International Journal of Architectural, Civil and Construction Sciences
ISSN: 2415-1734
Vol:6, No:2, 2012

Neural Network Evaluation of FRP Strengthened RC Buildings Subjected to Near-Fault Ground Motions having Fling Step

Alireza Mortezaei and Kimia Mortezaei

Abstract**—**Recordings from recent earthquakes have provided evidence that ground motions in the near field of a rupturing fault differ from ordinary ground motions, as they can contain a large energy, or "directivity" pulse. This pulse can cause considerable damage during an earthquake, especially to structures with natural periods close to those of the pulse. Failures of modern engineered structures observed within the near-fault region in recent earthquakes have revealed the vulnerability of existing RC buildings against pulse-type ground motions. This may be due to the fact that these modern structures had been designed primarily using the design spectra of available standards, which have been developed using stochastic processes with relatively long duration that characterizes more distant ground motions. Many recently designed and constructed buildings may therefore require strengthening in order to perform well when subjected to near-fault ground motions. Fiber Reinforced Polymers are considered to be a viable alternative, due to their relatively easy and quick installation, low life cycle costs and zero maintenance requirements. The objective of this paper is to investigate the adequacy of Artificial Neural Networks (ANN) to determine the three dimensional dynamic response of FRP strengthened RC buildings under the near-fault ground motions. For this purpose, one ANN model is proposed to estimate the base shear force, base bending moments and roof displacement of buildings in two directions. A training set of 168 and a validation set of 21 buildings are produced from FEA analysis results of the dynamic response of RC buildings under the near-fault earthquakes. It is demonstrated that the neural network based approach is highly successful in determining the response.

Keywords**—**Seismic evaluation, FRP, neural network, near-fault ground motion

I. Introduction

IMPULSIVE type motions can cause considerable damage during an earthquake, especially to structures with natural periods close to those of the pulse. Near-fault effects can be broken down into three types depending on the pulses, i.e. whether they are of acceleration, velocity, or displacement type. The velocity pulse motion, sometimes referred to as "fling," represents the cumulative effect of almost all of the seismic radiation from the fault [1]. From a seismological perspective, the velocity pulse is more commonly found in earthquake records than are acceleration or displacement pulses.

Alireza Mortezaei, Assistant Professor, Department of Civil Engineering, Semnan Branch, Islamic Azad University, Semnan, Iran. Email: a.mortezaei@semnaniau.ac.ir. Tel: +98 231 3354030

Kimia Mortezaei, M.Sc. Student of Earthquake Engineering, Civil Engineering Faculty, Semnan University, Semnan, Iran. Email: kimia.mortezaie@gmail.com

Although, from an engineer's perspective, the velocity pulse is a better indicator of damage than the acceleration pulse, the damage potential is also dependent on the peak displacement during the pulse [2]. The displacement pulse without the high velocity pulse does not have a high damage potential because the structure has time to react to the displacements. After the 1971 San Fernando earthquake, engineers and seismologists realized the potential damage that may occur due to the effects of near-fault ground motions on structures. The damage observed during the 1994 Northridge, California, the 1995 Kobe, Japan, the 1999 Izmit, Turkey, and the 2003 Bam, Iran earthquakes proved the engineer's hypothesis that structures located within the near-fault area suffered more severe damage than structures located outside of this zone. Although design codes and provisions introduce site-source and distance-dependent near-source factors, the effectiveness of constant amplification factors in providing adequate ductility levels to structures located in the proximity of fault zones is questionable. This is because current design spectra were developed using stochastic processes having relatively long duration that characterizes more distant ground motions. On other hand, failures of modern engineered structures observed within the near-fault region in recent earthquakes revealed the vulnerability of existing RC buildings against pulse-type ground motions.

The objective of this paper is to discuss the feasibility and efficacy of a retrofitting intervention using FRP composite materials in order to upgrade a far-fault earthquake designed RC building to a near-fault one and to investigate the adequacy of Artificial Neural Networks (ANN) to determine the three dimensional dynamic response of FRP strengthened RC buildings under the near-fault ground motions.

II. Characteristics and Database of Near-Fault Ground Motions

The near-fault of an earthquake can be defined as the area in the close vicinity of the fault rupture surface. Besides strong shaking, the characteristics of near-fault ground motions are linked to the fault geometry and the orientation of the traveling seismic waves [3]. Vertical strike-slip faults can produce a directivity effect, and dip-slip faults can produce directivity effects as well as hanging wall effects. Hanging wall effects are felt on the hanging wall of a fault (the earth above a vertically dipping fault), and are due to the proximity of much of the fault to hanging wall sites. Directivity effects can be classified as forward, reverse, or neutral.

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The ground motion database compiled for nonlinear time-history (NTH) analyses constitutes a representative number of far-fault and near-fault ground motions from a variety of tectonic environments. A total of 14 records were selected to cover a range of frequency content, duration and amplitude. Hence the assembled database can be investigated in two sub-data sets. The first set contains seven ordinary far-fault ground motions recorded within 90 km of the causative fault plane from earthquakes in the magnitude (M_W) range of 6.5 to 7.4. The second set includes seven near-fault ground motions. These records come from earthquakes having a magnitude (M_W) range of 6.5 to 7.4, and recorded at closest fault distance of 0.0 to 10 km. Information pertinent to the ground motion data sets, including station, component of earthquake and peak ground acceleration (PGA), peak ground velocity (PGV), and peak ground displacement (PGD), are presented in Tables I and II. Utilized in this study is a data processing technique proposed in Iwan *et al.* [4] and refined in Iwan and Chen [5] to recover the long period components from near-fault accelerograms.

TABLE I
FAR-FAULT GROUND MOTION DATABASE

NO.	Earthquake	Year	Station	Comp.	M_w	Dis. (km)	PGA (g)	PGV (cm/s)	PGD (cm)
1	Kern County	1952	Taft	111	7.4	81	0.17	17.47	8.83
2	Tabas	1978	Dayhook	TR	7.4	107	0.4	26.17	9.1
3	Imperial Valley	1979	Calexico	225	6.5	90.6	0.27	21.23	8.98
4	Loma Prieta	1989	Presidio	000	6.9	83.1	0.099	12.91	4.32
5	Loma Prieta	1989	Cliff House	90	6.9	84.4	0.107	19.78	5.06
6	Manjil	1990	Abbar	L	7.3	74	0.51	42.46	14.92
7	Kocaeli	1999	Ambarli	90	7.4	78.9	0.18	33.22	25.84

TABLE II
NEAR FIELD GROUND MOTION DATABASE

NO.	Earthquake	Year	Station	Comp.	Mw	Dis. (km)	PGA (g)	PGV (mm/s)	PGD (mm)
1	Kocaeli	1999	Sakarya	90	7.4	3.1	0.37	794.9	705.6
2	Chi-Chi	1999	TCU052	N	7.6	0.24	0.41	1185.1	2462.7
3	Chi-Chi	1999	TCU052	W	7.6	0.24	0.34	1590.4	1845.1
4	Chi-Chi	1999	TCU068	N	7.6	1.09	0.46	2631	4300
5	Chi-Chi	1999	TCU068	W	7.6	1.09	0.56	1766.5	3242.7
6	Chi-Chi	1999	TCU102	W	7.6	1.79	0.3	1124.7	892.3
7	Chi-Chi	1999	TCU128	W	7.6	9.7	0.139	730.6	906.6

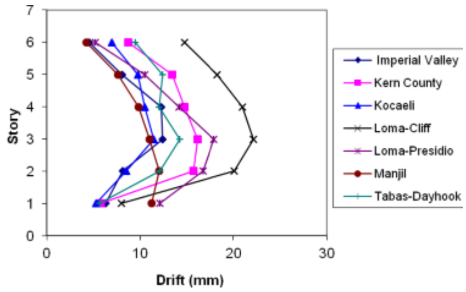
* Data source: PEER (http://peer.berkeley.edu/smcat)

III. SEISMIC EVALUATION AND RETROFITTING

To select an appropriate retrofitting method, an accurate evaluation of both the seismic performance and the condition of an existing structure is necessary. Based on this evaluation, engineers can choose the most effective retrofit among the various intervention techniques and optimize the improvement in seismic performance for an existing structure. Seismic deficiencies should first be identified through a seismic evaluation of the structure.

Six existing reinforced concrete special moment-resisting frame buildings of 3, 6, 10, 14, 16 and 19 stories were selected as representative case studies to evaluate their seismic demands when subjected to near-fault ground motions and to compare their respective responses to typical far-fault ground motions.

In total, 168 nonlinear time history (NTH) analyses were conducted on the six buildings. Inter-story drift ratio (IDR), defined as the relative displacement between two consecutive story levels, displacements at different story levels, base shear force, base bending moment and shear forces at different story levels are used as the primary measure of seismic demand. Additional demand measures, such as component and story ductility were also investigated. In general, there is a reasonable correlation between the inter-story drift demands and component/story-level ductility demands; hence these results have not been included here. The peak inter-story drift profiles obtained from NTH analyses of the 10-Storey building subjected to the two sets of ground motions (i.e., far-fault and near-fault motions) are presented in Fig. 1.



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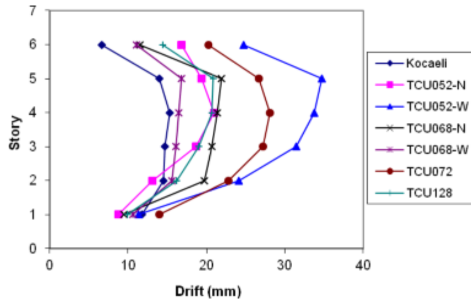

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Fig. 1 Maximum inter-story drift for each building subjected to (a) far-fault earthquakes, (b) near-fault earthquakes

The variation in story demand for the far-fault records is less significant. While higher-mode effects are expected to contribute to the response of the 6- and 10-story buildings, the response of the 3-story building demonstrates that even for low rise buildings, higher-mode effects could be significant.

The analytical results showed that typical RC buildings can be subjected to large displacement demands at the arrival of the velocity pulse, which require the structure to dissipate considerable input energy in a single or relatively few plastic cycles. This demand will impact those structures with limited ductility capacity. In contrast, far-fault motions build input energy more gradually, and the displacement demands are on average lower than the demands in near-fault records.

For all of the near-fault earthquakes investigated in this study, the severity of the demand is controlled by nonlinear finite element analysis. Results show that near-fault motions are potentially more damaging in the upper one-third of buildings. Therefore, in this paper, all panel zones and top and bottom of columns were strengthened with FRP sheets.

On average, the rehabilitated buildings had a total shear force capacity *V*, 1.5 times that of the original buildings. Application of FRP increased the stiffness and ductility of the rehabilitated buildings. The rehabilitated buildings had an elastic stiffness which was 1.4 times that of the original building.

IV. Artificial Neural Networks

An artificial neural network can be described as a model which processes information that emulates the human nervous system to solve complex problems. Those kinds of networks learn, through a training stage, the way in which two or more patterns are associated. The networks can then make generalizations from the knowledge acquired in the learning phase and can forecast specific behaviours when confronted with conditions different from those identified in the patterns.

A neuron is the fundamental element in a biological neural network and its main feature is that it communicates with other neurons using chemical or electric signals. This produces a change in the condition of the neuron thereby passing from an active to a non active stage or vice-versa. In an artificial network processor elements are represented by nodes which can have a large number of connections, as do neurons in biological networks. Multiple connections allow the integration of systems that can acquire adaptive knowledge through a self organization process. In an artificial neural network each node has a value associated to it and this value is the sum of the inputs that arrive to the node following weighted pathways. The values reaching the node are also measures of the strengths of the connections with other nodes. A typical architecture (structure) of a feed-forward ANN model can be demonstrated by Fig. 2, in which the left column is the input layer, the most right column is the output layer, and in between the input and output layers, is a hidden layer.

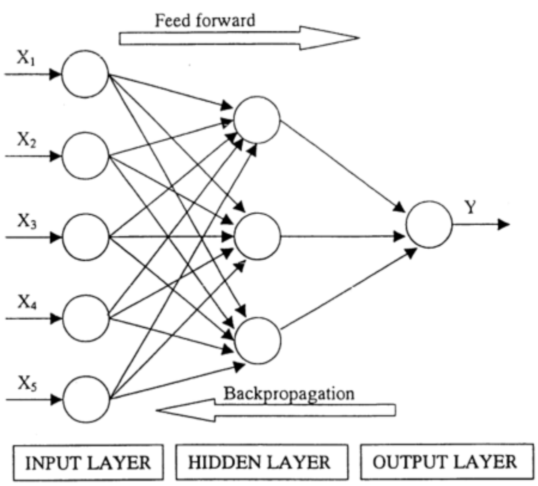


Fig. 2 General structure of an artificial neural network

V. ANN Model for Prediction of Dynamic Analysis

The ANN used in this paper is a Multilayer Perceptron (MLP) [6], having an architecture based on an arrangement of nodes contained in one hidden layers and one output layer. The input layer transmits information from the outside into the first hidden layer and the process continues up to reach the output layer. Each unit in a layer is connected to all the nodes of the following layer, but elements in the same layer are not interconnected; i.e., it is a feed-forward ANN because the signals only propagate in the direction that goes from the input into the one hidden layers and then to the output layer (Fig. 2). Regarding the learning rule, a back propagation algorithm with a sigmoid transfer function as an initial stage was used to explore the power of the ANN.

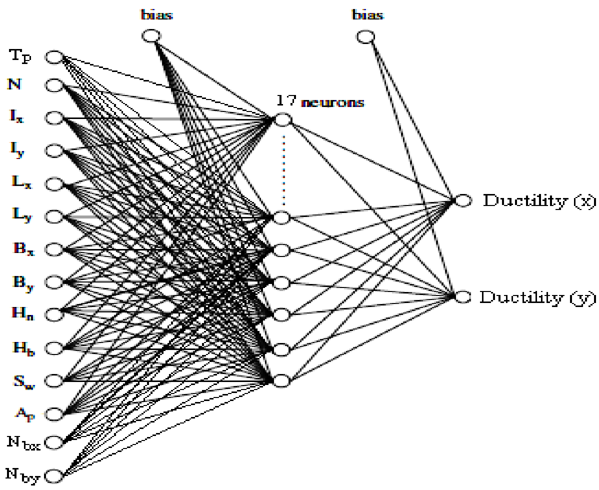


Fig. 3 Architecture of proposed ANN model

A well trained ANN requires that the phenomenon to be modelled be known as amply as possible, in order to select accurately the parameters that define it or influence it. It is also very important to have an adequate data base that includes as many characteristic cases of the phenomenon being considered as can be found and in which the defining parameters are actually involved. An ANN model was developed, as shown in Fig. 3, for simulating the ductility. Inputs of ANN models consisted of 14 data sets in terms of general properties of buildings and earthquake (Table III).

TABLE III
Inputs for ANN models

Notations	Inputs
A_p	Peak acceleration
S_w	Shear wall
I_x	Total moment of inertia (in x direction)
I_y	Total moment of inertia (in y direction)
H_n	Story height
H_b	Story height of base floor
L_x	Max width of bay in x direction
L_y	Max width of bay in y direction
B_x	Widths of building in plan in x direction
B_y	Widths of building in plan in y direction
N	Number of stories
N_{bx}	Number of bay in x direction
N_{by}	Number of bay in y direction
T_p	Pulse period

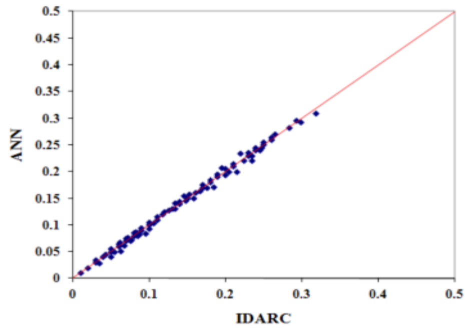
An important task in an ANN model is to determine the number of PEs in the hidden layer, which in turn affects the accuracy of the model. There is no general rule for selection of the number of neurons in a hidden layer and the number of the hidden layers. Hence, they are determined by trial and error in this study. Several different NN models with various hidden neurons are trained and tested for 3500 epochs. Each NN model is initialized with different random weights. The most appropriate NN models are chosen according to the performance of training and testing sets. Therefore, the ANN model is selected as 14 neurons in input layer, 17 neurons in hidden layer and 2 neurons in output layer to define the ductility (Fig. 3).

Sensitivity analysis determines the influence of input variable contributions in neural networks sensitivity. Traditional sensitivity analysis involves varying each input variable across its entire range while holding all other input variables constant; so that the individual contributions of each variable are assessed. The sensitivity analysis results show that amongst the many parameters that potentially may affect the behavior, the ones shown in Table III are the most important ones affecting the network outputs [7].

A MATLAB based computer program was developed to train and test the ANN model based on the data generated from the Finite Element Analysis (FEA) results. In the ANN model, the type of back-propagation is the scaled conjugate gradient algorithm; the activation function is Sigmoidal Function, and number of epochs is about 30000.

VI. Results and Discussion

In order to test the capability of the proposed ANN model, the results were compared with FEA. The performance of the ANN models shows that the correlations between targets and outputs are consistent as shown in Figs. 4. All values in validation set for ANN model have good correlation with FEA results (Fig. 4b). For testing of data, a different plan was selected. The roof displacements (Fig. 5), base shear forces (Fig. 6) and base bending moments (Fig. 7) along the two directions of strengthened RC buildings were computed and compared with ANN models and the FEA. The sum of the squares error (SSE), the root-mean-squared (RMS) and the absolute fraction of variance (R^2) for the testing sets of ANN models were tabulated in Table IV. All of these statistical values proved that the proposed ANN model is appropriate predicting the dynamic response of strengthened RC buildings, in terms of the roof displacement, base shear forces and base bending moments, accurately when compared with the results of FEA.The results for R^2 are 0.999689, 0.99057, 0.97895 and 0.942561 for the periods, roof displacements, base shear force and base bending moment respectively and demonstrate a good correlation. The advantages of ANN over FE analysis are now quite obvious as the former requires no simplifying assumptions, preliminary modeling or calibrations to name a few.



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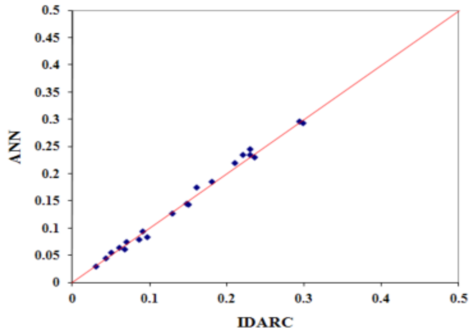

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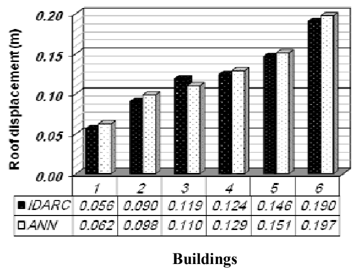
Fig. 4 Performance of proposed ANN model: (a) training set and (b) testing set

TABLE IV
THE STATISTICAL VALUES FOR TESTING BUILDING

Statistical values	Period	Roof displacement	Base shear force	Base bending moment
SSE	0.002658	0.008567	0.1576	0.2943
RMS	0.012637	0.025473	0.10258	0.17586
R^2	0.999689	0.99057	0.97895	0.942561



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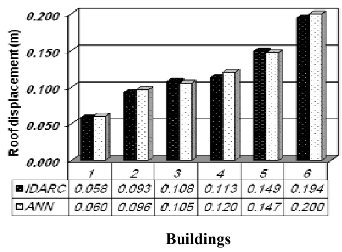

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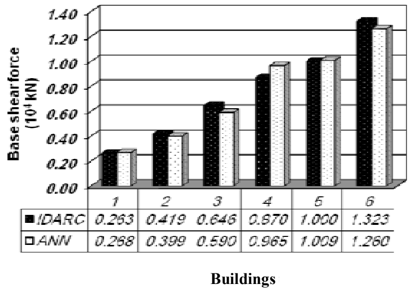
Fig. 5 Roof displacements in two directions; (a) x direction, (b) y direction



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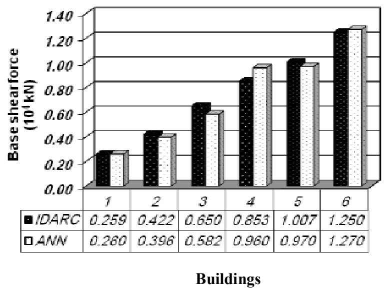

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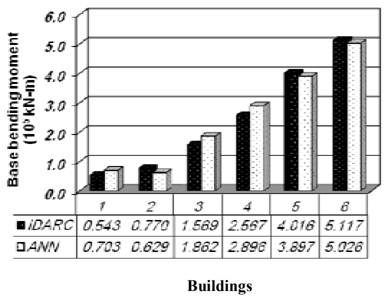
Fig. 6 Base shear forces in two directions; (a) x direction, (b) y direction



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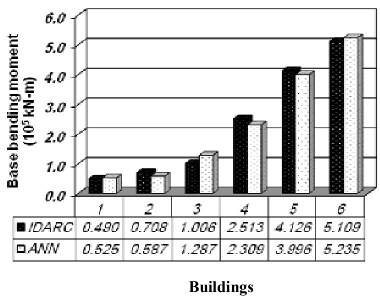

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Fig. 7 Base bending moments in two directions; (a) x direction, (b) y direction

VII. Conclusions

Artificial neural networks have been widely used for simulating the behavior of complex physical phenomena applicable to many branches of science and engineering. However, there have been relatively few applications in the field of structural engineering. In this study, an ANN based model was developed and its predictions compared with the results obtained from numerical analyses. The dynamic response of 189 different buildings were selected and used as a database. 168 of these data were employed as the training set and 21 data were used as the validation set. The ANN model was checked with a testing set that was not used in the training process. It was proven that the ANN-based model can successfully determine the response of strengthened RC buildings in terms of the maximum values of base shear forces, base bending moments and roof displacement time histories. Results obtained by the ANN model were truly competent and showed good generalization. A careful study of the results leads to observations of excellent agreement between ANN predictions and FEA outcomes. This study has shown the feasibility of the potential use of ANN models in determining the response of strengthened RC buildings subjected to earthquakes. The promising results observed in the dynamic analysis of strengthened RC buildings indicate that the ANN models enable the designers to rapidly evaluate the response buildings during the preliminary design stage.

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