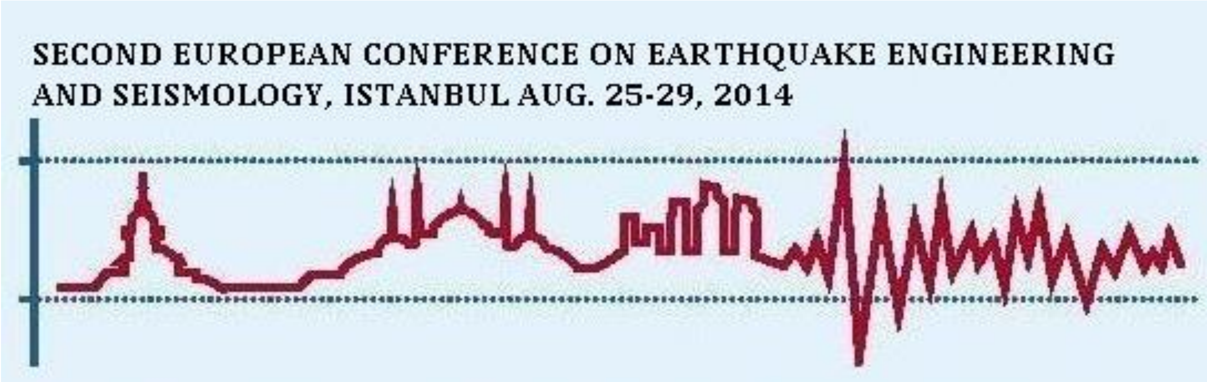

DOES THE AZIMUTH AFFECT STRONG GROUND MOTION DURATION?

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ABSTRACT

One of the most important objectives in seismic engineering is to provide quantitative estimations of expected ground-motions for earthquake-resistant design, evaluation of seismic hazards, and seismic risk assessment. Since the first strong-motion accelerograms were recorded a large number of parameters have been defined to characterize movements. Once a parameter has been selected to characterize the ground motion, it is necessary to develop relationships between this parameter and important seismic features as earthquake source, travel path, and site conditions.

In the case of structural or geotechnical systems, shaking duration parameter has been considered a meaningful predictor of their performance. Nowadays, several expressions have been developed to estimate seismic duration, but the essence of such predictive relationships depends very heavily on the definition of duration employed (i.e. bracketed duration, uniform duration, significant duration and structural response duration). In general terms those expressions are in function of magnitude, distance to the seismic source and some of them include a kind of parameter to take into consideration the subsoil conditions where the recording site is placed. However, they do not include any parameter to evaluate the effect (if any) between the spatial location of the seismic source and the recording site.

In this investigation, and considering the definition of significant duration (strong ground motion duration) the connection between data and knowledge is found using a soft computing SC tool: the neural networks NNs. This alternative improves the theory and understanding of the driven parameters (of all kinds including indeterminate ones, possibly expressed in words) of ground-motion duration behavior. SC, NNs particularly, utilize a discovery approach to examine the multidimensional data relationships simultaneously and to identify those that are unique or frequently represented, permitting the acquisition of structured knowledge.

Here is proposed a neuronal empirical model for strong motion duration which is derived from seismic information registered in the city of Oaxaca in Mexico. This model predicts the strong ground motion duration as a function of earthquake magnitude, epicenter distance, focal depth, azimuth (established from epicenters to stations) and soil characterization. The final scheme permits a direct estimation of the duration since easy-to-obtain variables and does not have restrictive hypothesis.

The results presented in this paper indicate that the soft computing alternative, via the neural model, is a reliable recording-based approach to explore and to quantify the effect of seismic and site conditions on duration estimation. An essential and significant aspect of this new model (neural network) is that, while being extremely simple, it also provides estimates of strong ground motions duration with remarkable accuracy that includes the effect of the Azimuth in the significant duration.

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INTRODUCTION

Currently, a wide range of proposals to determine strong ground motion duration have been developed. Those expressions are in terms of magnitude and distance to the seismic source (Esteva and Rosenblueth 1964, Housner 1965, Bolt 1973, Dobry et al., 1978). Some others have included a kind of parameter that takes into account the subsoil conditions (rock or soil) Trifunac and Brady (1975) or even more specifically the dominant period of the site.

In the other hand, to establish a definition for strong ground motion has been subject of numerous studies Bommer and Martinez-Pereira (1996), but all of these definitions are reduced to three generic groups: 1) the *Bracketed duration*, the interval between the first and last excursion of particular threshold amplitude, 2) the *Uniform duration*, the sum of all of the time intervals during which the amplitude of the record is over the threshold, 3) the *Significant duration*, which is determined from the Husid plot, based on the interval during which a certain portion of the total Arias intensity is accumulated (Arias, 1970). Arias intensity is given by Eq. (1).

$$I_A = \frac{\pi}{2g}\int_0^T a^2(t)dt \tag{1}$$

Here $a(t)$ is the acceleration time history, g is the acceleration of gravity, and T represents the complete duration of recording $a(t)$. Fig.1 presents the procedure followed to determine the significant parameters (Husid, 1969). The most common measure of significant duration is a time interval between 5-95% of I_A and is denoted by $D_{a5\text{-}95}$.

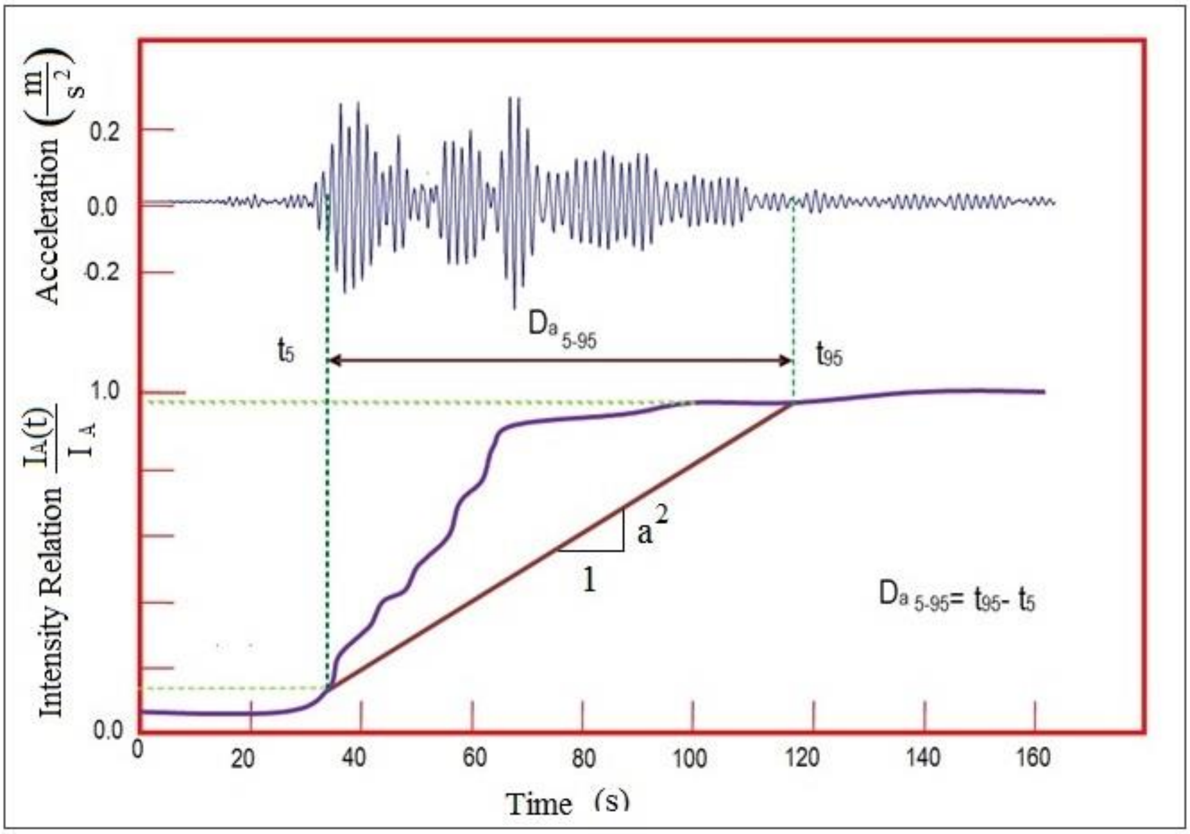

Figure 1. Significant duration (acceleration 5-95%)

Predictive relationships have also been proposed to estimate certain seismic parameters including threshold or significant duration. They consider magnitude and source-site distance and a kind of parameter to represent the local site conditions. The vast majority have been developed considering the Arias definition for 5 to 95 percentage of energy. In the case of Mexican earthquakes Reinoso and Ordaz

(2001), have proposed Eq. (2) which includes in the duration the effects of seismic source, source-site distance and the local conditions of subsoil.

$$D = 0.01e^{M} + (0.036M - 0.07)R + (4.8M - 16)(Ts - 0.5) \quad (2)$$

Here M is the earthquake magnitude, R the hypocenter distance and T_S the dominant site period. In general terms it can be seen that the proposals do not consider any parameter to evaluate the effect (if any) between the spatial location of the seismic source and the recording site.

This paper presents a proposal to implement a neural model to evaluate significant duration in the city of Oaxaca in Mexico. The model considers: 1) seismic effects associated to magnitude, 2) focal distance, 3) soil conditions and 3) the azimuth between epicenter and site recording. Significant duration, from the Arias integral, was selected because of the stability of the method with respect to the definitions of initial and final threshold (Bommer and Martinez-Pereira, 1999).

NEURAL NETWORK

The developing of Neural Networks (NN) is based on the neural system behavior of human beings. A neural model starts from a training process to recognize patterns and find the relationships behind complex data and that define a particular phenomenon. The main purpose is to generalize the acquired knowledge and therefore provide projections to unseen conditions during the training stage (Romo et al., 1998, Romo 1999, García et al., 2002, García 2009).

A NN is a network consisting of connected neurons where the nucleus is the center of the neuron and it is connected to other nuclei through the dendrites and the axon. This connection is called a synaptic connection. The neuron can fire electric pulses through its synaptic connections, which are received by the dendrites of other neurons. When a neuron receives enough electric pulses through its dendrites, as is presented in Fig.2, it activates and fires a pulse through its axon, which is then received by other neurons. In this way information can propagate through the NN. The synaptic connections change throughout the lifetime of a neuron and the amount of incoming pulses needed to activate a neuron (the threshold) also change. This process allows the NN to learn (Tettamanzi and Tomassini, 2001).

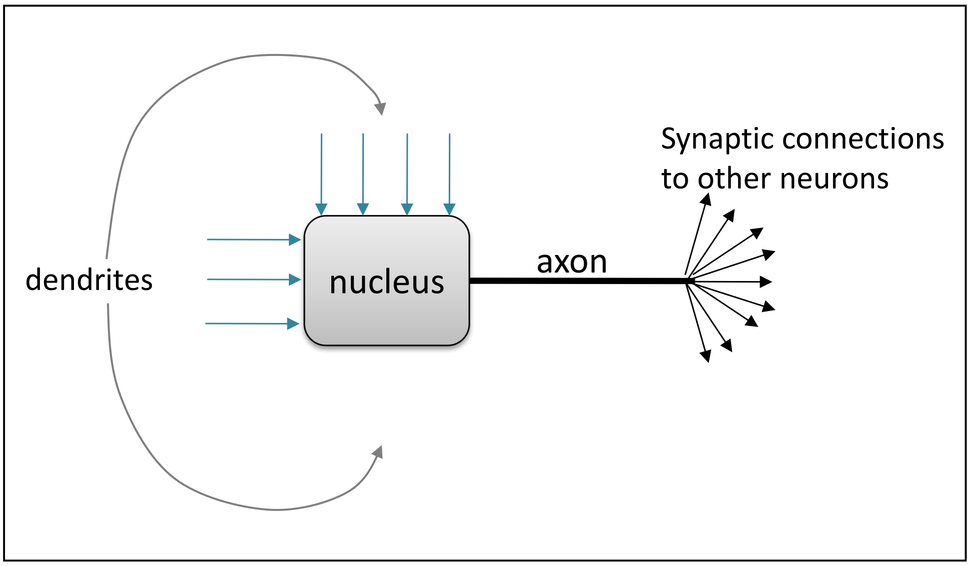

Figure 2. Simplified biological neuron

Fig.3 presents a view of an artificial neuron where x is a neuron with n input dendrites $(x_0, \ldots, x_n)$ and one output axon $y(x)$ and $(w_0, \ldots, w_n)$ are weights determining how much the inputs should be weighted; g is an activation function that weights how powerful the output (if any) should be from the neuron, based on the sum of the input.

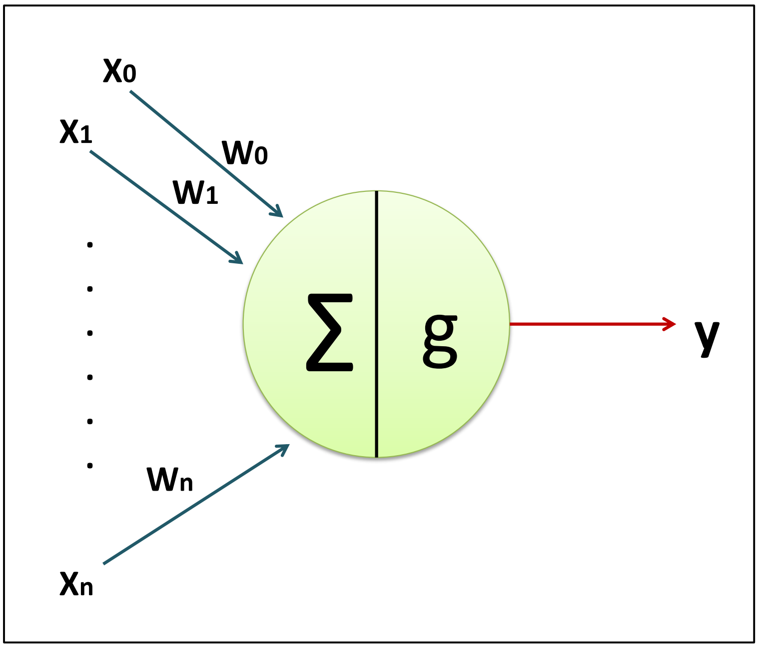

Figure 3. An artificial neuron

Considering the above, the mathematical definition is given by Eq. (3).

$$y(x) = g\left(\sum_{i=0}^{n} w_i x\right) \tag{3}$$

The NN used in this investigation is a multilayer feed forward neural network MFNN. In a MFNN, the neurons are ordered in layers, starting with an input layer and ending with an output layer. There are a number of hidden layers between these two layers. Connections in these networks only go forward from one layer to the next (Hassoun, 1995). They have two different phases: a training phase (sometimes also referred to as the learning phase) and an execution phase. In the training phase the NN is trained to return a specific output given particular inputs, this is done by continuous training on a set of data or examples. In the execution phase the NN returns outputs on the basis of inputs. In the NN execution an input is presented to the input layer, the input is propagated through all the layers until it reaches the output layer, where the output is returned. Fig.4 shows a MFNN where all the neurons in each layer are connected to all the neurons in the next layer, what is called a fully connected network.

For a satisfactory training process of a NN and an adequate generalization capability is essential: 1) a good knowledge about the phenomenon to model in order to make a proper selection of the parameters that represent it , 2) integration of a database that includes a significant number of cases, as well as a wide variety of them, 3) a good design of the model architecture, correct selection of learning rules, transfer functions, etc., and 4) test the model integrity and his ability to generalize learned knowledge by using patterns that were not seen during training stage.

To achieve the above, an iterative adjusting process of the weights of each node is done. This procedure is typical of an optimization problem, which can be solve from the use of heuristic methods to more specialized techniques as genetic algorithms or the so-called gradient descent. One of the most frequently used is the well-known back-propagation algorithm (BP).

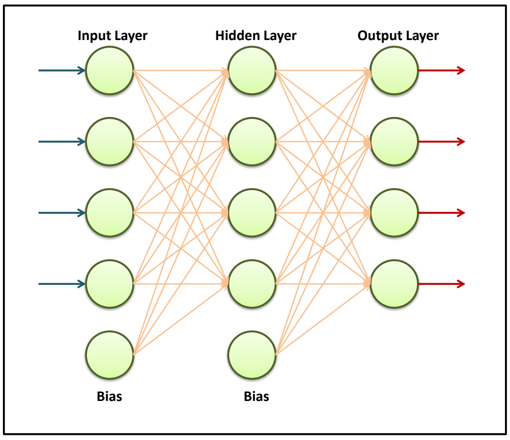

Figure 4. A multilayer feed forward network

DATABASE

The city of OAXACA has currently an accelerograph network composed of 7 seismic stations, deployed around the urban area, as illustrated in Fig.5 and are located in a wide variety of subsoil conditions ranging from compressible to stiff deposits and one on a rock outcrop (see Table.1). Instruments installed are digital accelerographs with a wide frequency-band and wide dynamic range.

This network initiated operation in 1973 so an important collection of recordings has been obtained. Recordings from events with poorly defined magnitude or recordings with low signal to noise ratios were not integrated in the database. Both horizontal components and vertical direction of each seismic event were considered. The final data set comprises 147 three-component accelerograms from earthquakes with magnitudes ranging from 4.1 to 7.8. These accelerograms were obtained from records of both subduction and normal-faulting earthquakes, originated, respectively, at the contact of the North America and Cocos plates, and by the fracture of the subducted Cocos plate. Therefore this catalogue represents wide-ranging values of directivity, epicenter distances and soil-type conditions (see Fig.6).

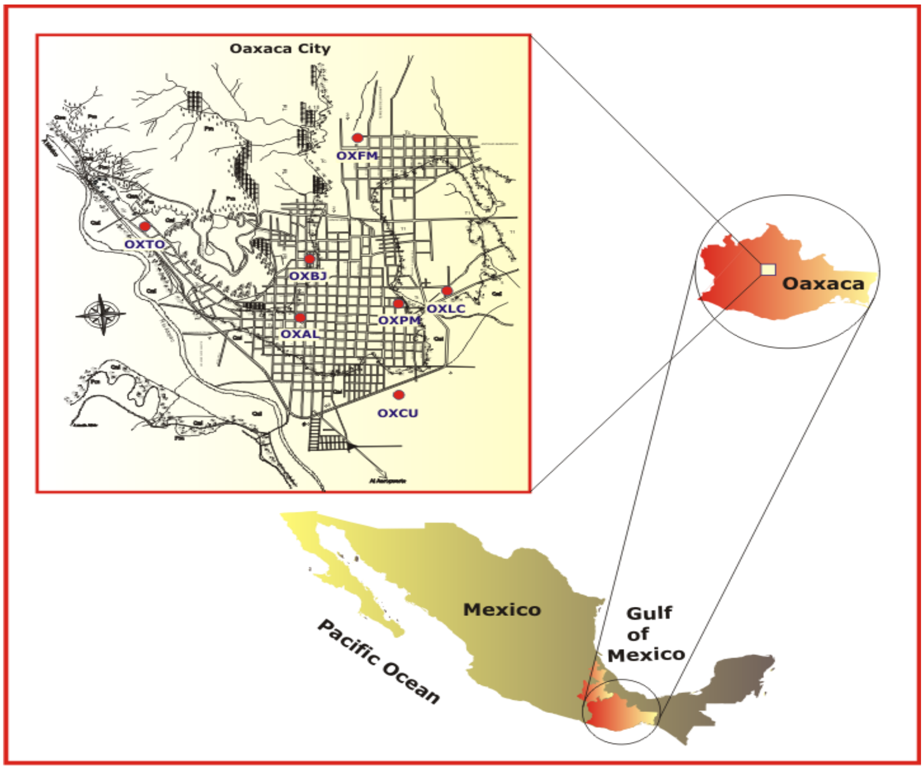

Figure 5. Strong motion network in Oaxaca City

Table 1. Accelerograph Network in Oaxaca City

Station Code	Station name	Soil	Geo-Coordinates	
			N Latitude (°)	W Longitude (°)
OXFM	School of Medicine	Alluvium	17.084	-96.716
OXLC	The Canteras Area	Rock	17.065	-96.703
OXPM	Mugica Elementary School	Clay	17.061	-96.717
OXBJ	Benito Juárez Elementary School	Clay	17.067	-96.744
OXAL	Alameda de León Park	Clay	17.061	-96.725
OXCU	University Zone	Clay	17.049	-96.713
OXTO	Oaxaca Institute of Technology	Alluvium	17.078	-96.744

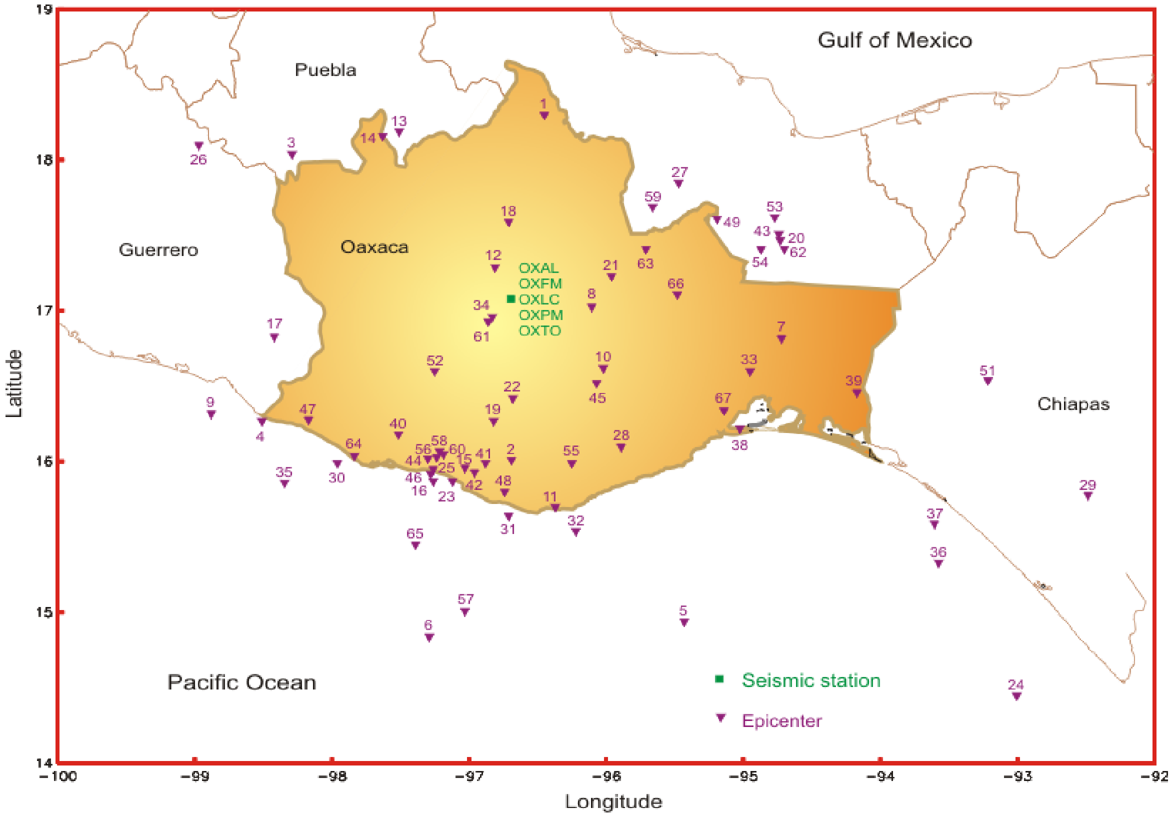

Figure 6. Epicenters and Seismic stations

NEURAL MODEL IN THE MEXICAN CITY OF OAXACA

The database has been modeled using the BP learning algorithm and Feed Forward Multilayer architecture. Time duration (D) in horizontal (north-south and east-west) and vertical components are included as outputs for neural mapping and this attempt was conducted using five inputs Magnitude (M), Epicenter distance (R), Focal depth (FD), Soil class (Sc) and Azimuth (Az).

After trying many topologies, we found out that the best model during the training and testing stages has two hidden layers with 200 nodes each.

Some results of the neural model are presented in Fig.7. Left picture shows the predictive capacity of the model as target durations are compared with those of the Arias definition in the training stage. There are a good correlation for all the range of magnitudes and epicenter distances. Right picture present estimations using a testing set, it is important to remark that this set was no presented to the model in the training stage. The values predicted by the model in this testing stage are also very consistent.

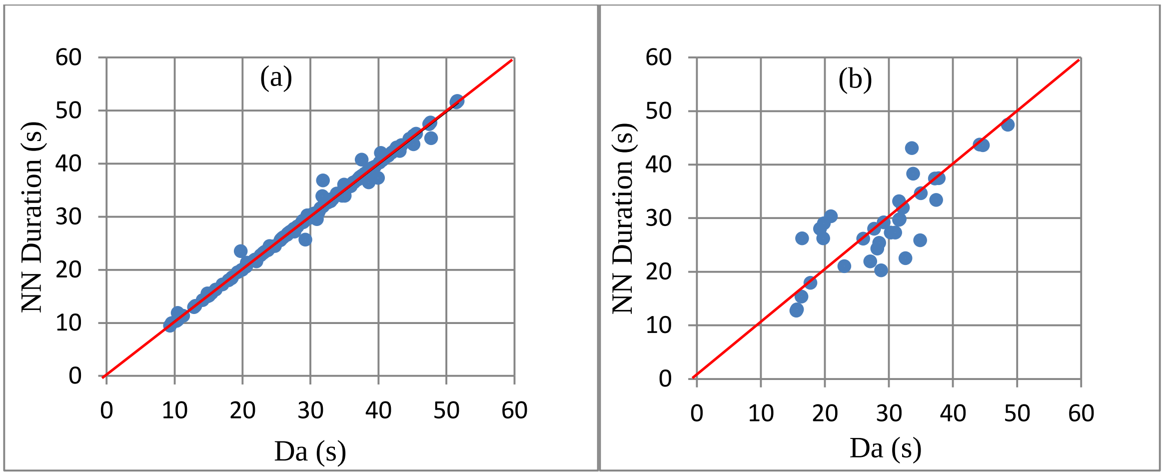

Figure 7. Neural model results a) training and b) testing stage

In order to evaluate the influence of the input parameters (M, R, FD, Sc, Az) on the neural model a sensitivity study was conducted. The results are shown in Fig.8 and are valid for the database included.

From them it can be concluded that the parameters that have the larger relevance to estimate significant duration are Sc and Az.

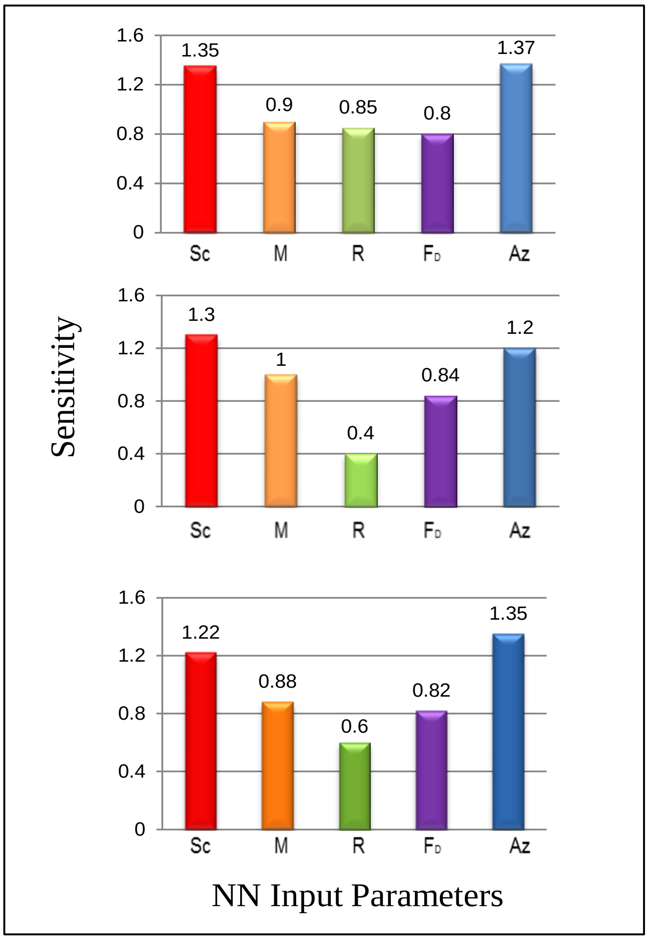

Figure 8. Sensitivity Analysis

Considering the previous study we decided to train the neural model excluding the Az parameter. In that way we only use as input parameters M, R, FD and Sc and for the output D. We also used the same database, architecture of the model, transfer functions and learning rule. The results in training stage (excluding Az) as well as in testing test are presented in the left side of Fig.9 and Fig.10. Although the estimated values excluding Az have an acceptable tendency, they do not reach the better correlation level when Az is included as the right side of the figures shows.

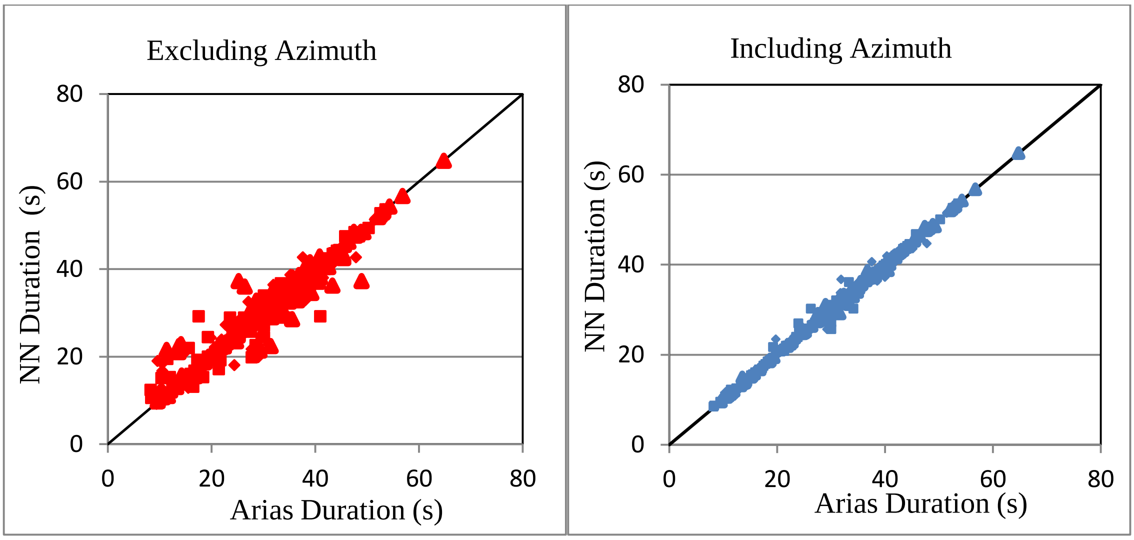

Figure 9. Training stage

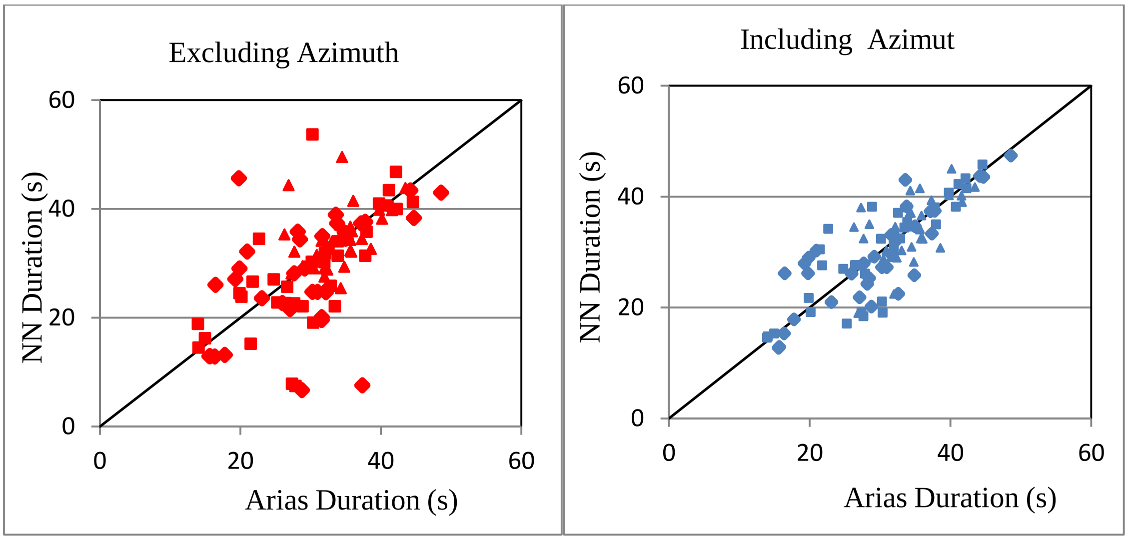

Figure10. Testing Stage

CONCLUSIONS

A neural model to estimate strong ground motion duration was implemented using the recordings gotten in the accelerograph network of Oaxaca City in Mexico. To implement the model was considered that the most significant input parameters are magnitude, epicenter distance, focal depth, soil type and azimuth. And the only one output parameter is the significant duration as it was defined by the Husid procedure.

The artificial neural network was training using a back propagation algorithm and multi-layer-feed-forward architecture. After different topologies tested the network was integrated by one input layer (with 5 parameters), two hidden layers of 200 nodes and one output layer (Target duration).

From the results and the sensitivity analysis it can be established that the azimuth together with the type of soil have the greatest influence to estimate the strong ground motion duration. This situation also was confirmed when the model was trained excluding the Az parameter. By doing this, the correlation between actual and estimated durations decreases and the situation turns even worst in the testing stage.

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