STRONG GROUND MOTION DURATION AND RESPONSE SPECTRA USING ARTIFICIAL NEURAL NETWORKS

Alcántara L., Ovando E., Macías M. A. and Ruiz A. L.

Instituto de Ingeniería de la Universidad Nacional Autónoma de México
Ciudad Universitaria, Apdo. Postal 70-472
Coyoacán 04510, México, DF, México
Tel: (52)-(55) 5623-3600 Ext. 3657 Fax: (52)-(55) 5616-1514
E-mail: leonardo@pumas.ii.unam.mx

ABSTRACT :

Artificial neural networks (ANN) were used to estimate strong ground motion duration and response spectra using accelerograms recorded in and around the Mexican cities of Puebla and Oaxaca. These networks were developed using a back propagation algorithm and multi-layer feed-forward architecture in the training stage.

For strong ground motion duration, we integrate data considering that the phenomenon is characterized by seismic magnitude, epicenter distance, site period and azimuth. Results were compared with those obtained from the Arias method and Reinoso&Ordaz equation. Regarding to response spectra, besides the previous parameters we also considered a vector of spectral amplitudes. In order to evaluate the forecasting capacity of the ANN strong ground motion duration and response spectra were estimated from earthquakes whose data were not included in the training phase. An acceptable concordance is observed between them and those provided by the ANN.

Overall, the results presented show that ANN provide good and reasonable estimates of strong ground motion duration and response spectra in each one of the three orthogonal components of the accelerograms recorded in the cities of Puebla and Oaxaca. Furthermore, the networks have a good predictive capacity to estimate duration and response spectra.

KEYWORDS: Strong Ground Motion Duration, Artificial Neural Network, Response Spectra, Accelerogram Recording, Arias Intensity, Earthquake.

1. INTRODUCTION

Based on the processes that carry out into the human brain and inspired by its functioning several researchers have been working with the theory of ANN, which emulate the behavior of the Biological Neural Networks. ANN have provided a different alternative to deal with problems, in which traditional methods cannot offer a reliable solution. In Mexico, ANN have been used to face problems related to seismic response of soils, buildings, tunnels and so on (Romo *et al.*, 1999 and García, *et al.*, 2003).

For the Mexican cities of Puebla and Oaxaca (figure 1), herein we present two ANN approaches. The first one estimates strong ground motion duration in the former city; where we developed independent ANN for each seismic station. We considered that magnitude, epicenter distance, azimuth and period site are the main parameters that characterized the strong motion duration. The second approach deals with the evaluation of the response spectra in Oaxaca City. In this case, apart from the parameters mentioned we also included a vector integrated by the response spectra amplitudes of several accelerograms recorded. In both proposals, time-series were obtained from The Mexican Strong Ground Motion Data Base (Alcántara *et al*., 2000).

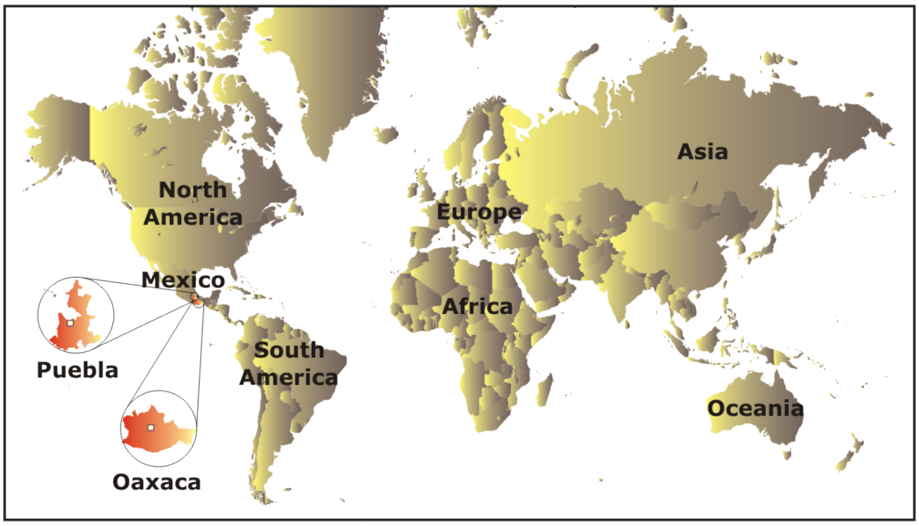

Figure 1 Location of Mexico and its States of Puebla and Oaxaca

2. 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 o more patterns are associated. The networks can then make generalizations from the knowledge acquired in the learning phase and can forecast specific behaviors 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. According to Figure 2 the value associated to a typical node *j* is given by:

$$I_{Tj} = I_1W_1 + I_2W_2 + \ldots\ I_iW_i \ldots . + I_nW_n \qquad (2.1)$$

Where I_{Tj} is the total value associated to node j; I_iW_i is the dot product between input I_i and its associated weight, W_i. The total input signal is reduced by a previously fixed threshold value and then passed by a transfer function that evaluates if the node becomes active; if it does, the node transmits its outgoing signal to other units.

The ANN used in this paper is a Multilayer Perceptron (MLP) (Shepherd, 1997), having an architecture based on an arrangement of nodes contained in two 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 two hidden layers and then to the output layer. 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.

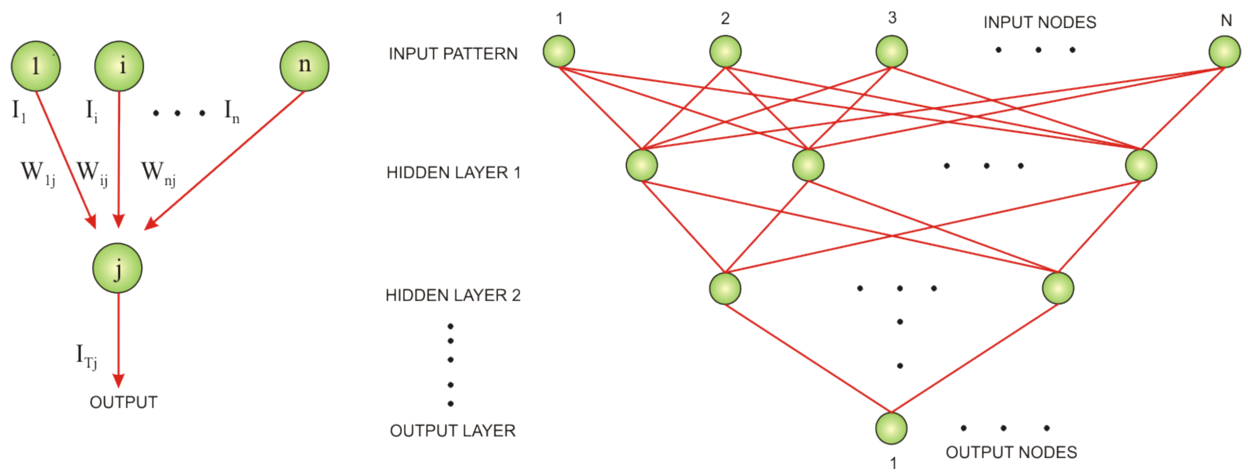

Figure 2 Processing unit and ANN architecture

A well trained ANN requires that the phenomenon to be modeled 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.

3. ARTIFICIAL NEURAL NETWORKS TO ESTIMATE STRONG GROUND MOTION DURATION

The Accelerograph Network of Puebla city is integrated by 11 seismic stations which have recorded more than 100 accelerogram records from 50 earthquakes having magnitudes varying between 3.7 and 8.1. The historical peak ground acceleration is 279 cm/s^2 recorded during the June 15, 1999 Tehuacan earthquake, M=6.5 (Singh, *et al.*, 1999).

3.1. Data set and Training stage

In developing the ANN to estimate strong ground motion duration we integrated a data base comprised by records from three soft soil stations of Puebla city (PBPP, SRPU, SXPU) and rock outcrop records from the Aceelerograph Network that the Engineering Institute of the Universidad Nacional Autónoma de México (UNAM), operates along the Pacific coast in the Mexican Subduction Zone. We considered that records on soil sites contain information related to local soil conditions and site effects and rock outcrop records obtained at sites near epicentral regions contain information about seismic sources; whereas records far from epicentral regions have characteristics associated to distance or trajectory. Figure 3 shows the locations of the seismic stations which are represented by small squares and seismic epicenters are illustrated by inverted triangles.

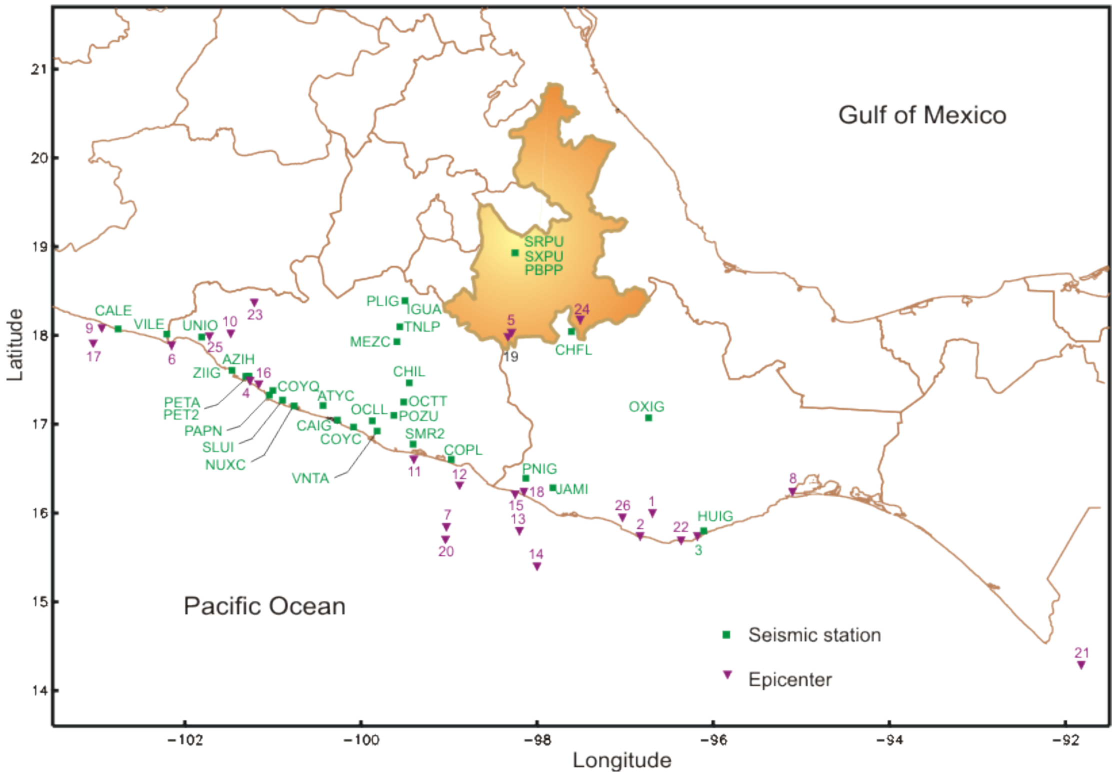

Figure 3 Location of Epicenters and Seismic stations

For training phase, we considered in the input layer of the ANN four parameters: Magnitude (M), Epicenter Distance (R), Azimuth (A) and Site Period (T). The values of the first two were obtained from catalogues furnished by the Mexican Seismological Service. R and A were established from the geographical coordinates of each epicenter given in that same catalogues and from the coordinates of each individual station. Local site periods (T) at stations in the city of Puebla were obtained from response spectra and from horizontal to vertical component Fourier spectrum quotients. For rock sites T was considered equal to 0.2 seconds. The output layer has one node for strong motion ground duration (D_A), which is calculated using the Arias intensity measure (Arias, 1970). This duration is defined as the time over which a certain arbitrary percentage of the total motion energy is delivered. The Arias intensity is given by:

$$Ia = \frac{\pi}{2g}\int_0^t a_x^2(t)dt \tag{3.1}$$

Where: Ia is the Arias intensity measure; $a_X(t)$ acceleration amplitude; t is the record duration and g the acceleration of gravity.

If one assumes that strong motion duration is the time span over which 90 percentage of the seismic energy is delivered at a locality, then such duration D_A can be expressed as:

$$D_A = t_{95} - t_5 \tag{3.2}$$

Where t_{95} and t_5 are the times at which 95 % and 5 % of the energy is delivered during a seismic event. The values of D_A were computed using domestic software (Ruiz, 2002).

Independent ANN were developed for motions recorded along each of the three orthogonal components (i.e. north-south, east-west and vertical) for each station. For training stages, we used the *Neuronal Network System* for Windows, *Thinks Pro*, 2005, which is based on interactive processes that permit to adjust the number of nodes in the hidden layers. Table 3.1.1 presents the final arrangements for PBPP station. The values included in the last column have the format I-H_1-H_2-O, in which letter I indicates the number of input nodes or training patterns, H_1 and H_2 are the number of the nodes of the corresponding hidden layers. Finally, letter O establishes the number of nodes in the output layer. For the architecture of all ANN developed here, we always set the values of the parameters I and O to 4 and 1. Similar arrangements were prepared for training the ANN for stations SXPU and SRPU.

Table 3.1.1 ANN Architectures at PBPP station

Component	Arrangement
	I - H_1 - H_2 – O
east-west	4 - 10 - 10 – 1
north-south	4 - 15 - 15 – 1
vertical	4 - 15 - 10 – 1

3.2. Results from trial runs

ANN were evaluated using data that not were used during the training stage. Such data include two important events recorded in Puebla, the June 15, 1999 (M=6.5) and the September 30, 1999 (M=7.5) earthquakes. In order to compare our results with a different proposal we also include the durations given by the equation 3.3 (Reinoso and Ordaz, 2001).

$$D_{R\&O} = 0.01e^{M} + (0.036M - 0.07)R_d + (4.8M - 16)(T - 0.5) \qquad (3.3)$$

The first term on the right hand side is related to the seismic source and magnitude (M); the second one reflects the dependency of duration on the radial distance (R_d) to the observation point and the last one includes site dependent effects through T, the soil site period.

Strong ground motion durations yielded by the neural networks (D_{ANN}) are, in general, similar to those obtained with Arias' proposal. Regarding to results given by equation 3.3 and the ANN, it can be stated that they are fairly similar except for September 30, 1999 in station PBPP and June 15, 1999 in SRPU. The former gives a longer duration than the others and according to figure 4 such duration seems not to be realistic. Table 3.2.1 includes the results gotten, in seconds, for 3 events in station PBPP and 1 in station SRPU.

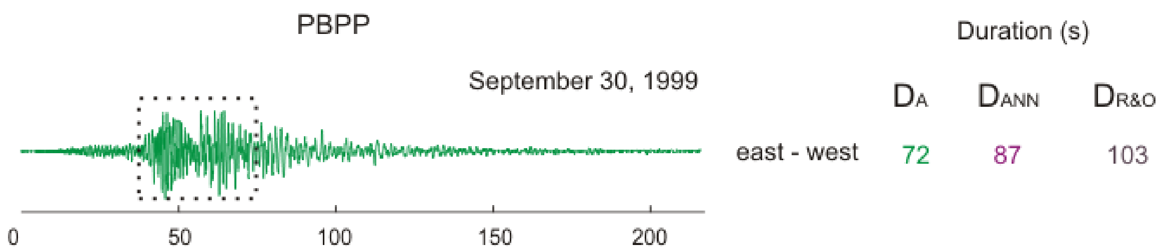

Figure 4 Duration of strong ground motion at station PBPP

Table 3.2.1 Strong ground motion durations at PBPP and SRPU stations

Record	M	R (Km)	A (rad)	T (s)	east-west			north-south			vertical		
					D_A	D_{ANN}	$D_{R\&O}$	D_A	D_{ANN}	$D_{R\&O}$	D_A	D_{ANN}	$D_{R\&O}$
PBPP8904.251	6.8	313	3.6107	1.1	69	**73**	74	50	**72**	74	55	**78**	74
PBPP9906.151	6.5	121	2.4241	1.1	24	**32**	36	29	**37**	36	35	**27**	36
PBPP9909.301	7.5	365	2.7963	1.1	72	**87**	103	80	**80**	103	86	**105**	103
SRPU9906.151	6.5	118	2.3405	0.7	19	**16**	29	26	**18**	29	26	**31**	29

4. ARTIFICIAL NEURAL NETWORK TO ESTIMATE RESPONSE SPECTRA

Herein we include a proposal to estimate elastic response spectra using records obtained in the Accelerograph Network of Oaxaca city. The array has 7 stations deployed in different subsoil conditions, which have collected around 170 accelerograms produced by 67 earthquakes with magnitudes varying from 4.1 to 7.8. The maximum acceleration registered up to now by the array is 370 cm/s^2 and was recorded during the September 30, 1999 (M=7.5) earthquake (Singh, *et al.*, 2000).

4.1. Data set and Training stage

In developing ANN we integrate data set using records from 5 stations: OXLC, OXFM, OXTO, OXAL and OXPM. The former is placed on rock site and the others on soils. As training patterns we selected the following: Seismic Magnitude (M), Epicenter Distance (R), Azimuth (A) and a vector (t_i), which is defined by time increments associated to the response spectra values. Finally, a vector (a_i) that is integrated by the spectral amplitudes associated to the corresponding values of t_i. According to the above, we define the input layer with the parameters M, R, A and t_i, and the output node or target by the vector a_i. The elastic response spectrum of acceleration was estimated using *Degtra System* (Ordaz and Montoya, 2005). For the spectral ordinates, we computed 50 values, for periods between 0 to 3 seconds, and we considered 5 percentage of critical damping.

According to the epicenter distribution of the earthquakes recorded by the Accelerograph Network of Oaxaca city we proceeded to classify them into superficial and deep groups as is shown in figure 5. Inverted triangles represent deep earthquakes and circles superficial earthquakes. Then we developed independent ANN for each station and for each group defined.

All spectral amplitudes of the response spectra, used as a pattern training, were normalized dividing each one to the corresponding spectral amplitude value for T=0 (i.e. the ground peak acceleration recorded). That was done in order to facilitate the learning process to the ANN. The final architectures are integrated by 4 training patters in the input layer, two or three hidden layers with up to 60 nodes each and one node for the output layer.

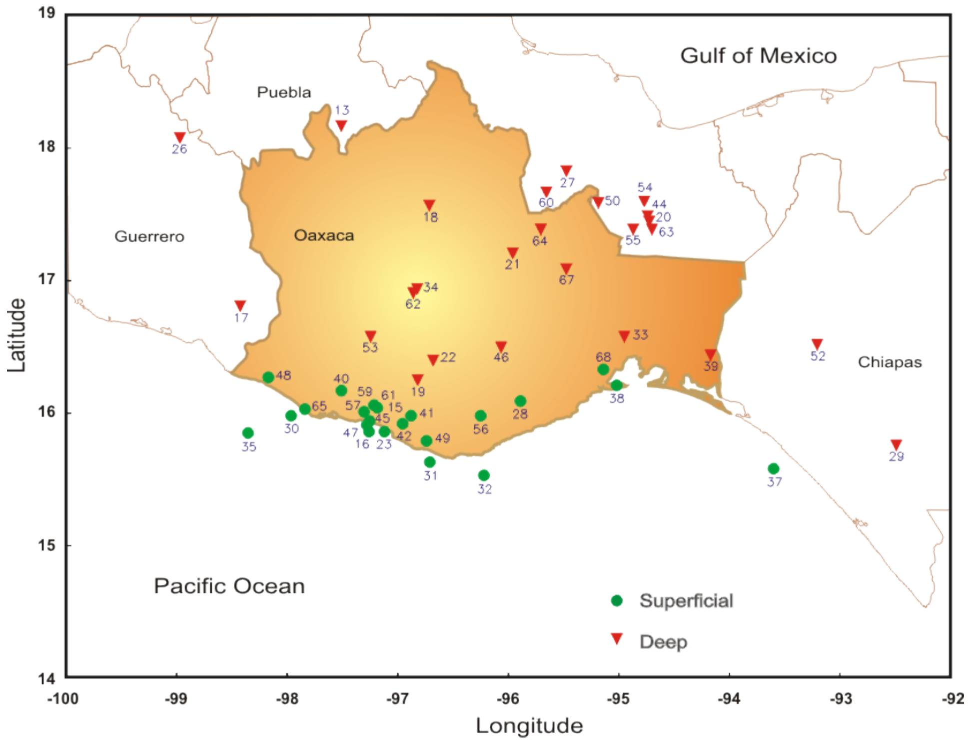

Figure 5 Location of Superficial and Deep earthquakes

4.2. Results from trial runs

In figure 6 we present an example of the response spectra obtained for OXPM station. Left side shows the result during training stage for a superficial earthquake. In this case, we can appreciate that the ANN achieves his aim, because it is completely similar to the real response spectra. Right side depicts the predicted response spectra for another superficial earthquake. That event was not included into the data set used during the training stage. Real and ANN response spectra are very similar. It is important to remark that the spectral amplitudes are normalized. For that matter to get the real response spectra, it will be necessary to multiply such amplitudes by the corresponding value of the ground peak acceleration.

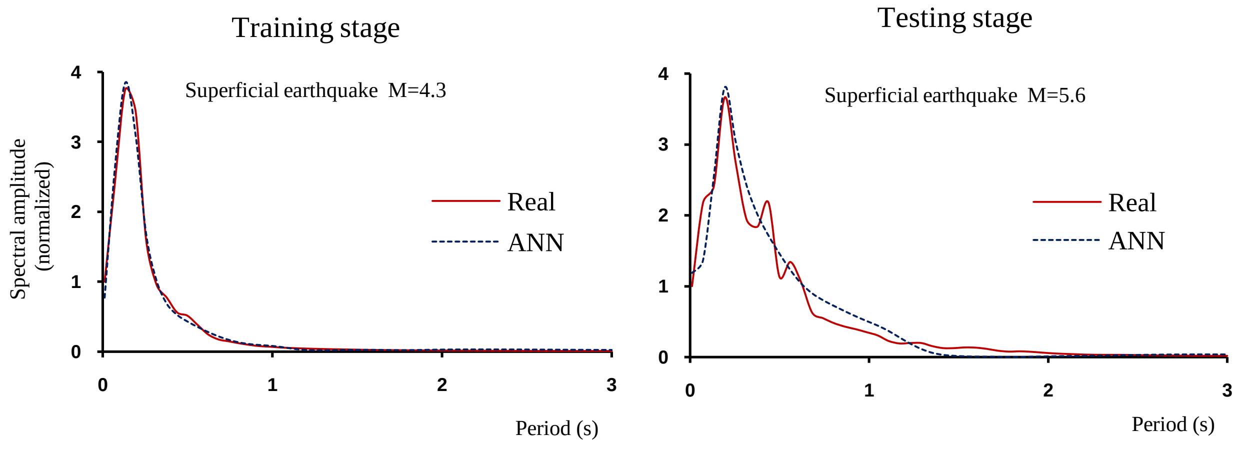

Figure 6 ANN Response Spectra obtained in OXPM station during training and testing stages

CONCLUSIONS

Artificial neural networks were used to estimate strong ground motion duration and response spectra. These networks were developed using a back propagation algorithm and multi-layer feed-forward architecture in the training stage.

Overall, the results presented here show that artificial neural networks provide good and reasonable estimates of strong ground motion duration and response for the accelerograms recorded in the cities of Puebla and Oaxaca. Furthermore, the networks have a good predictive capacity.

Finally, it is important to highlight that the capabilities of an artificial neural network ultimately depend on various factors that demand the knowledge of the user about the problem under consideration. This knowledge is essential for establishing the pattern parameters that best represent it. Experience to set and to select the better network architecture (including learning rules, transfer functions, etc) and the integration of training and test data sets are also very important.

AKNOWLEDGMENTS

We wish to acknwledge the efforts to keep the networks in good condition to: David Almora, Miguel Torres, Mauricio Ayala, Juan M. Velasco, Gerardo Castro, Eduardo O. Vázquez, Ricardo Vázquez, Héctor Sandoval, Citlali Pérez, Rosario Delgado, Jesús G. Ylizaliturri, Luis A. Aguilar, Israel Molina, Alejandro Mora and Miguel A. Soto at the UNAM and the support of Guillermo González-Pomposo, Ana E. Posada-Sánchez and Janet Jiménez Barroso from the Benemérita Universidad Autónoma of Puebla. We are also grateful to professor Miguel P. Romo for his useful comments and to Silvia García for her valuable suggestions.

REFERENCES

Alcántara, L., Quaas, R., Pérez, C., Ayala, M., Macías, M.A., Sandoval, H., (*II-UNAM*), Javier, C., Mena, E., Andrade, F., González, E., Rodríguez, (*CFE)*, Vidal, A., Munguía, L., Luna, M. (*CICESE)*, Espinosa, J.M., Cuellar, A., Camarillo, L., Ramos, S., Sánchez, M. (*CIRES)*, Quaas, R., Guevara, E., Flores, J.A., López, B., Ruiz, R. (*CENAPRED)*, Guevara, E., Pacheco, J. *(IG-UNAM)*, Ramírez, M., Aguilar, J., Juárez, J., Vera, R., Gama, A., Cruz, R., Hurtado, F., Del campo, M., Vera, F. (*RIIS)*, Alcántara, L. (*SMIS)* (2000). Mexican Strong Motion Data Base, CD-Rom, vol. 2, Mexican Society for Earthquake Engineering.

Arias, A. (1970). A measure of earthquake intensity, *Seismic Design of Nuclear Power Plants*, R. Hansen, Editor, MIT Press, Cambridge, Mass., pp. 438-483.

García, S., Romo, M. and Sarmiento, N. (2003). Modeling ground motion in Mexico City using artificial neural networks. *Geofísica Internacional*, **Vol. 42**. Num. 2. pp. 173-183

Ordaz, M. and Montoya, C. (2005). Degtra System A4 v 5.2, *Software* developed at the Engineering Institute of the Universidad Nacional Autónoma de México and CENAPRED, México.

Reinoso, E. and Ordaz, M. (2001). Duration of strong ground motion during Mexican earthquakes in terms of magnitude, distance to the rupture area and dominant site period, *Earthquake Engineering and Structural Dynamics*, **30**, pp. 653-673.

Romo, M.P., Rangel, J.L., Flores, O. and García, S.R. (1999). Applications of Artificial Neural Networks to Geotechnical Problems. Proceedings *XIX National Conference for Soil Mechanics* (in Spanish), Puebla, Puebla, México, pp.418-427.

Ruiz, A. L. (2002). Mexican Accelerogram Processing Software, Internal Report, for the Engineering Institute of the Universidad Nacional Autónoma de México, México.

Singh, S. K., Ordaz, M., Pacheco, J.F., Quaas, R., Alcántara, L., Alcocer, S., Gutiérrez, C., Meli, R. and Ovando, E. (1999). A Preliminary Report on the Tehuacan, Mexico Earthquake of June 15, 1999 (Mw=7.0). *Seismological Research Letters*, **Vol. 70**, Num. 5, Sep/Oct, pp. 489-504.

Singh, S.K., Ordaz, M., Alcántara, L., Shapiro, N., Kostoglodov, V., Pacheco, J.F., Alcocer, S., Gutiérrez, C., Quaas, R., Mikumo, T., Meli, R. and Ovando, E. (2000). The Oaxaca Earthquake of September 30, 1999 (Mw=7.5): A Normal-Faulting Event in the Subducted Cocos Plate**,** *Seismological Research Letters*, **Vol. 71**, Num. 1, Jan/Feb**,** pp. 67-78.

Shepherd, A. J. (1997). Second-Order Methods for Neural Networks Fast and Reliable Training Methods for Multi-Layer Perceptrons, ISBN 3-540-76100-4 Springer-Verlag Berlin Heidelberg New York.

ThinksPro (2005). Neural Networks for Windows, by Logical Designs Consulting, Inc.