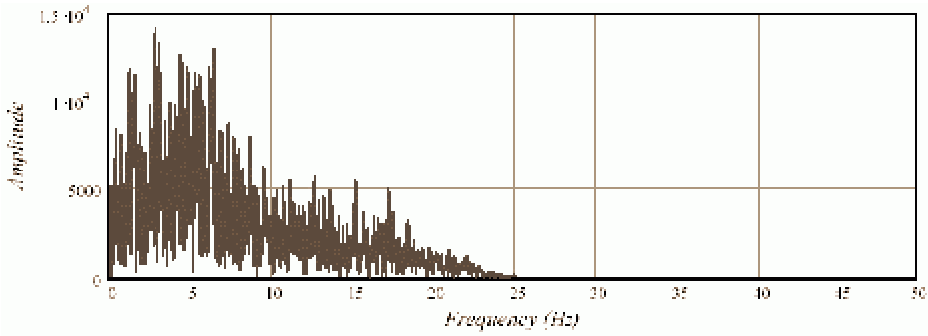


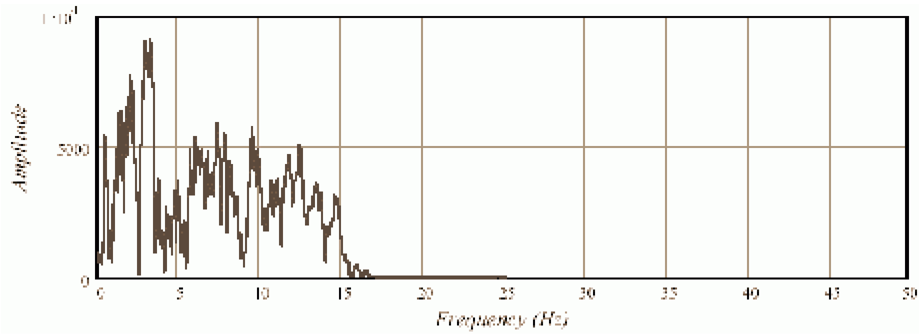
Figure 1.(Continued) Earthquake records acceleration time histories



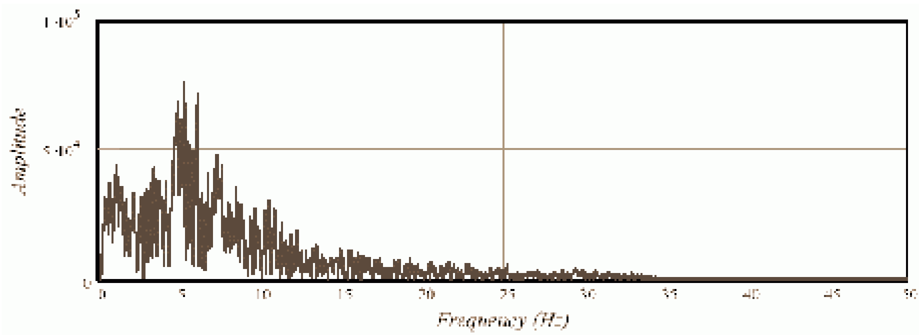
Tabas Fourier spectrum



Manjil Fourier spectrum

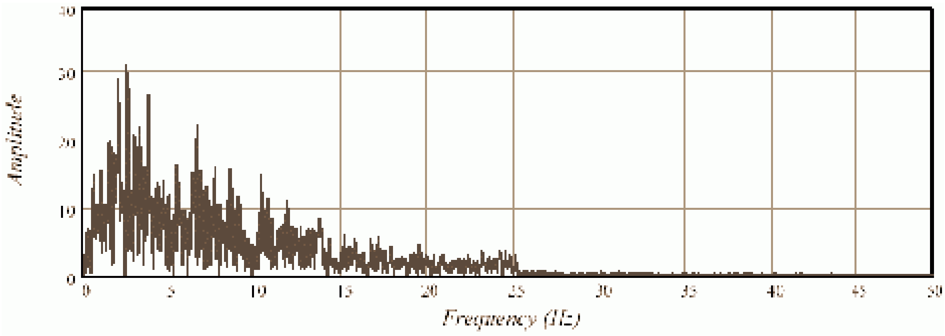


Naghan Fourier spectrum

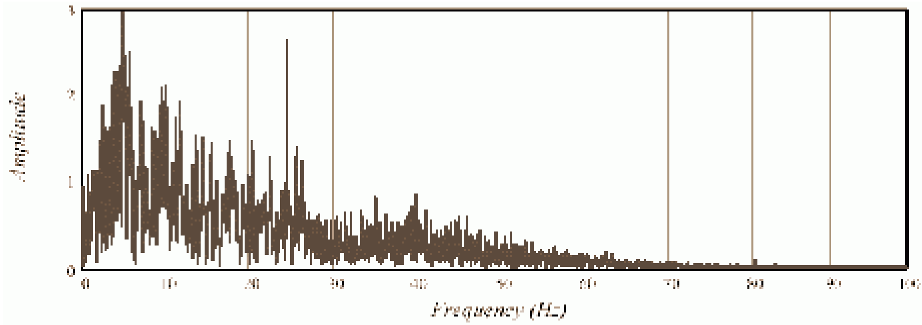


Bam Fourier spectrum

Figure 2. Earthquake records Fourier amplitudes



El-Centro Fourier spectrum



Taft Fourier spectrum

Figure 2. (Continued) Earthquake Records Fourier Amplitudes

3. ARTIFICIAL NEURAL NETWORKS

A model of an artificial neuron is shown in Figure 4 [15]. A set of input signals (X_1, X_2,..., X_n) are applied to the neuron. Each signal is multiplied by a proportional weight before arriving at summation unit (Σ). All weighted inputs are summed to make the output NET. Then the activation function is applied to the NET producing the OUT signal. In the current work, two mostly used activation functions, *i.e.*, sigmoid and hyperbolic tangent shown in Figure 5, are employed which have been frequently used in artificial neural network (ANN) problems [15].

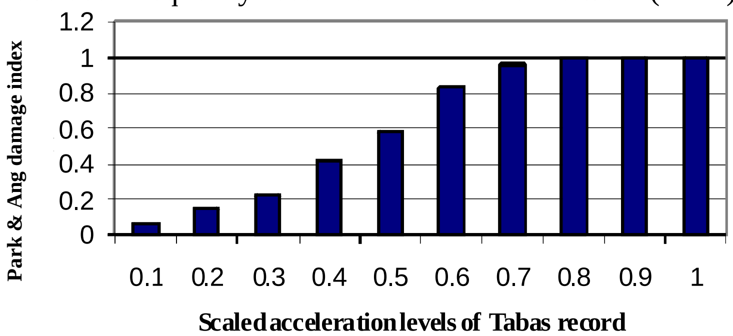


Figure 3. Damage indices for a 3 story-1 bay model under Tabas earthquake record.

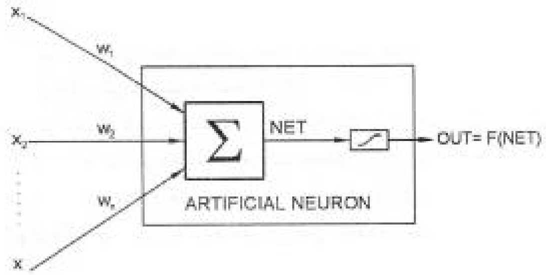
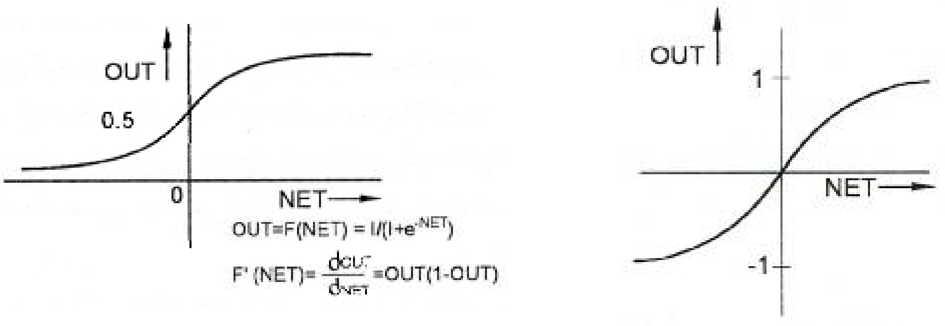


Figure 4. Mathematical model of an artificial neuron [15]



(a) (b)

Figure 5. Activation Functions (a) Sigmoid, (b) Hyperbolic tangent [15]

Sigmoid function maps the value of NET within the (0,1) distance, while the Hyperbolic Tangent function maps the NET value on (-1,1) range. Also, in this work, the Back Propagation Network (BPN) is used which is the most applicable type of ANNs. Due to back propagation of the output values in this type of network, the error will be minimized, since they are compared with the outputs of the previous stage.

4. EVALUATION OF THE LEARNING AND PERFORMANCE OF THE NEURAL NETWORKS

A well trained ANN can present acceptable response to the inputs either within or outside of the training set. The performance of the ANN can be evaluated using various mathematical methods. Two of the important parameters for measurement of learning and performance of the ANNs are the RMS and the correlation factor.

RMS error is the square root of sum of squares of errors between actual and desired outputs of the network [15]. This parameter is considered as the target function in back propagation network and the weights of the network are considered as function variables. During training of a network, RMS reduction indicates the progress in network learning. As the RMS is reduced, the network learns better and gives more accurate answers to the existing inputs in training set. But this procedure does not indicate that the network can give accurate answers to the nonexistent inputs in the training set. In other word, it is possible that the value of RMS be very small, while the network does not provide acceptable answers to new inputs.

On the other hand, if RMS is reduced more than the required limit, it is possible that the network recites the existent data in training set and loses the ability of generalization and response to new inputs. Therefore, one cannot absolutely verify the appropriate learning and performance of a network according to low RSM value.

On the other hand, the correlation factor that is defined as the harmonic variation of two variables[15], can be determined from the following equation:

$$r(x,y) = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\left[\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2\right]^{1/2}} \tag{2}$$

in which:

$\bar{x}$: is the average of *x* variables

$\bar{y}$: is the average of *y* variables

The correlation factor could be positive or negative if the two variables change in agreement with each other in the same direction or opposite direction respectively. Finally the variables are called uncorrelated, if they do not change in agreement with each other. Value of *r* is between –1 and 1. If *r*=1, correlation is perfect and if *r*=-1, correlation is perfect and negative. In case of *r*=0, the variables are uncorrelated. Also in ANN, the correlation factor between actual and desired outputs from training and testing sets together can be used as a criterion for evaluating the performance and learning of the network. The closer the value of this factor gets to 1 for both data, existing in training and testing set, the better is the learning and performance of the network. It is notable that correlation factor between the actual and desired outputs from training set can never be used for evaluation of the performance of a network. Because, it is possible for the network to recite the existing data in the training set. Therefore, the correlation factor between the actual and the desired output could be close to 1, while the network may not be able to provide acceptable answers to new nonexistent inputs.

For data classification and training of the ANNs in predicting the vulnerability of the structures, the data were divided into 3 groups for training and testing of the ANNs as below:

- Group A: Network for assessment of damage in 3, 4, and 5 stories structural models.
- Group B: Network for assessment of damage in 6 to 10 stories structural models.
- Group C: Network for assessment of damage in 3 to 10 stories structural models.

In order to train the AANs, the “Neural Works” program has been employed [16]. In all the networks, training set includes the following seven parameters: the ratio of the number of stories to number of bays for each structural model, the period of the first vibration mode of the structural models, peak ground acceleration (PGA), earthquake dominant frequency, scaled earthquake acceleration, maximum displacement of the top floor of the structural models, and the computed damage index. The testing set includes all the above parameters except the damage index.

In each group (i.e. A, B and C), the test set data were selected randomly from the database generated by performing the dynamic time history analyses for the structural models of that group. In order to train the networks, back propagation algorithm was used. Architecture of the networks consists of one input layer, one (or two) hidden layer(s), and one output layer. Both hyperbolic tangent and sigmoid functions were employed in training the networks and their performances were compared. The number of neurons in hidden layer were increased to achieve the best prediction possible. The results of training of group A networks have been briefly shown in Table 3. As it is seen in that Table, network AT-12 with 12 neurons in its first hidden layer has the best prediction.

Table 3. Training and test results of group A network

Network name	Number of pairs		Number of neurons in layers				Learning rule	R^2	RMS	Act. func.
	Train	Test	Input	1st hidden	2nd hidden	Output				
AT-8	300	30	6	8	0	1	Delta	0.9949	0.0227	tanh
AT-9	300	30	6	9	0	1	Delta	0.9956	0.0214	tanh
AT-12	300	30	6	12	0	1	Delta	0.9971	0.0192	tanh
AT-14	300	30	6	14	0	1	Delta	0.9961	0.0205	tanh
AT-12-2	300	30	6	12	2	1	Delta	0.9971	0.0195	tanh
AT-12-4	300	30	6	12	4	1	Delta	0.997	0.0192	tanh
AT-12-6	300	30	6	12	6	1	Delta	0.9969	0.0195	tanh
AT-12-8	300	30	6	12	8	1	Delta	0.9968	0.0193	tanh
AS-8	300	30	6	8	0	1	Delta	0.9944	0.0239	S
AS-9	300	30	6	9	0	1	Delta	0.9953	0.0224	S
AS-12	300	30	6	12	0	1	Delta	0.9954	0.0222	S
AS-14	300	30	6	14	0	1	Delta	0.995	0.0226	S
AS-12-2	300	30	6	12	2	1	Delta	0.9921	0.0297	S
AS-12-4	300	30	6	12	4	1	Delta	0.9923	0.0293	S
AS-12-6	300	30	6	12	6	1	Delta	0.9925	0.0291	S
AS-12-8	300	30	6	12	8	1	Delta	0.9925	0.0291	S

According to Table 3, no substantial improvement was obtained using two hidden layers in training of the networks. In fact, that has increased the time needed for training of the network. The same results obtained for increasing the number of neurons in the second hidden layer.

The results of training group B networks are shown in Table 4. In this group, network BT-12 with 12 neurons in first hidden layer has the best prediction. In this group also, no substantial improvement was obtained in using two hidden layers except increasing the needed time for the training operation. The results of training group C networks are shown in Table 5. According to this Table, the network CT-14 with 14 neurons in first hidden layer has the best prediction. Similarly in this group no considerable improvement was obtained using two hidden layers, while the training time was increased.

Predicted damage indices by the networks AT-12, BT-12, and CT-14 are plotted versus those calculated by IDARC program in Figures 4, 5, and 6 respectively. These figures show that the trained neural networks can properly predict the level of damage in structural models under earthquake excitation.

Table 4. Training and test results of group B network

Network name	Number of pairs		Number of neurons in layers				Learning rule	R^2	RMS	Act. func.
	Train	Test	Input	1st hidden	2nd hidden	Output				
BT-8	500	40	6	8	0	1	Delta	0.9897	0.0297	tanh
BT-9	500	40	6	9	0	1	Delta	0.9904	0.0289	tanh
BT-12	500	40	6	12	0	1	Delta	0.9969	0.0177	tanh
BT-14	500	40	6	14	0	1	Delta	0.9927	0.0243	tanh
BT-12-2	500	40	6	12	2	1	Delta	0.9965	0.02	tanh
BT-12-4	500	40	6	12	4	1	Delta	0.9966	0.0194	tanh
BT-12-6	500	40	6	12	6	1	Delta	0.9964	0.0199	tanh
BT-12-8	500	40	6	12	8	1	Delta	0.9961	0.0201	tanh
BS-8	500	40	6	8	0	1	Delta	0.989	0.0306	S
BS-9	500	40	6	9	0	1	Delta	0.99	0.0299	S
BS-12	500	40	6	12	0	1	Delta	0.9918	0.0268	S
BS-14	500	40	6	14	0	1	Delta	0.9893	0.0302	S
BS-12-2	500	40	6	12	2	1	Delta	0.9876	0.0323	S
BS-12-4	500	40	6	12	4	1	Delta	0.9868	0.0327	S
BS-12-6	500	40	6	12	6	1	Delta	0.987	0.0323	S
BS-12-8	500	40	6	12	8	1	Delta	0.987	0.0324	S

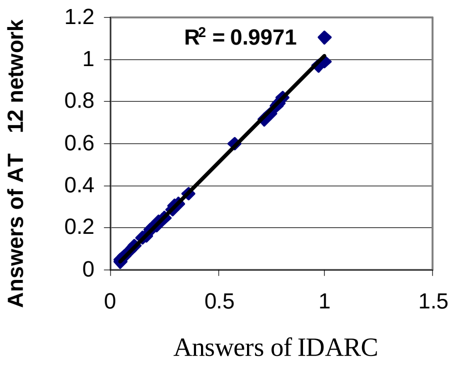


Figure 4. AT-12 network prediction vs. IDARC answers

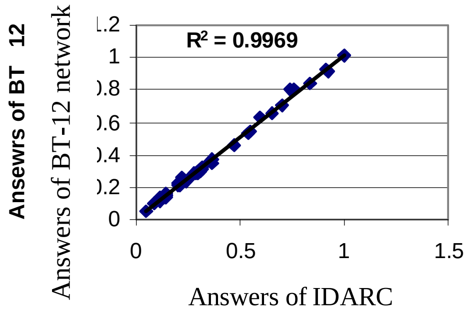


Figure 5. BT-12 network prediction vs. IDARC answers

Table 5. Training and test results of group C network

Network name	Number of pairs		Number of neurons in layers				Learning rule	R^2	RMS	Act. func.
	Train	Test	Input	1st hidden	2nd hidden	Output				
CT-6	830	40	6	6	0	1	Delta	0.9901	0.0232	tanh
CT-8	830	40	6	8	0	1	Delta	0.9917	0.0209	tanh
CT-10	830	40	6	10	0	1	Delta	0.9928	0.0196	tanh
CT-12	830	40	6	12	0	1	Delta	0.9931	0.0191	tanh
CT-14	830	40	6	14	2	1	Delta	0.9984	0.0094	tanh
CT-16	830	40	6	16	4	1	Delta	0.9949	0.0165	tanh
CT-18	830	40	6	18	6	1	Delta	0.9937	0.0181	tanh
CT-20	830	40	6	20	8	1	Delta	0.9931	0.0191	tanh
CT-22	830	40	6	22	0	1	Delta	0.9933	0.0187	tanh
CT-23	830	40	6	23	0	1	Delta	0.993	0.019	tanh
CT-24	830	40	6	24	0	1	Delta	0.9928	0.0194	tanh
CT-14-2	830	40	6	14	2	1	Delta	0.995	0.0163	tanh
CT-14-4	830	40	6	14	4	1	Delta	0.9955	0.0158	tanh
CT-14-6	830	40	6	14	6	1	Delta	0.9953	0.016	tanh
CT-14-8	830	40	6	14	8	1	Delta	0.9952	0.0161	tanh
CS-6	830	40	6	6	0	1	Delta	0.9886	0.0256	S
CS-8	830	40	6	8	0	1	Delta	0.9893	0.025	S
CS-10	830	40	6	10	0	1	Delta	0.9894	0.0248	S
CS-12	830	40	6	12	0	1	Delta	0.9899	0.0245	S
CS-14	830	40	6	14	2	1	Delta	0.9977	0.0112	S
CS-16	830	40	6	16	4	1	Delta	0.9932	0.0192	S
CS-18	830	40	6	18	6	1	Delta	0.9919	0.0212	S
CS-20	830	40	6	20	8	1	Delta	0.9918	0.0218	S
CS-22	830	40	6	22	0	1	Delta	0.9919	0.0215	S
CS-23	830	40	6	23	0	1	Delta	0.9921	0.0215	S
CS-24	830	40	6	24	0	1	Delta	0.9926	0.0208	S
CS-14-2	830	40	6	14	2	1	Delta	0.9841	0.0304	S
CS-14-4	830	40	6	14	4	1	Delta	0.9831	0.0313	S
CS-14-6	830	40	6	14	6	1	Delta	0.9937	0.031	S
CS-14-8	830	40	6	14	8	1	Delta	0.9936	0.0309	S

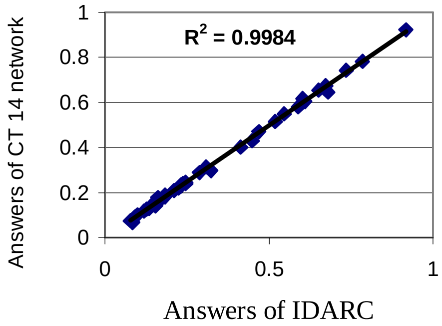


Figure 6. CT-14 network prediction vs. IDARC answers

5. CONCLUDING REMARKS

The following conclusions can be made:

1. It is possible to estimate the vulnerability of concrete MRF building structures using Artificial Neural Networks.
2. Although for earthquake records with small peak ground accelerations (PGA), the structural models remain within the elastic range without dissipating any hysteretic energy, but the computed damage index still becomes non-zero due to resulting elastic deformation.
3. Application of one hidden layer in training the networks for estimation of seismic vulnerability of structures is sufficient.
4. Using hyperbolic tangent activation function, slightly better prediction of damage index was obtained than sigmoid function.
5. No substantial improvement was obtained using two hidden layers in training the networks with larger training time.
6. No considerable improvement was obtained by increasing the neurons in the second hidden layer of the networks.
7. Artificial neural networks could provide acceptable damage assessment of the concrete MRF building models caused by the earthquake records that were not included in the training set.

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