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Article:

Prediction of seismic demand model for pulse like ground motions using artificial neural networks

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27 **Abstract:** A probabilistic seismic demand model that relates ground motion intensity measures (IMs) to
28 the structural demand measures is a useful tool for reliability analysis of structures. It is common to utilize
29 the scalar seismic parameters or a vector of a few seismic parameters to reveal ground motion uncertainty.
30 However, for the qualification of an IM for representing the ground motion uncertainty, a larger vector of
31 greater seismic component is required. This study aims to use more parameters as vector IMs in the
32 demand model to achieve better estimation of the ground motion uncertainty. In this study, three-layer
33 feed forward neural network was used to predict the seismic demand model of the mid-rise RC buildings
34 for pulse like ground motions. The results indicate that due to the complexity of the relationship between
35 seismic response of structures and seismic intensity parameters, using artificial neural networks method is
36 more suitable than numerical methods to show uncertainties.

37 *Keywords:* Seismic demand model, near-fault earthquakes, artificial neural network

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1. Introduction

Assessment of the structural seismic damage under earthquake ground motions is an important issue in the seismic risk analysis in the context of seismic performance levels (Kostinakis and Athanatopoulou 2015). In engineering evaluation of structures with regards to performance levels, one of the most important parts of the errors is caused by ground motion uncertainty (Jalayer et al. 2012). To include uncertainties rather than a full probabilistic explanation of the ground motion through the time, a probabilistic model consisting of a scalar parameter (like peak ground acceleration, Arias intensity, cumulative absolute velocity and spectral acceleration) or a few parameters as a vector, is used (Cornell and Luco 2007; Goulet et al. 2007; Jalayer et al. 2012). This creates many errors in specifying the uncertainty caused by ground motions (Jalayer et al. 2012). The parameter or parameters known as Intensity Measure (IM) relate the ground excitation to structural seismic response in the probabilistic demand model. Thus far, various seismic parameters have been proposed as IM by researchers, but none of them have satisfied the sufficiency rule for the ground motion uncertainty (Cornell and Luco 2007; Goulet et al. 2007; Bradley et al. 2008; Jalayer and Cornell 2009; Elenas et al. 2011; Lin et al. 2011(I), 2011(II); Jalayer et al. 2012). Damage measure (DM) of structures after an earthquake is another important parameter that plays a significant role in predicting the demand model. Several parameters are considered to estimate structural damage including maximum inter-storey drift ratio or various damage indices (Krawinkler and Zohrei 1983; Park and Ang 1985; Dipasquale and Cakmak 1989; Colombo and Negro 2005; Kim et al. 2007; Padilla and Rodriguez 2009; Cao et al. 2014; Paal et al. 2015). Park-Ang damage index (DI_{PA}) (Park and Ang 1985) is one of the most popular damage indices to measure component and global structural damage, especially for concrete structures. It is a linear combination of the maximum ductility and the hysteretic energy dissipation.

The seismic response of structures under the earthquake ground motions in near-fault areas can be significantly different from far-field areas (Liel and Champion 2012). These earthquakes have higher accelerations, velocities and restricted frequency content corresponding to the higher frequencies compared to those farther away. The amount of structural damage is more considerable in near-fault

regions (Tothong and Cornell 2008; Liel and Champion 2012). Therefore, the behavior of the structures in these areas is more important for engineers.

There are several methods for solving an engineering problem, such as numerical methods, statistical methods, and methods based on intelligent calculations. Numerical methods are highly accurate methods. However, hybrid methods based on observations can also be more accurate in predicting engineering problems (Elenas et al. 2011; Baghirli 2015). In statistical methods, data collection is employed for analyzing a theoretical model and unknown model parameters are estimated. When the data is incomplete, statistical methods are not accurate. Moreover, these methods need an identified mathematical model (Baghirli 2015). It has been shown that artificial neural networks (ANNs) of modern computational methods are able to estimate various engineering problems, accurately (Reda Taha et al. 2003; Seleemah et al. 2005; Cobaner et al. 2008). The neural network can predict engineering problems well using past data and incomplete data or data associated with errors.

Neural networks can be very effective in solving various engineering problems that cannot be solved by statistical methods. They find relationships between input and output data, without any mathematical models and statistical approach. Hence, if there are several ways to solve a problem, the results of neural networks are with minimal errors (Rafiq et al. 2001; Seleemah et al. 2005; Lazarevska et al. 2014). There are several types of neural networks any of which can be employed depending on the nature and complexity of the problem. Backpropagation neural networks are one of the most important kinds of ANNs that are able to solve a wide range of issues (Jeng et al. 2003; Lagaros and Fragiadakis 2007).

This study proposes neural network techniques for developing a seismic demand model of RC structures, for near-fault pulse like ground motions. First, three different mid-rise RC moment resisting frames with 4, 6 and 8 story levels were chosen, and then nonlinear dynamic analysis was used to determine DI_{PA} of frames under 30 near-fault pulse like ground motions with different intensity scales. A set of 13 major seismic parameters was selected as IM (Elenas et al. 2011; Jalayer et al. 2012; Kostinakis and Athanatopoulou 2015). A three-layer backpropagation neural network that consists of one input, one hidden and one output layer is employed for estimating the demand model. The number of neurons in the

hidden layer for each training algorithm is modified so as to obtain the best performance. The log-sigmoid transfer function was used for the neurons in the hidden layer while the output neuron uses the Purelin transfer function. Four types of training algorithms, namely, Levenberg-Marquardt, Scaled Conjugate Gradient, Broyden-Fletcher-Goldfarb-Shanno and Bayesian Regularization backpropagation algorithms were investigated for their accuracy of predictions. The performance was estimated based on mean square error (MSE). The early stopping method was employed for improving generalization and preventing the over fitting of the networks. The adequacy of the demand model using neural networks was compared with classical methods and the effect of increasing the number of IMs on improving the model was evaluated. Finally, the steps for network training and estimating the seismic demand models for maximum inter-storey drift (MSID), as a common and simple measure of structural damage, are described.

2. Seismic demand model

In seismic risk analysis, an important area of research is the evaluation of expected seismic damage of the structures under a specific earthquake ground motion (Ramamoorthy 2006). In order to estimate the structural damage of an earthquake, it is necessary to introduce a demand model, which is composed of two important variables. One explains the ground motion intensity and the other explains the structural performance. A good estimation of seismic performance and reduction in the variability of structural response prediction depend on a successful correlation of these variables (Jalayer and Cornell 2009; Jalayer et al. 2012).

The seismic performance of the structure is usually examined by DM. Amongst different response quantities of structures, the overall damage indices (DIs) are highly regarded (Kim et al. 2007). The global Park-Ang damage index model (DI_{PA}) (Park and Ang 1985), i.e. a linear combination of ductility and energy absorption capacity parameters, was utilized as DM in this study. Consequently, the identification of an IM, which sufficiently correlates with an appropriate engineering demand parameter, is very important. Previous studies have used different scalar or vector IMs with two seismic parameters

in order to estimate the damage potential of ground motions (Cornell and Luco 2007; Goulet et al. 2007; Bradley et al. 2008; Jalayer and Cornell 2009; Elenas et al. 2011; Jalayer et al. 2012).

In this study, a set of thirteen important seismic parameters that were introduced in previous studies as the effective parameters to represent ground motion intensity, was chosen as IM. In other words, the demand model is assumed as follows:

$$DI_{PA} = f(PGA, PGV, ARMS, VRMS, SI_H, SED, CAV, VSI, ARIAS, S_a(T_1), S_a^*, EPA, T_p) \quad (1)$$

where f is a function of the seismic parameters, and the other parameters are described in Table 1.

3. Selected structural models and ground motion records

To estimate the seismic demand model of RC structures for near-fault ground motions using ANN, three different mid-rise RC moment resistant structures (4, 6 and 8 storeys) were considered. Plan and elevations of the model frames and design details are shown in Figure 1. These frames were loaded and designed according to Iranian Codes (Iranian National Building Codes; Part 9, 2013; Standard No. 2800-5, 2014). In addition, the sectional dimensions and properties of loading are presented in Figure 1. The selection of the critical frame depends on earthquake records. Longitudinal and transverse frames for different earthquake records were investigated and finally the frame A on the plan was selected and damage analysis was carried out by IDARC-2D (Kunnath et al. 2010). The value of 0.15 for β in Park-Ang damage model correlates closely with results based on other damage models (Cosenza et al. 1993). Thus, this value of β is used in this study. This value shows moderate deterioration in IDARC software. The main periods of frames were 0.61, 0.71 and 0.75 s. The Kent and Park model (Kent and Park 1971) was utilized for concrete stress-strain curve. For each component cross-section, the moment-curvature relation is specified as a non-symmetric trilinear envelope with three degrading hysteretic parameters. Damage analysis was carried out to provide a measure of the accumulated damage sustained by the components of the structure, for each story level and the entire building.

The amount of information regarding the structural damage level induced by pulse like ground-motions can play a significant role in seismic design and evaluation of structures. Past research has shown

that near-fault pulse like records tend to increase the displacement response of structures and its variation relative to non-pulse-like excitations (Liel and Champion 2012). In this study, a set of important near-fault pulse like earthquake records was chosen to estimate the demand model of near-fault structures. The ground motions were recorded through events with moment magnitude (M_w) ranging from 5.6 to 7 and distance less than 30 km. Table 2 shows the characteristics of the selected near-fault pulse like records. All records were selected from soft soil sites.

4. Artificial neural network

Artificial neural network is modeled from a biological nervous system of human beings. It has the ability to model any type of complex non-linear relationship (Jeng et al. 2003; Lagaros and Fragiadakis 2007). When the data is incomplete, neural networks are very effective. They are able to learn from experience and adapt to changing conditions (Beale et al. 2011).

4.1. Network's Architecture

A neural network is composed of a large number of neurons, which are connected to each other at different layers. A network complexity varies according to the number of layers and the number of neurons in each layer (Lazarevska et al. 2014; Chojaczyk et al. 2015). A network consists of input layer, output layer, and a few hidden layers. The outputs are the final results of the network that are employed for analysis or solving problems. Each neuron has its own weight coefficient which shows the relative importance of the input (Jeng et al. 2003; Chojaczyk et al. 2015). Various types of neural networks exist according to their architecture (Baghirli 2015). Backpropagation networks have widespread applications in engineering problems (Lagaros and Fragiadakis 2007) and were utilized in this article. Figure (2-a) shows the architecture of a backpropagation neural network with two hidden layers. In backpropagation networks, the propagation takes place in a feed-forward manner, from the input layer to the output layer.

4.2. Activation function

The purpose of the transfer function is to check whether an output is generated with assigned weight and bias (Beale et al. 2011; Lazarevska et al. 2014). Multilayer networks utilize the log-sigmoid, tan-sigmoid

and linear transfer functions as shown in Figure (2-b). When the sigmoid transfer function is used for the last layer, the output is limited to a small range. Assuming a log-sigmoid transfer function for the hidden layer and linear transfer function for the output layer, the model for seismic demand is as follows (Beale et al. 2011):

$$DI_{PA} = w_2 * \left(\frac{1}{1 + e^{-(w_1 \times IM + b_1)}} \right) + b_2 \quad (2)$$

where w_i and b_i are weight and bias matrix of layer i , respectively. The use of nonlinear activation functions enhances the ability of the ANN to learn a nonlinear relationship (Lagaros and Fragiadakis 2007).

4.3. Network's training process

The proper training of a neural network plays an important role in their application for solving engineering problems. There are different types of backpropagation training algorithms, where each one has certain advantages and disadvantages depending on the complexity of the problem. In this study, Broyden-Fletcher-Goldfarb-Shanno (BFGS) (Dai 2013), Levenberg-Marquardt (LM) (Ardıçlıoğlu et al. 2007; Yu and Wilamowski 2011), Scaled Conjugate Gradient (SCG) (Möller 1993; Baghirli 2015) and Bayesian Regularization (BR) (Kayri 2016) algorithms were compared together. The configuration parameters of the algorithms are as shown in Table 3. These algorithms have represented better performance were compared to other algorithms in previous studies (Beale et al. 2011). Over fitting is an important problem that may occur during neural network training. The error on the training data becomes very small, but when new data is presented to the network, the error is large. An early stopping and regularization methods are two different techniques for improving generalization. In the early stopping technique, the available data is divided into three categories (Training, Validation and Testing). The training set is employed for computing the gradient and updating the network weights and biases. When the network begins to over fit the data, the error on the validation set begins to increase. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The test set error is used to compare different

models (Beale et al. 2011; Demuth et al. 2014). A regularization method corrects the MSE performance function by adding a term comprising the mean of the sum of squares of the network weights and biases for preventing the over fitting. Using modified performance function leads to having smaller weights and biases for the network, and less likely to over fit (Beale et al. 2011; Demuth et al. 2014).

5. Results and Discussion

In this paper, backpropagation neural network with three layers (one input, one hidden and one output layer) was employed. The optimal number of neurons in the hidden layer for each training algorithm was determined based on the best network performance. The samples (total of 90 data from 30 analyses) were divided into three categories; training, validation and testing with ratios of 0.6, 0.2 and 0.2, respectively and the early stopping method was used for improving generalization and preventing the over fitting of the networks. To increase the network efficiency, all data was normalized to the range of 0 to 1. As shown in Figure (2-c), the log-sigmoid and Purelin transfer functions were utilized for neurons in the hidden and output layer, respectively. The performance of four algorithms in training the network were examined based on the error and better correlation of measured and predicted values of structural damage. To measure the accuracy of the network, MSE tool was employed. MATLAB software (2011) was used to design and train the network.

Proximity between calculated and estimated DI by different neural network algorithms is given in Figure 3. High correlation can be seen between the calculated and predicted DI by BR, LM and SCG algorithms. Furthermore, a great similarity can be seen between the training, validation and test data. For BR algorithm, correlation coefficients were almost one and the three sets of data matched, indicating the very good learning of the network. The variation of MSE in the network training with different algorithms through 5 epochs is shown in Figure 4. More details can be seen in Table 4. According to the results, it was observed that LM algorithm reached the highest rate in reduction of the amount of errors. In this algorithm, the network error reduced to zero after 5 epochs. Also, a similar trend is observed in the MSE

error of testing and validation sets affirming that over fitting has not occurred. A comparison between different algorithms in reducing the errors of training data can be seen in Figure 5. High speed of LM algorithm in reducing errors can be clearly seen in this figure. After LM algorithm, BR and SCG algorithms had a good rate in reducing errors, noting that SCG had a large error margin compared to the other algorithms in the first step.

Figure 6 shows the variation of correlation coefficient by increasing the number of hidden layer neurons for three data sets and four experimental algorithms. As can be seen, the BR algorithm showed the best correlation and training. By increasing the number of the hidden layer neurons, this correlation has slightly improved. For this algorithm, the correlation coefficient is almost equal to 1.0. After BR algorithm, LM and SCG algorithms had a good performance and a slight increase in the hidden layer neurons will improve the network performance. However, the further increase will reduce the network performance. For BFGS algorithm, there is a major difference between the correlation coefficient of the training data with the other two categories; hence the learning of this algorithm is not satisfactory.

To investigate the role of seismic parameters' numbers as IM to reduce uncertainty, a comparison between the proposed IM and several IMs with different seismic parameters was performed using ANNs. The seismic parameters of IMs are described in Table 5. The correlation coefficient between the calculated values of DI_{PA} and the predicted values and the MSE were compared in Figure 7. For network training, the LM method and 30 neurons in the hidden layer were used. As can be seen, by considering more seismic parameters as an IM, the correlation coefficient increased and MSE significantly reduced.

In other words, for more accurate estimation of the demand model, the effect of more parameters of the seismic ground motions should be taken into account. The residual plot that represents the remaining values of the structural response relative to the predicted values was used to assess the adequacy of models. The residual plots for the four IMs with different numbers of seismic parameters and neural network techniques were compared in Figure 8. According to Figure 8, for IM1, the points are well distributed around the zero line without a particular trend. Thus, the assumption of homogeneity of variances on the errors can be concluded. For this IM, the correlation coefficients between the residuals

tend towards zero, which is very suitable. By reducing the vector space for IM, the average amount of data away from the zero line and the correlation coefficient between the residuals increases which indicates the inadequacy of the model. In addition, the range of the remaining changes significantly increased by reducing the vector space of IM. The probability and density plot of residuals for these IMs can be seen in Figure 9. For IM1, the standard deviation of residuals is less than three other IMs and the probability of occurrence has a steeper slope. These results suggest that the use of scalar or small vector IMs is not sufficient to show earthquake uncertainty and a more accurate demand model requires consideration of more parameters of the earthquake. In addition, a comparison between the ANN method and the classical method was made for two IMs (S_a^* and $[S_a(T_1), S_a(T_2)]$). In the classical method, according to previous studies, exponential relationship is assumed for the demand model (Cornell et al. 2002; Gardoni et al. 2002; Ramamoorthy 2006; Baker 2007; Jalayer et al. 2012). A logarithmic transformation of demand model is as follows:

$$\ln(DI) = a + b \ln(S_a^*) \quad (3a)$$

$$\ln(DI) = a + b \ln(S_a(T_1)) + c \ln(S_a(T_2)) \quad (3b)$$

The correlation coefficient between the calculated values and predicted values of the structural response and the error of models for these IMs are shown in Table 6. According to Table 6, it is observed that the use of neural networks compared with classical methods leads to greater solidarity and less error. By investigating the residual plot for the two IMs shown in Figure 10, better efficiency of the demand model using neural networks compared to the classical model can be seen.

In the following, seismic demand curves for some scalar IMs and vector IMs with two seismic parameters using neural networks are shown in Figure 11. For IMs with three or more seismic parameters, slicing is used for better representation. For example, a few slices of CAV, VSI and ARIAS for demand curve with $[CAV, VSI, ARIAS]$ as IM are shown in Figure 11. According to Figure 11, it is observed that demand curves are monotonic and physically understandable which represents a good training of networks. Given that maximum inter-storey drift (MISD) is simple and is a common measure for damage assessment of structures, we consider MISD as DM in addition to the Park-Ang damage index. For MISD

as well as DI_{PA} , the trained networks had a good performance to predict the seismic demand model. In this case, in general, networks with more seismic parameters as IM had a better performance. For example, the correlation coefficient between the predicted values of damage measure and the calculated values for MISD and DI_{PA} as DMs, are compared in Figure 12. A high correlation for PGV (IM13) and MISD compared with DI_{PA} is an interesting point. Figure 13 shows the seismic demand models for some scalar and vector IMs and MISD as DM.

According to above comparisons, the use of modern techniques such as neural networks to estimate the relationship between IM and DM, due to the complexity of the problem, is more efficient and better suited to demonstrate uncertainties. On the other hand, the superiority of ANNs over classical methods revealed that assuming a simple mathematical model relationship between IM and DM is not suitable for this purpose. Neural networks are less sensitive to errors in data and can work well with incomplete data. The ability to learn from examples is what makes neural networks more powerful and flexible. They can be connected to a large number of input and output data with minimum error.

6. Conclusion

In this study, a three-layer back propagation neural network was employed for predicting the demand model of mid-rise RC structures, and the accuracy of four different training algorithms (LM, BR, SCG and BFGS) was investigated. The input layer consisted of a set of 13 seismic parameters as IM that were determined for 30 near-fault pulse like ground motions with different intensity scales. The output vector with the same length was composed of the Park-Ang damage index and the maximum interstorey drift, corresponding to each input vector. High correlation between the calculated values and the predicted values by the trained neural network demonstrates the ability of neural networks (especially with BR and LM algorithms) to estimate the structural demand model. For the BR and LM algorithms, correlation coefficients of the results for the training data set, were 0.997 and 0.95 respectively, indicating an excellent accuracy of these methods in training the network. Furthermore, the correlation coefficient for training, validation and testing data set were similar and close together indicating the high-quality of the

network. SCG algorithm also performed well, but BFGS is not recommended for this issue. For different algorithms, increasing the number of neurons in the hidden layer to a certain extent will improve the network performance, but a further increase will reduce the network performance. In addition, based on the ability of the trained networks, using the networks with more hidden layers, due to the complexity, is not recommended. The adequacy analysis of different demand models indicates that the classical method, assuming a mathematical model with a linear relationship between the logarithms of the seismic response of structures and the intensity measure of earthquakes, is not very accurate and non-classical methods like neural networks can be very effective, especially for pulse like earthquakes. The comparison of different demand models with different number of seismic parameters as IM suggests that to achieve better evaluation of the structural performance after the earthquake, especially in near-fault areas, the seismic effect of various parameters should be considered together.

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Table 1. The intensity measures (IMs) considered

No.	Seismic Intensity Parameters (IMs)	Description the IM	Definition
X ₁	PGA	Peak Ground Acceleration	-
X ₂	PGV	Peak Ground Velocity	-
X ₃	ARMS	Root Mean Square Acceleration	$\sqrt{\frac{1}{t_e} \int_0^{t_e} (\ddot{x})^2 dt}$
X ₄	VRMS	Root Mean Square Velocity	$\sqrt{\frac{1}{t_e} \int_0^{t_e} (\dot{x})^2 dt}$
X ₅	SI _H	Spectrum Intensity after Housner	$\int_{0.1}^{2.5} PSV(T, \xi) dT$
X ₆	SED	Specific Energy Density	-
X ₇	CAV	Cumulative Absolute Velocity	$\int_0^{t_e} \dot{x} dt$
X ₈	VSI	Velocity spectrum intensity	$\int_{0.1}^{2.5} S_v(T, \xi) dT$
X ₉	ARIAS(I _a)	Arias intensity	$\frac{\pi}{2g} \int_0^{t_e} \ddot{x}^2 dt$
X ₁₀	S _a (T ₁)	Spectral acceleration at the fundamental period	-
X ₁₁	S _a *	Geometric mean of the spectral acceleration values at T ₁ and T ₂	$(S_a(T_1) \cdot S_a(T_2))^{0.5}$
X ₁₂	EPA	Effective Peak Acceleration	$\frac{\overline{S\ddot{A}}}{2.5}$
X ₁₃	T _P	Predominant Period	-

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Table 2. Characteristics of the selected pulse like records

No	Event	Event date Y-M-D	Station	Magnitude (M_w)	Closest Dist. (km)	Depth (km)	PGA (g)	T_p (s)	Soil Class
1	San Fernando	1971-02-09	Pacoima Dam (upper left abut)	6.6	1.8	8.4	1.055	1.64	C
2	Coyote Lake	1979-08-06	Gilroy #6	5.7	3.1	10	0.315	1.23	C
3	Coyote Lake	1979-08-06	Coyote Lake Dam (southwest abut)	5.7	6.13	10	0.245	2.11	C
4	Coyote Lake	1979-08-06	San Juan Bautista - Hwy 101/156 Overpass	5.7	20.67	10	0.2	2.84	C/D
5	Morgan Hill	1984-04-24	Coyote Lake Dam (SW abut)	6.2	0.5	9	1.138	1.07	C
6	Sierra Madre	1991-06-28	San Marino - Southwestern Academy	5.6	18.74	12	0.19	1.58	C
7	Sierra Madre	1991-06-28	LA-City Terrace	5.6	25.69	12	0.12	1.3	C/D
8	Palm Springs	1986-08-07	North Palm Spring	6.1	4	12	0.23	1.4	D
9	Loma Prieta	1989-10-18	Gilroy Array#2	6.9	11.1	18	0.370	1.73	D
10	Loma Prieta	1989-10-18	Saratoga-Aloha Ave	6.9	8.5	18	0.530	4.57	C
11	Cape Mendocino	1992-04-25	Petrolia	7	8.2	15	0.685	3.00	C
12	Cape Mendocino	1992-04-25	Fortuna-Fortuna Boulevard	7	19.95	15	0.120	3.9	C
13	Northridge	1994-01-17	Pacoima Dam (upper left abut)	6.7	7	19	1.260	0.84	C
14	Northridge	1994-01-17	LA-Century City CC North	6.7	23.4	19	0.262	1.12	D
15	Imperial Valley	1979-10-15	EC Meloland Overpass FF	6.5	0.1	12	0.318	3.3	D
16	Imperial Valley	1979-10-15	EC Country Center FF	6.5	7.3	12	0.237	4.42	D
17	Imperial Valley	1979-10-15	Holtville Post Office	6.5	7.7	12	0.258	4.8	D
18	Imperial Valley	1979-10-15	El Centro Differential Array	6.5	5.1	12	0.486	6.27	D
19	Imperial Valley	1979-10-15	El Centro Array#06	6.5	1.4	12	0.453	3.77	D
20	Imperial Valley	1979-10-15	El Centro Array#07	6.5	0.6	12	0.468	4.38	D
21	Imperial Valley	1979-10-15	El Centro Array#08	6.5	3.9	12	0.619	5.4	D
22	Imperial Valley	1979-10-15	El Centro Array#04	6.5	7	12	0.488	4.79	D
23	Imperial Valley	1979-10-15	El Centro Array#10	6.5	8.6	12	0.231	4.52	D
24	Imperial Valley	1979-10-15	El Centro Array#03	6.5	12.9	12	0.268	4.50	D
25	Imperial Valley	1979-10-15	El Centro Array#11	6.5	12.5	12	0.380	7.4	D
26	Kobe	1995-01-16	Takatori	6.9	1.5	1.5	0.693	1.55	D
27	Whittier Narrows	1987-10-01	Downey-Co Maint Bldg	6	20.8	9.5	0.2	0.88	D
28	Whittier Narrows	1987-10-01	Norwalk-Imp Highway	6	20.4	9.5	0.213	0.90	D
29	Whittier Narrows	1987-10-01	Lakewood-Del Amo Boulevard	6	26.68	9.5	0.245	0.93	D
30	Whittier Narrows	1987-10-01	Bell-Gardens	6	17.8	9.5	0.3	0.82	D

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Table 3. Parameters of training algorithms

Configuration Parameters	BFGS	LM	SCG	BR
Maximum learning time (epochs)	1000	1000	1000	1000
Performance goal	0	0	0	0
Maximum validation failures	6	6	6	6
Initial mu	-	0.001	-	0.005
Mu decrease factor	-	0.1	-	0.1
Mu increase factor	-	10	-	10
Minimum performance gradient	1e-6	1e-10	1e-6	1e-10
Scale factor that determines sufficient reduction (α)	0.001	-	-	-
Scale factor that determines sufficiently large step size (β)	0.1	-	-	-
Initial step size in interval location step (δ)	0.01	-	-	-
Parameter to avoid small reductions in performance (γ)	0.1	-	-	-
Determine change in weight for second derivative approximation (σ)	-	-	5e-5	-
Parameter for regulating the indefiniteness of the Hessian(λ)	-	-	5e-7	-

Table 4. MSE error of ANN for different training algorithms from step 1 to step 5

epoch	LM			BR			SCG			BFG		
	Train	Validation	test	Train	Validation	test	Train	Validation	test	Train	Validation	test
1	0.280	0.271	0.279	0.302	0.298	0.283	0.314	0.345	0.310	0.755	0.718	0.729
2	0.033	0.045	0.033	0.242	0.238	0.232	0.204	0.182	0.201	0.446	0.408	0.397
3	0.012	0.014	0.012	0.192	0.189	0.187	0.189	0.162	0.179	0.410	0.362	0.384
4	0.010	0.012	0.010	0.168	0.164	0.164	0.125	0.111	0.121	0.248	0.243	0.233
5	0.009	0.010	0.009	0.045	0.043	0.045	0.090	0.087	0.095	0.099	0.087	0.074

Table 5. Different IMs with varies number of seismic parameters

No.	Seismic parameters of IMs
IM1	[PGA, PGV, ARMS, VRMS, SI_H , SED, CAV, VSI, ARIAS(I_a), $S_a(T_1)$, S_a^* , EPA, T_p]
IM2	[PGV, ARMS, VRMS, SI_H , SED, CAV, VSI, ARIAS(I_a), $S_a(T_1)$, S_a^* , EPA]
IM3	[PGA, PGV, CAV, VSI, ARIAS(I_a), $S_a(T_1)$, EPA]
IM4	[PGV, CAV, VSI, ARIAS, $S_a(T_1)$]
IM5	[CAV, VSI, ARIAS]
IM6	[CAV, ARIAS, S_a^*]
IM7	[$S_a(T_1)$, S_a^*]
IM8	[CAV, $S_a(T_1)$]
IM9	[$S_a(T_1)$, $S_a(T_2)$]
IM10	$S_a(T_1)$
IM11	ARIAS
IM12	S_a^*
IM13	PGV
IM14	PGA

Table 6. Summary of regression analysis for two important IMs with two different methods

IM	R ²		MSE	
	Classical	ANN	Classical	ANN
S _a [*]	0.442	0.523	0.302	0.272
[S _a (T ₁),S _a (T ₂)]	0.608	0.726	0.236	0.206

Figure Captions

Figure 1. Plan and elevation of the concrete frames

Figure 2. (a) Architecture of a back-propagation neural network; **(b)** Transfer Functions for back-propagation networks; **(c)** Network used as a general function approximator

Figure 3. Comparison between calculated and estimated DI by different ANN algorithms

Figure 4. Changes in the error function MSE, for 3 sets of data with different algorithms

Figure 5. Comparison between different algorithms in reducing the errors

Figure 6. Variation of correlation coefficient, by increasing the hidden layer neurons

Figure 7. Comparison of results for different IMs using ANN method

Figure 8. Comparison of Adequacy of demand models with the residual plot

Figure 9. The probability of occurrence and density for the remaining of structural response using ANN method

Figure 10. Check the adequacy of demand models with two important IMs with different methods

Figure 11. Seismic demand curves for some scalar and vector IMs and DI_{PA} as DM

Figure 12. Correlation coefficient between the predicted values of damage measure and the calculated values for MISD and DI_{PA}

Figure 13. Seismic demand curves for some scalar and vector IMs and MISD as DM

Notes

- Restraints:**
Columns fixed at base.
- Connections:**
Moment resisting connections were used.
- Loading:**
Dead load for all storeys: 500 kg/m²;
Dead load of perimeter walls: 700 kg/m;
Live load for storeys: 200 kg/m²;
Live load for roof: 150 kg/m²;
Mass participation ratio of live load: 20%
- Material properties:**
Characteristic strength of concrete: 250 Mpa;
Yield stress of reinforcements: 400 Mpa
- Sections:**
Columns and Beams:
Beam and column dimensions are assumed to be similar.

Figure 1.

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(a)

(b)

(c)

Figure 2.

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Figure 3.

Figure 4.

Figure 5.

Figure 6.

Figure 7.

Figure 8.

Figure 9.

Figure 10.

Figure 11.

Figure 12.

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Figure 13.

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