ASIAN JOURNAL OF CIVIL ENGINEERING (BHRC) VOL. 17, NO. 2 (2016)
PAGES 225-234

PREDICTION OF THE DAMPING REDUCTION FACTOR BY NEURAL NETWORKS

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Received: 10 June 2015; **Accepted:** 25 August 2015

ABSTRACT

The damping reduction factor is used in earthquake engineering in order to estimate the response of buildings with high damping ratio from its with damping ratio equal to 5%. This factor has been studied by a number of researchers, and many expressions were given to this factor as function of many parameters, All the formulations found in the literature were based on a linear or nonlinear regression; this regression analysis is conducted to find a formulation for DRF. The aim of the work reported in this paper is to develop a new method to estimate the damping reduction factor (DRF) using the neural networks. In order to measure the quality of the network prediction; a correlation analysis is performed between the network outputs and the corresponding targets DRF. The simulation results are then presented for different values of damping and conclusions are given. This method gives very interesting results compared to the exact results and thos given by the formulation of Lin et al. (2007).
This formulation is one of the best formulation that describe the DRF. On the other hand, Lin in his paper gives the detailed database used to its DRF formulation that allows to use the same data base to estimate the DRF with ANN and make the comparison.

Keywords: Ground motions; damping reduction factor; neural networks; regression.

1. INTRODUCTION

The damping factor is acknowledged as an important factor in the design of structures that are sensible to dynamic actions. The most important damping mechanisms are mainly due to the materials used and to the interfacial damping. Thus, when the need to increase the level of structural damping systems is felt, one can resort to damping devices like viscoelastic dampers that can dissipate large amounts of energy, or in some cases, to dynamic vibration

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absorbers that isolate buildings from earthquake-induced ground motions or to mass dampers that reduce the structural response by adjusting their vibration mode to the fundamental mode of the structure.

Thus, for design purposes, the common 5% damped elastic design response spectra used in the design codes, must be considered for higher damping ratios and extended to longer periods when designing structure comprising such mechanical devices (dampers, isolators and tuned mass) to enhance their seismic performance [1-3], or when dealing with direct displacement-based design approaches that make use of equivalent linearization [4].

In this context, the interest of the researchers was oriented to either predictive equations that directly estimate spectral ordinates at various levels of damping [4], or scaling factors, named herein Damping Reduction Factors (DRF), that translate spectral ordinates at 5% damping into ordinates for other damping ratios [5-15].Considering this last purpose, several studies for the formulation of the scaling factor have been conducted by different researchers, the outcomes of which have been implemented in most seismic codes. In addition to its obvious dependence on damping and period, investigations are currently underway to study the dependence of the scaling factor on seismological parameters such as magnitude, distance to the source and local site conditions [9, 16, 17].

In this work, interest is given to the development of a simulation procedure which directly generates the desired values of the DRF without having to resort to the use of any formulation. Thus, an artificial neural network (ANN) is implemented for realistic estimation of DRF values (output) associated with pairs of input data values, each corresponding to the fundamental period T and the damping ξ of a considered SDOF system. A number of 200 period values and 19 damping values contained in the Intervals [0.05 sec -10 sec] and [0.01 -0.25], respectively, are considered.

The database used to implement this ANN is represented by DRF values derived from 338 acceleration ground motions recorded during the 21 September 1999 Chi-Chi Earthquake and classified into four classes according to local site conditions in accordance with Taiwan's seismic isolation design code. The implementation of the ANN is made on the basis of training, and testing against test sets made with known inputs (fundamental period and damping value) and output (DRF value) picked from the database. These two phases allow the determination of the number of hidden layers as well their nodes. The applicability of the proposed methodology is illustrated using the formulation developed by Lin [12] (designed herein as LF method) for the considered site classes. In order to measure the quality of the network prediction; a correlation analysis is performed between the network outputs and the corresponding targets DRF. The simulation results are then presented for different values of damping and conclusions are given.

2. GROUND MOTION DATABASE

In this study a total of 338 ground motion accelerations recorded during the 21 September 1999 Chi-Chi Earthquake (Taiwan) constitute the selected database [18].The large number of the selected acceleration time histories allow to obtain a reliable statistical values of DRF.

These records have the following characteristics:

- Recorded on sites with enough informations on geological and geotechnical conditions that enable their classification in accordance with recent code recommendations.
- The magnitude (M) of this earthquake is 7.6.
- Recorded on free field stations or on the first floor of low-rise buildings with negligible soil–structure interaction effects.
- Have a peak ground acceleration (PGA) greater than 20 gal in one of the two horizontal components.

The selected earthquake ground motions are divided into four groups according to the local site conditions at the recording station. The first group includes 100 ground motions recorded at stations located on the very dense soils or soft rocks with average shear-wave velocities greater than 360 m/s which are classified as site classes I in accordance with Taiwan's seismic design provision for buildings with isolation systems. The second group includes 100 records obtained from stations located on the very stiff soils with average shear-wave velocities between180 m/s and 360 m/s which fall into site class II. The third group includes 100 ground motions recorded at stations located on the soft soils with average shear-wave velocities smaller than180 m/s which belongs to site class III. The fourth group includes 38 ground motions recorded at the stations located on the Taipei Basin which is a special site class in Taiwan. The soil in this area is, in general, soft. A complete list of all ground motions including station names, closest distance to surface projection of rupture, site classes at the recording stations and peak ground accelerations (PGA) is given in reference [18,19].

3. ARTIFICIAL NEURAL NETWORK ANALYSIS

3.1 Network design

In order to obtain realistic prediction of the DRF, a contemporary data analysis technique, which is capable of searching nonlinear relationships more thoroughly, is used. This technique is referred to as "the Artificial Neural Network Analysis".

Artificial Neural network constitutes a branch of artificial intelligence which has recently undergone rapid evolution and improvements. Its development started in the 1940s to help cognitive scientists understand the complexity of the nervous system 20]. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the learning process in the human brain, the key element of this paradigm is the novel structure of the information processing system. This computational technique has the ability to process the information at the same architecture as the human brain. It is capable of recognizing, capturing and mapping features known as patterns contained in a set of data mainly due to the high interconnections of neurons that process information in parallel. A network that has learned the patterns defining the relationship between the input and output of a certain test or process can later be used to predict new conditions for which the results (output) are not known. Neural networks consist of three basic layers such as input, hidden and output layers. The first layer contains the input parameters while the last layer contains the output parameters (solution). One or more layers known as hidden layers are usually placed between the input and output layers. In this study, we have used the feed - forward multi-layer neural network in which the neurons are spread in layers in such a way that two consecutive layers are fully connected; all the neurons of an input layer receive the outputs of all neurons in the previous layer. Therefore, a signal moves from the input layer to the output layer through several hidden layers. For each set of input signals, a cell performs a weighted sum in which a transfer function is applied, and the output is transmitted to the next layer. The number of hidden layers, the number of cells per layer and their connections define the architecture of the neural network. The transfer function allowing to calculate the cell output is often a linear sigmoidal function [21].

This explains the general topology of a multilayer feed forward neural network. Neurons in each layer connect to each other's via a weight coefficient. There is a transfer function which change inputs to output. Before using an artificial neural network, it is necessary to train it. Neural training is a method used to calculate the synaptic weights and bias in an iterative way until produces data compatible outputs. At the beginning of training process, initial weights are randomly given to connections, then the inputs are inserted the first layer and then move forward through the hidden layer of neurons to the output layer. At the end, outputs will be compared with the real data [20].

The choice of the network architecture is very important, as it affects both the model precision and the computing time. In order to determine the optimal architecture, we have considered various numbers of neurons in the hidden layer. For this purpose, we have considered the number of neurons in the hidden layer to be equal to 32. The configuration of the ANN is 1-32-1, it expresses a neural network of 2 neurons in the input layer, 32 neurons in the hidden layer and 1 neuron in the output layer.

3.2 Inputs and outputs of the ANN procedure

We first compute the DRF values (target values) associated with the linear response of a SDOF oscillator, with natural period T and damping ratio ξ, subjected to a series of seismic ground accelerations associated with a given class of seismic ground motions. The natural period T and damping ratio ξ are the inputs of the procedure. For each acceleration ground motion a given damping ratio ξ value is considered and DRF's (target values) are computed for a range of natural period values T lying in the interval [0.05 sec. to 10 sec], corresponding structures of engineering interest. The procedure is then repeated for a series of 19 values of damping ratio contained in the interval [1 % to 25%] are successively used.

In a second step, the ANN is trained and tested in an iterative way in order to compute DRF values (outputs) that match well the target DRF values obtained in the first step from the real seismic ground time histories. The training and testing procedures are conducted for a series of pairs (T, ξ), considered as the inputs of the procedure, and for each of the considered classes of seismic ground accelerations. A total of 2,568,800 values of Damping Reduction Factor (DRF) were computed using the 676 selected ground motions with each of the 200 periods of vibration and each of the 19 levels of damping ratio.

3.3 Correlation with data

In order to appreciate the efficiency of the selected network (with 32 cells in the hidden layer), the entire set of data (i.e., data used for learning, validation and testing) has been passed through the network to perform a linear regression between the network output values A and the corresponding target ones T. The correlation coefficient R allows us to measure the quality of the network prediction; a perfect prediction suggests that all the points are aligned along the diagonal A = T and the correlation coefficient is R = 1.

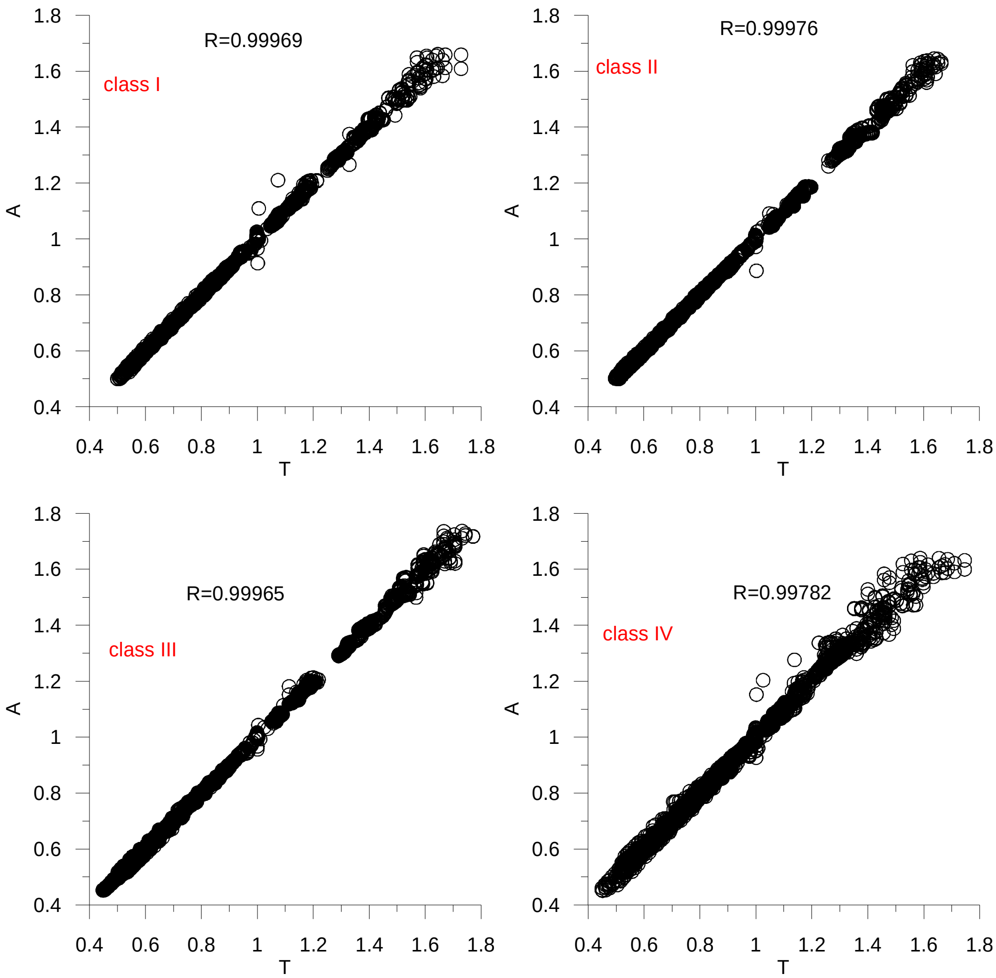

Figure 1. Neural network outputs versus target DRF for the four classes of sites

The Fig. 1 represents the linear regression between the network outputs A and the corresponding targets T for the 4 site classes. For these structures (Fig. 1), the fitting lines are practically superposed with the diagonal, and the correlation coefficient is very close to 1, which means that the outputs values obtained with the neural network match very well those of the database.

To further appreciate the efficiency of the proposed method we compute the relative errors $ERR_{ANN}(T,\xi)$ for the different pairs of values of (T,ξ) by using ANN procedure:

$$ERR(T,\xi)=\left|\frac{DRF_{real}-DRF_{ANN}}{DRF_{real}}\right| \tag{1}$$

And compare it to the corresponding parameter $ERR_{LF}(T,\xi)$ evaluated by using the LF method. For sake of clarity, we only present in Fig. 2 the results obtained, for each of the four classes and for the damping value ξ =20 %. We can observe that a maximum level of

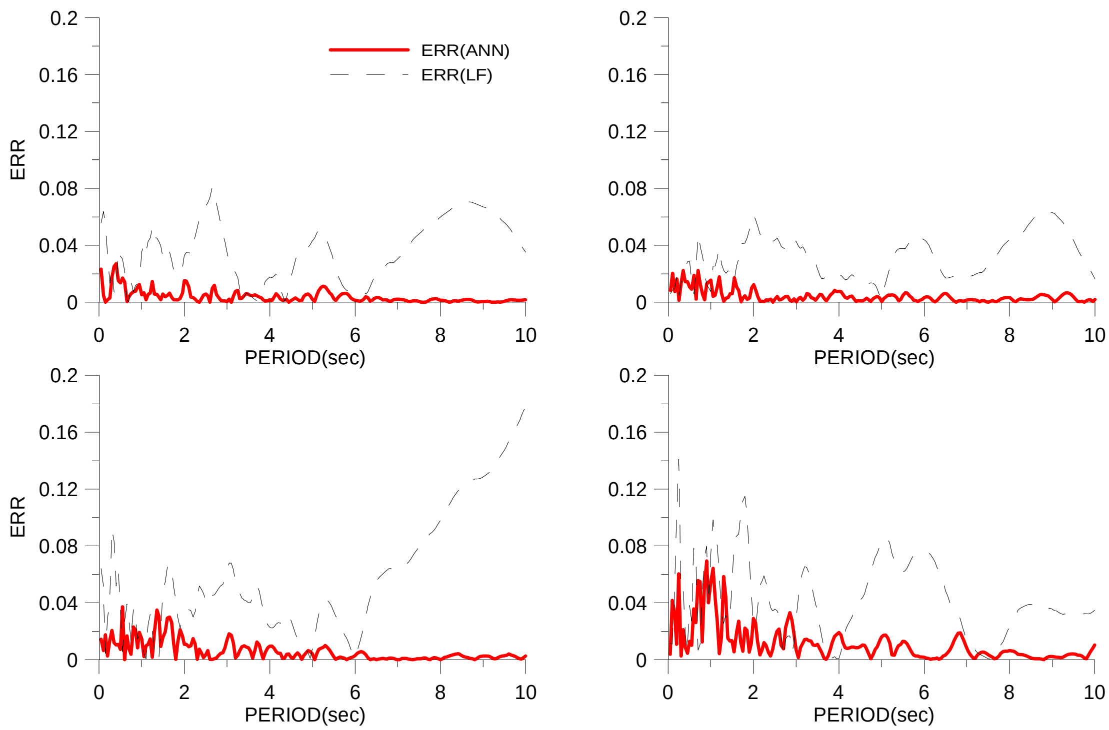

Figure 2. Relative errors between the exact DRF and the ANN and LF

0.04 $(ERR_{ANN})_{\max} < 0.04$ for the classes 1 to 3 and 0.08 $(ERR_{ANN})_{\max} < 0.08$ for class 4 while these values growth to 0.08 and 0.13, respectively, when using LF approach. Same results are obtained when considering the other values of ξ.

It can be concluded, from this nonlinear regression, that the ANN procedure constitutes a more efficient method than the LF one for predicting the DRF values.

4. STATISTICAL STUDY

The accuracy of the ANN is now examined in the light of the comparison between each of two statistical indexes, the mean spectral ratio MSR (T, ξ) and the standard error SE (T, ξ) computed by using ANN approach and the LF nonlinear regression method. These statistical indexes are expressed as follows:

$$MSR(\mathrm{T},\xi)=\frac{1}{n}\sum_{i=1}^{n}\frac{\mathrm{DRF}(\mathrm{T},\xi)\times Sd_i(\mathrm{T},\xi=5\%)}{Sd_i(\mathrm{T},\xi)} \tag{2}$$

$$SE(\mathrm{T},\xi)=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{\mathrm{DRF}(\mathrm{T},\xi)\times Sd_i(\mathrm{T},\xi=5\%)-Sd_i(\mathrm{T},\xi)}{Sd_i(\mathrm{T},\xi)}\right)^2} \tag{3}$$

Where $Sd_i(T,\xi)$ is the value of the displacement spectrum of the linear SDOF oscillator estimated for the period T and the damping ratio ξ, associated with the ith ground acceleration- time history of the considered class in the database and DRF (T, ξ) the damping reduction factor associated with the used method (ANN or LF).

The standard error SE measures the scattering of the approximate maximum displacements around the associated target values. Values of SE close to zero imply a good accuracy of the considered approximate method in the prediction of the real maximum displacements. Values of MSR (T, ξ) smaller than 1.0 indicate that the used method underestimates, on average, the amplitude of displacement spectrum associated with the period T and damping ratio ξ and values of MSR (T, ξ) larger than 1.0 mean that the approximate method overestimates on overall this amplitude.

In this paper, results are presented for viscous damping ratios equal to 20%, and, as stated above, with a set of 200 periods of vibration between 0.05 s and 10 s with an increment $\Delta t =$ 0.05 s.

Fig. 3 shows the MSR (T, ξ) computed for site classes I, II, III and Taipei Bassin of the 21 September 1999 Chi-Chi earthquake database. It can be seen that mean spectral ratio values computed by using the ANN method vary with little perturbation around the value 1.This means that the damping reduction factor values estimated by the ANN method are close to the real values. On the other hand, the MSR values obtained by the LF are characterized by significant perturbations.

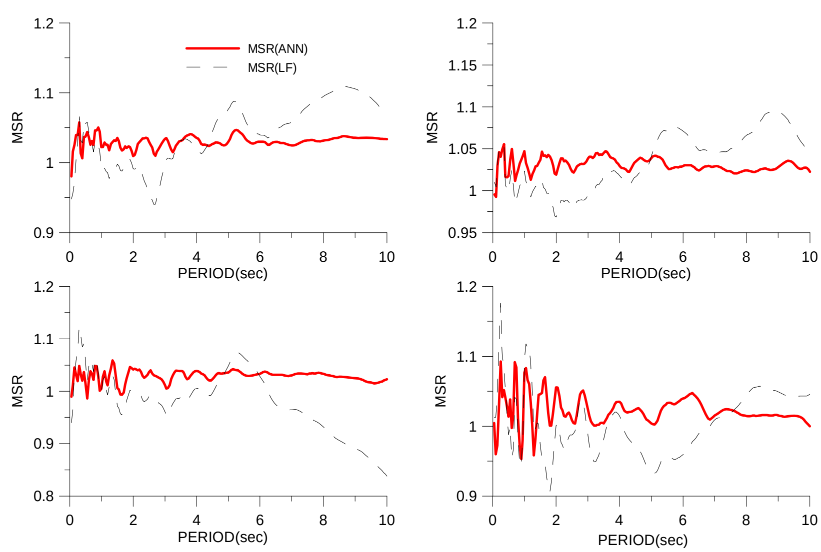

Figure 3. Mean spectral ratio of DRF for four classes of chi-chi

This means that the LF leads to DRF values quite different from the real ones. We can easily conclude that the DRF values obtained by the ANN method are more accurate than those obtained by the LF. Fig. 4, which display the standard error SE, show that the error committed when using the ANN to compute the DRF is less than the error committed when using LF. Indeed, the variations of the SE values associated to the ANN are closer to zero than those associated to the LF, especially for the class 3 when the error for Lin's results has a value greater than 0.25 while those of the ANN remaine less than 0.17.

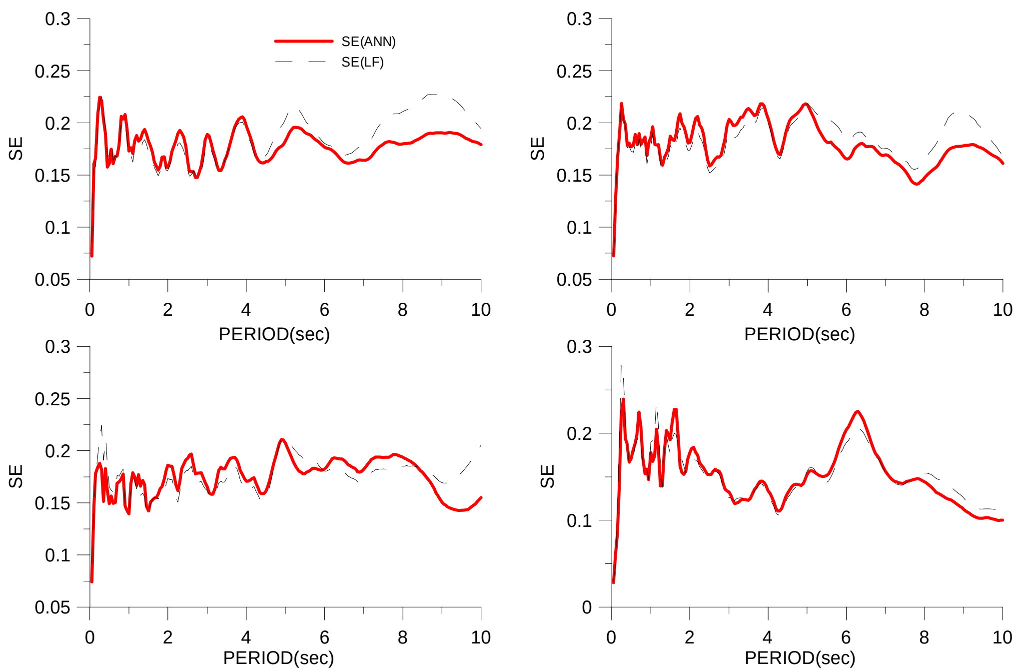

Figure 4. Standard error of DRF for four classes of chi-chi

5. CONCLUSION

When designing structure for damping ratios higher than the common used value 5% and extended to longer periods, elastic design response spectra used in the design codes (for 5% damping ratio) must be adjusted by using the Damping Ratio Factor (DRF). For this purpose, a procedure using ANN was developed which allows to compute DRF compatible with target ones derived from the 21 September 1999 Chi-Chi Earthquake strong ground motion database. This database was classified in four classes with reference to soil conditions at the recording sites. For each class, DRF values have been estimated for ranges of natural periods T and damping ratios ξ corresponding to structures of engineering interest.

The efficiency of the developed ANN procedure was examined in the light of three parameter characterizing the regression analysis: the correlation coefficient R, the mean spectral ratio MSR (T, ξ) and the standard error SE (T, ξ). The obtained results corroborate for a good matching of the estimated DRF values with the target ones. On another hand, the coefficients associated with the ANN procedure was compared with those corresponding to the regression procedure developed by Lin (designed by LF method). The results show that the fluctuations of the estimated DRF values around the real are more pronounced for the LF method attesting that the ANN procedure leads to more accurate estimations.

The developed ANN can be used to estimate the DRF for databases with several ground motions events and to estimate the DRF for different seismic codes with a very good approximation.

The ANN is new method for estimating accurate values of damping reduction factor, the proposed approach is original and the associated results are interesting and promising.

REFERENCES

1. Tomás Castillo, Sonia E. Ruiz, reduction factors for seismic design spectra for structures with viscous energy dampers, *Journal of Earthquake Engineering*, No.3, **18**(2014) 323-49.
2. Ramirez OM, Constantinou MC, Kircher CA, Whittaker AS, Johnson MW, Gomez JD, et al. Development and evaluation of simplified procedures for analysis and design of buildings with passive energy dissipation systems. Report no: MCEER-00-0010, New York: Multidisciplinary Center for Earthquake Engineering Research (MCEER), University of New York at Buffalo, 2000.
3. Ramirez OM, Constantinou MC, Whittaker AS, Kircher CA, Chrysostomou CZ. Elastic and inelastic seismic response of buildings with damping systems, *Earthquake Spectra*, No. 3, **18**(2002) 531-47.
4. Akkar S, Bommer JJ. Prediction of elastic displacement response spectra in Europe and the Middle East, *Earthquake Engineering and Structural Dynamics*, No. 10, **36**(2007) 1275-1301.
5. Lin YY, Chang KC. A study on damping reduction factor for buildings under earthquake ground motions, *Journal of Structural Engineering, ASCE*, No. 2, **129**(2003) 206-14.
6. Hatzigeorgiou GD. Damping modification factors for SDOF systems subjected to near-fault, far-fault and artificial earthquakes, *Earthquake Engineering and Structural Dynamics*, **39**(2010) 1239-58.
7. Ashour SA. Elastic seismic response of buildings with supplemental damping, Ph.D. dissertation, Department of Civil Engineering, University of Michigan, January 1987.
8. Newmark NM, Hall WJ. Earthquake spectra and design, EERI monograph series, Oakland (CA), Earthquake Engineering Research Institute, 1982.
9. Cameron WI, Green RU. Damping correction factors for horizontal ground-motion response spectra, *Bulletin of the Seismological Society of America*, No. 3, **97**(2007) 934-60.

10. Stafford PJ, Mendis R, Bommer JJ. The dependence of spectral damping ratios on duration and number of cycles, *Journal of the Structural Engineering (ASCE)*, No. 8, **134**(2008) 1364-73.
11. Tolis SV, Faccioli E. Displacement design spectra, *Journal of Earthquake Engineering*, **3**(1999) 107-25.
12. Lin YY, Chang KC. Effects of site classes on damping reduction factors, *Journal of Structural Engineering, ASCE*, No. 11, **130**(2004) 1667-75.
13. Lin YY, Miranda E, Chang KC. Evaluation of damping reduction factors for estimating elastic response of structures with high-damping, *Earthquake Engineering and Structural Dynamics*, No.9, **34**(2005) 375-88.
14. Anmin Hao, Deyuan Zhou, Yaming Lib, Hui Zhang, Effects of moment magnitude, site conditions and closest distance on damping modification factors, *Soil Dynamics and Earthquake Engineering*, No. 9, **31**(2011) 1232-47.
15. Wu JP, Hanson RD. Inelastic response spectra with high damping, *Journal of the Structural Division, ASCE*, No. 6, **115**(1989) 1412-31.
16. Abrahamson NA, Silva WJ. Empirical Ground Motion Models, Section 4: Spectral Scaling for Other Damping Values, Report to Brookhaven National Laboratory, 1996.
17. Akkar S, Sandıkkaya MA, Ay BÖ. Compatible ground-motion prediction equations for damping scaling factors and vertical-to-horizontal spectral amplitude ratios for the broader Europe region, *Bulletin of Earthquake Engineering*, No. 1, **12**(2014) 517-47.
18. Lin YY. Statistical study on damping modification factors adopted in Taiwan’s seismic isolation design code by using the 21 September 1999 Chi-Chi earthquake, Taiwan, *Engineering Structures*, **29**(2007) 682-93.
19. Pacific Earthquake Engineering Research Center. PEER Strong Motion Database, Available from: http://peer.berkeley.edu/smcat. Last access: 2009/02/25.
20. Tardast A. Rahimnejad M, Najafpour GH, Ghoreyshi A. Use of artificial neural network for the prediction of bioelectricity production in a membrane less microbial fuel cell, *Fuel*, **117**(2014) 697–703.
21. Badaoui M, Chateauneuf A, Fournely E, Bourahlaand N, Bensaïbi M. Evaluation of accidental eccentricity for buildings by artificial neural networks, *Structural Engineering and Mechanics*, No. 4, **41**(2012) 527-38.