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NEURAL-ATTENUATION LAWS FOR THE MEXICAN SUBDUCTION: AN UPDATING EFFORT

S. García [1], L. Alcántara [2] and L.F. Manjarrez [3],

[1] *Researcher, Geotechnical Department, Instituto de Ingeniería, Universidad Nacional Autónoma de México MEXICO, 04510,* *sgab@pumas.iingen.unam.mx*
[2] *Researcher, Seismology Department, Instituto de Ingeniería, Universidad Nacional Autónoma de México MEXICO, 04510,* *LAlcantaraN@iingen.unam.mx*
[3] *PhD Student, University of Arizona, USA* *linofm2@email.arizona.edu*

Abstract

The most recent shaking experiences have demonstrated that the predictions of the seismic models are not always in agree with the registered responses. A deep examination of the current subduction attenuation laws for PGA (peak ground acceleration) has pointed out that most of them uses older information than fifteen years and the functions are not taking into consideration the latest source-station configurations and the aging of materials.

In this paper a neural network NN that permits to estimate PGA (vertical, east-west and north-south components) via the magnitude M, the focal depth FD and the epicentral distance ED (as classes and numerical parameters), is presented. For constructing this renewed attenuation law, 1270 records collected from 1960 to 2015 at rock-like sites are considered. The obtained results show that calculated PGAs using the neuronal model are remarkably close to those recorded. The proposed attenuation curves are compared with Ground Motion Prediction Equations (GMPEs) using events from México, Japan, Chile and USA. This evaluation raises the question of regional dependence of ground-motion which is a highly debated issue. The results also show that the NN performs considerably better than the traditional equations so it could be considered as a good alternative in seismic hazard assessment.

Keywords: neural networks, subduction, peak ground acceleration, attenuation law, ground motion prediction equations

1. Introduction

An important parameter for assessing the earthquake effects at a given location is the PGA. The importance of this parameter is revealed in the development of seismic zoning maps and the construction of design response spectra used in earthquake-resistant construction rules. In order to predict PGA at a site, one usually relies on empirical GMPEs (ground motion prediction equations). These equations relate PGA to earthquake (source and path) and site parameters using a physical model. The development of such equations requires large database of recorded responses and associated metadata on earthquakes and sites ([1], [2], [3], [4], [5], [6], [7]).

The western coast of the American continent is constantly affected by earthquakes due to subduction of Pacific Juan de Fuca, Rivera, Cocos and Nazca plates with North, Caribbean and South American plates. In spite of the frequent earthquakes that strike the region, the number of available accelerograms is rather scarce, being the most important records for the earthquake engineering of subduction those of Chile and Mexico. To obtain an updated GMPE for PGA useful for Mexican subduction zone, a new approach, based on artificial neural networks NNs, is proposed in this paper. The NNs have received a growing interest by the scientific community in the field of earthquake engineering and seismic risk assessment: site effect assessment in 1-D or 2-D ([8], [9]); generation of time histories compatible with target response spectrum ([10], [11]); estimation of artificial time history and related spectral response ([12], [13]), to name a few examples.

Regarding the estimation of PGA by some NN method, recent studies were conducted by [14], [15] and [16]. Some of these works have the disadvantage of have being constructed with a very limited number of stations -and recordings- restricting their use to the locality for which they were developed, while others used too complex input variables which also reduces their applicability.

In this paper an empirical NN formulation that uses information about magnitude M, epicentral distance ED, and focal depth FD (with the advantageous inclusion of ED and FD as a crisp value plus a predefined class) for subduction-zone earthquakes is developed to predict PGAs at rock sites (*rock*/*very dense soil*/*soft rock*). The NN model was obtained from the latest information compiled in the Mexican strong motion database. The obtained results indicate that the proposed NN is able to capture the overall trend of the recorded PGA´s. This approach seems to be a promising alternative to describe earthquake phenomena based on reasoning of a partially defined behavior. Although this paper is aimed at obtaining PGA’s, similar techniques can be applied to estimate also spectral ordinates for any particular period.

2. Neural Networks

The scope of this section is to make a brief induction to Artificial Neural Networks (or just Neural Networks NNs) for people who have no previous knowledge of them. Much of the formality is skipped for the sake of simplicity. Detailed explanations and demonstrations can be found in the referred readings ([17], [18], [19], [20], [21]). Since the first neural model published by McCulloch and Pitts (1943) there have been developed hundreds of different models considered as NN. Because the function of NNs is to process information, they are used mainly in fields related with this topic. The wide variety of NNs used for engineering purposes work mainly in pattern recognition, forecasting, and data compression.

A NN is characterized by two main components: a set of nodes and the connections between nodes. The nodes can be seen as computational units that receive external information (inputs) and process it to obtain an answer (output), this processing might be very simple (such as summing the inputs), or quite complex (a node might be another network itself). The connections (weights) determine the information flow between nodes. They can be unidirectional, when the information flows only in one sense, and bidirectional, when the information flows in either sense.

The interactions of nodes through the connections lead to a global behavior of the network that is conceived as emergent “knowledge”. Inspired in the biological neurons (Fig. 1), the nodes, or artificial neurons, collect signals through connections (as the synapses located on the dendrites or membrane of the organic neuron). When the signals received are strong enough (go beyond a certain threshold) the neuron is activated and sends out a signal through the axon to another synapse and might activate other neurons. The higher the connections (weights) between neurons are, the stronger the influence of the nodes connected on the modelled system.

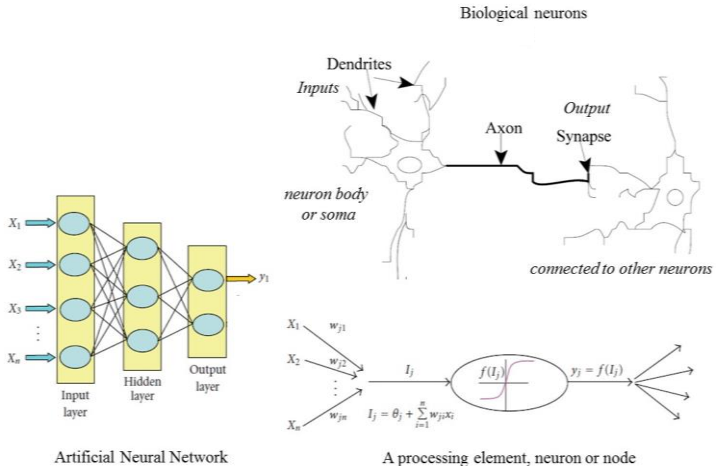

Fig. 1 – Biological and artificial NN

By adjusting the weights the desired output of a NN, for specific inputs, can be obtained in a process that is known as learning or training. For NNs with hundreds or thousands of neurons, it would be quite complicated to find the required weights so it is necessary to use algorithms which can, massively, adjust the NN weights based on desired outputs. In the following, a scheme to discover weights, the training backpropagation algorithm ([22]), will be explained. It is one of the most common and used method used in successful NN applications ([23], [24], [25]) and also it is the one used in this investigation.

The Backpropagation Algorithm

The backpropagation algorithm BP ([22]) is used in layered feedforward NNs. This kind of networks are organized in layers that send their signals forward. The information is received from the exterior in the input layer, the network final calculation is given in an output layer, and the processing is developed in intermediate or hidden layers.

The BP algorithm uses supervised learning, which means that the network modeler provides the algorithm with examples of the inputs and their corresponding outputs (those that the network must approximate). The objective of the backpropagation algorithm is to reduce the difference between actual and expected results, it says that doing this the NN is "learning" from the data (examples or "training" records). The procedure begins with random weights and the goal is to adjust them so that the error will be minimal. The activation function of the neurons in NN implementing the backpropagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their respective weights w_{ji}):

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \tag{1}$$

As can be seen, the neuron activation depends only on the inputs and the weights. If the output function would be the identity (activation = output) then the neuron would be called linear. But these have severe limitations, the most common output function is the sigmoidal function:

$$O_j = (\bar{x}, \bar{w}) = \frac{1}{1+e^{A_i(\bar{x}, \bar{w})}} \tag{2}$$

Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. In this investigation, the error function for the output of each neuron is defined as:

$$E_j(\bar{x}, \overline{w}, d) = \left(O_j(\bar{x}, \overline{w}) - d_j\right)^2 \tag{3}$$

In the BP algorithm once the output, inputs, and weights are known the weights adjustment is done using the method of gradient descendent:

$$\Delta w_{ji} = -\eta \frac{\delta E}{\delta w_{ji}} \tag{4}$$

Mathematical proof of the backpropagation algorithm can be checked in the suggested reading ([26], [27]), since this is out of the scope of this material.

3. Data Set

The database used in this study is an updated version of those used by other researchers to develop models for México. The selected events were recorded at rock and rock-like sites during subduction earthquakes and they were classified according the epicenters and a set of predefined seismic environments for subduction region (Fig. 2) ([28]). Episodes dates range from 1960 to 2015 and the recordings poorly defined (in magnitude, focal mechanism, or site-source distances) were removed from the set. To test the predicting capabilities of the neuronal model, 20% of all records was excluded from the data set used in the learning phase and will be used to validate the NN-generalization aptitudes. One of the most exceptional testing cases separated from the records used to build the model, was the September 19, 1985, Mw8.1 earthquake allowing assess the potential of the model to predict responses to extreme events.

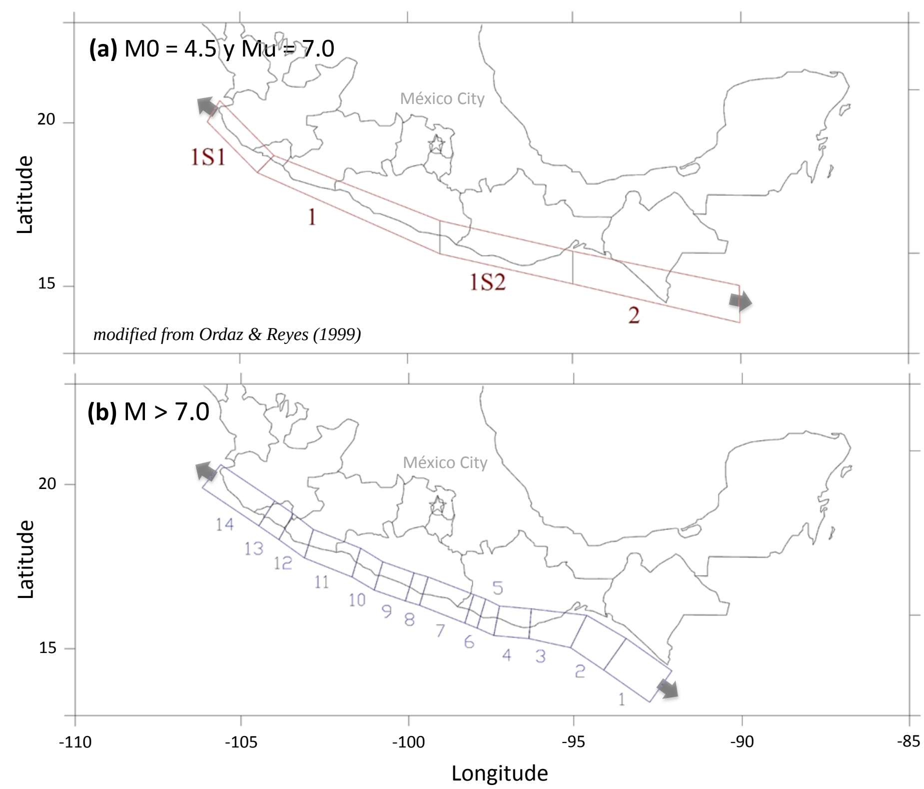

Fig. 2 – Predefined seismic environments for Mexican subduction.

The moment magnitude scale Mw is used to describe the earthquakes size, resulting in a uniform scale for all intensity ranges. If the user has another magnitude scale, the empirical relations proposed by Scordilis [29] can be used. In this paper the epicentral distance, ED, given in the database is considered to be the length from the point where fault-rupture starts to the recording site. ED was selected after many trials using hypocentral distance [30] and a free determination of the closest distance to the fault rupture [31] as input node for describing source-to-site distance, but the best results were obtained with ED (higher correlations).

ED is presented to the network as a pair of nodes: i) the crisp value (distance in km) and ii) a seismic environment (selection of a predefined class, interpreted as binary nodes). The third input parameter, FD, is the variable of the mechanism. Analogous to ED, using FD as crisp value (depth in km) plus a class (superficial-FD < 50 km/profound-FD >50 km) means that the NN identifies differences between shallow-focus earthquakes and those termed deep-focus earthquakes and also the subtle variances among examples that belong to the same class. The dynamic range of variables in the whole database is depicted in Fig. 3. As can be seen, the interval of Mw goes from 3 to 8.1 approximately and the events were recorded at near (a few km) and far field stations (about 900 km). The depth of the zone of energy release ranged from very shallow to about 150 km.

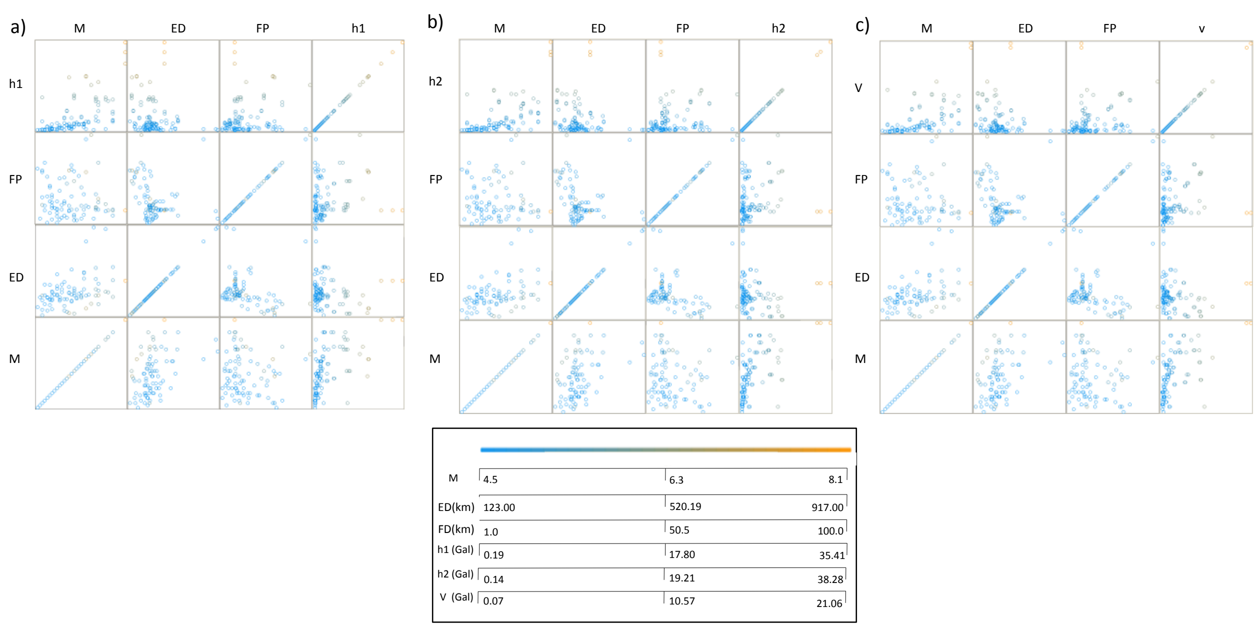

Fig. 3 – Dynamic range of {Mw, ED, FD} and h1-h2 horizontal components and v vertical component-Mexican subduction

4. Development of the Attenuation Model

The NN proposed here is a feed-forward back-propagation (FFBP) with total connection. The inputs are source-site parameters and the output is PGA (Fig. 4). These input parameters were chosen after several tests in order to quantify the influence of each variable and each group of them on the calculated PGAs. To build the neural network, the recommendations given by Seung and Sang [32] were applied using a single hidden layer whose number of neurons is the sum of the input and output neurons. The maximum error (ME) tolerated by the neural network is obtained through the following relationship [32]:

$$ME < \frac{1}{2}\left(minoutput^2 xNbr(neurons_{output})\right) \tag{5}$$

where *minoutput* represents the minimum value of the desired output, and *Nbr(neurons$_{output}$)* denotes the number of neurons in the output layer, in this investigation is 1. In addition, the number of epochs is set to 1000 and the updating of weights is done by batch (all the inputs in the training set are applied to the network before the weights are updated). The activation function for neurons in the input and hidden layers is *sigmoid* and *linear* for neurons in the output layers (which is the best combination after a trial an error process). For space restrictions the results from each combination is not presented but the best MSE (the mean squared error) between the PGAs calculated and those registered (MSE= 0.075 and MSE= 0.076 for the training and testing phases respectively) was reached considering all the input parameters previously explained, being the ED-seismic environment the key parameter affecting the PGA.

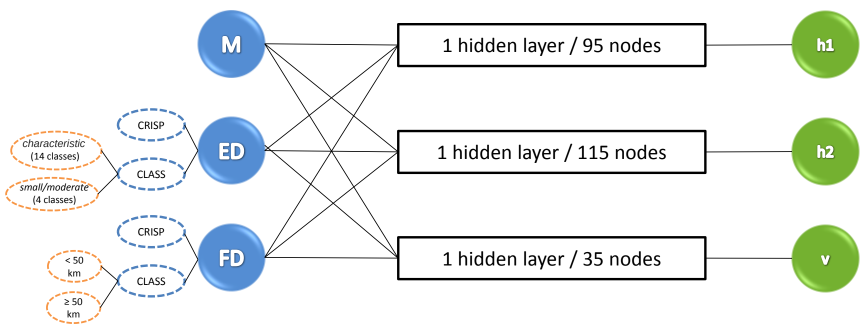

Fig. 4 – NN structure for the 3 components

Neural-PGAs

The neuronal attenuation model for {Mw, ED (crisp/class), FD (crisp/class)} → {PGA$_{h1}$, PGA$_{h2}$, PGA$_{v}$} (where *h1* is the horizontal component 1, *h2* is the horizontal component 2 and *v* is the vertical component) was evaluated by performing validation analyses. Because of space restrictions in this paper only the results obtained for the horizontal component, in which the highest values of accelerations were recorded, will be shown. The predictive capabilities of the NNs were verified by comparing the PGAs estimated to those induced by the 250 events excluded from the original database. In Fig. 5 are compared the PGAs computed during the training and testing stages to the measured values. The evaluations indicate that those topologies selected as optimal behave consistently within the full range of intensity, distances and focal depths depicted by the patterns. As indicated by the upper and lower boundaries, forecasting of all three seismic components are reliable enough for practical applications, especially for extreme earthquakes.

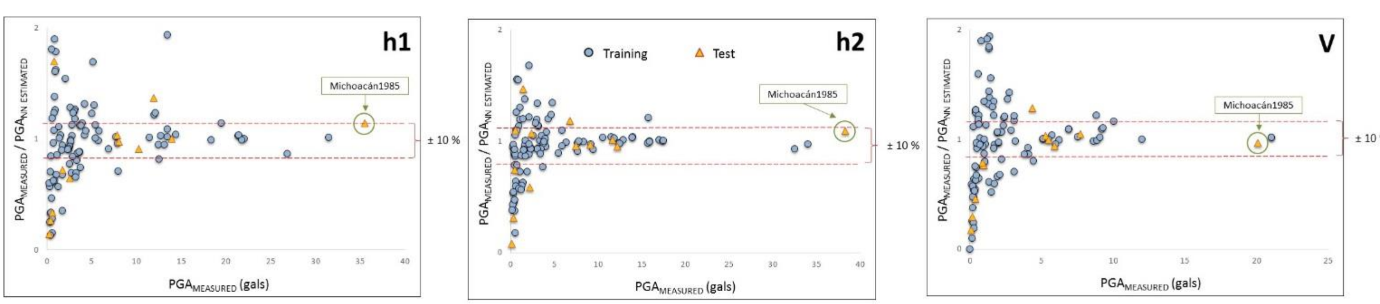

Fig. 5 – Measured and Calculated PGA's

Fig. 6 compares three, one is the NN-model, fitted relationships to PGA data from interface earthquakes recorded on rock and rock-like sites. The estimated values obtained for subduction events using the relationships proposed by Gómez, et al [33] and Atkinson and Boore [34] –proposed for rock sites– and the predictions obtained with the PGA_{h2} module are shown in the figure. The case histories correspond to a large and medium size events, it is important to mention that the measured PGA displayed (recording stations indicated in the bottom of the Fig.) were not included in the training set, so they are considered as *true* predictions. One of the most remarkable results is that obtained for the September 19, 1985 Michoacán earthquake M8.1. It can be seen that the estimation obtained with Gómez et al., [33] seems to underestimate the response for the extreme magnitude event. However, some exercises were done for lower magnitude events and Gómez et al. and Atkinson and Boore follow closely the measured responses; NN predictions also are very acceptable.

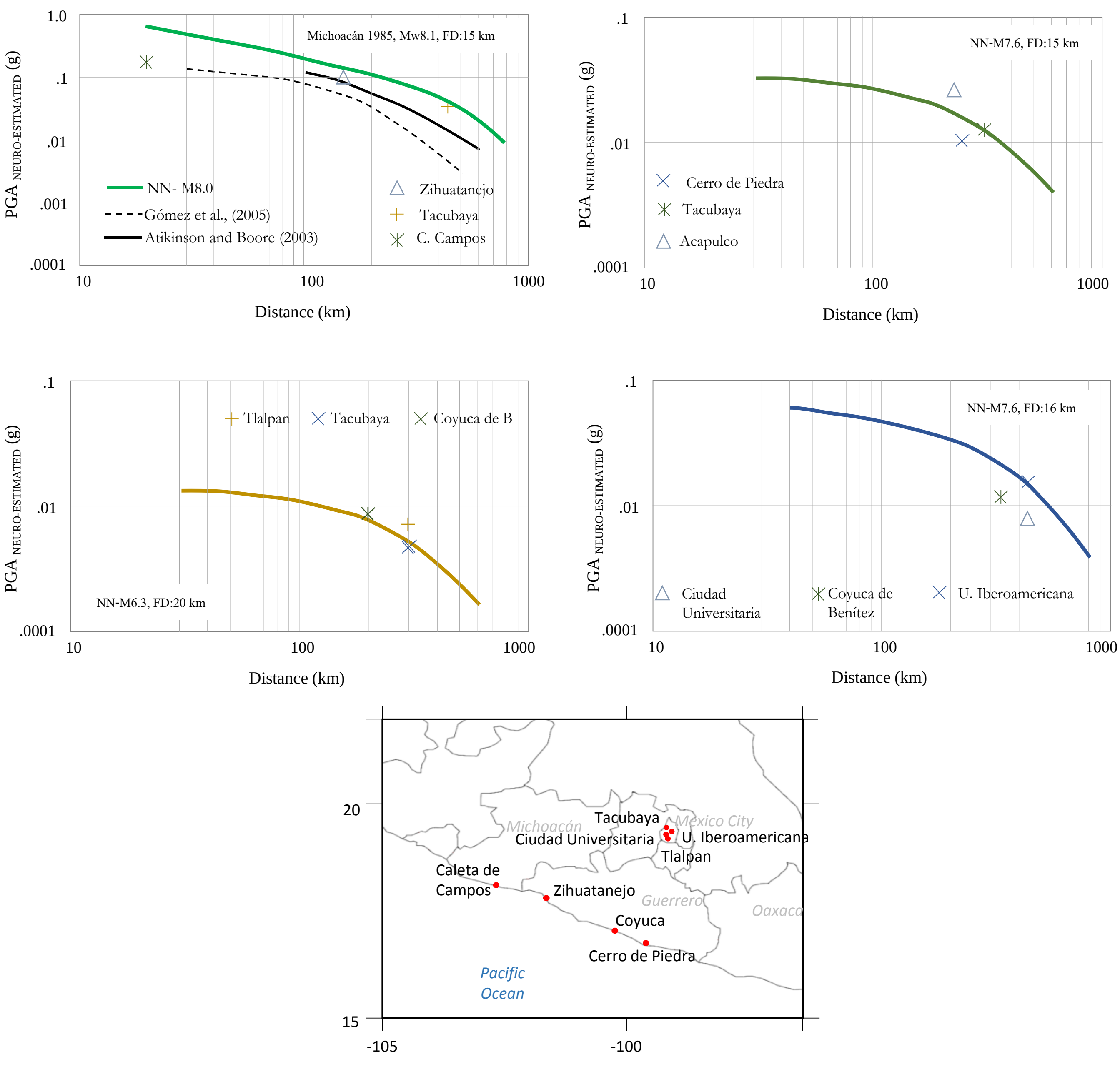

Fig. 6 – Attenuation curves for some FD+ED (four inputs) combinations

As can be seen in Fig. 6, the NN predicts, with acceptable accuracy, the maximum response measured in sites far from the epicenter (more than 300 km) and very close to it (<10 km). Actually the slight differences between sites in *rock* and *stiff-soil/rock-like* sites were taken into consideration during the learning process.

Although, as mentioned previously, the NN yielded higher errors in the testing phase than training stage, its predictions follow closely the trends and return a better behavior, in the full range of epicentral distances included in the data base, than traditional attenuation relations applied to the Mexican subduction zone. Furthermore, the NN show extrapolation capabilities that other models do not have. It is worth to note that while the NN trend follows the general behavior of the measure data, the traditional functional approaches have predefined extreme boundaries. Notice that for short distances the NN is closer to measured values than the traditional functional predictions, as indicated by Caleta de Campos station. On the other hand, when the intensity of the earthquake is moderate, most of the PGA's measured in rock sites are within a narrow band, thus generally the NN and traditional functionals follow similar patterns.

The generalization capabilities of the PGA_{h2} module can be explored even more by simulating other subduction zones events. Measured random horizontal PGA's taken from Japan and North America for two magnitude intervals (M7.8- M8.2 and M5.8 - M6.2) were compared to the NN predictions. These results are plotted in Fig. 7. It can be seen that the NN prediction agrees well with the general trend even considering averages of both earthquake magnitude and focal depth. As can be seen in Fig. 7, the NN approach allows great flexibility with respect to the magnitude and distances dependencies, as it is demonstrated by the good agreement between estimations and data recordings in the total dynamic range tested. This neural network module can be extrapolated beyond the range of available data, and this proves that the model is capturing the physical attenuation mechanisms of the Mexican subduction zone and even the deep continental earthquakes not related to any specific geologic structure. To prove the notable NN-abilities two recent earthquakes were displayed in the Fig. (01/12/14 and 18/94/14), both of them with "special" FD and ED (very close to the limits of the dynamic ranges of the input variables) and as can be verified, the estimated curves are very close to the trend of the measured PGA.

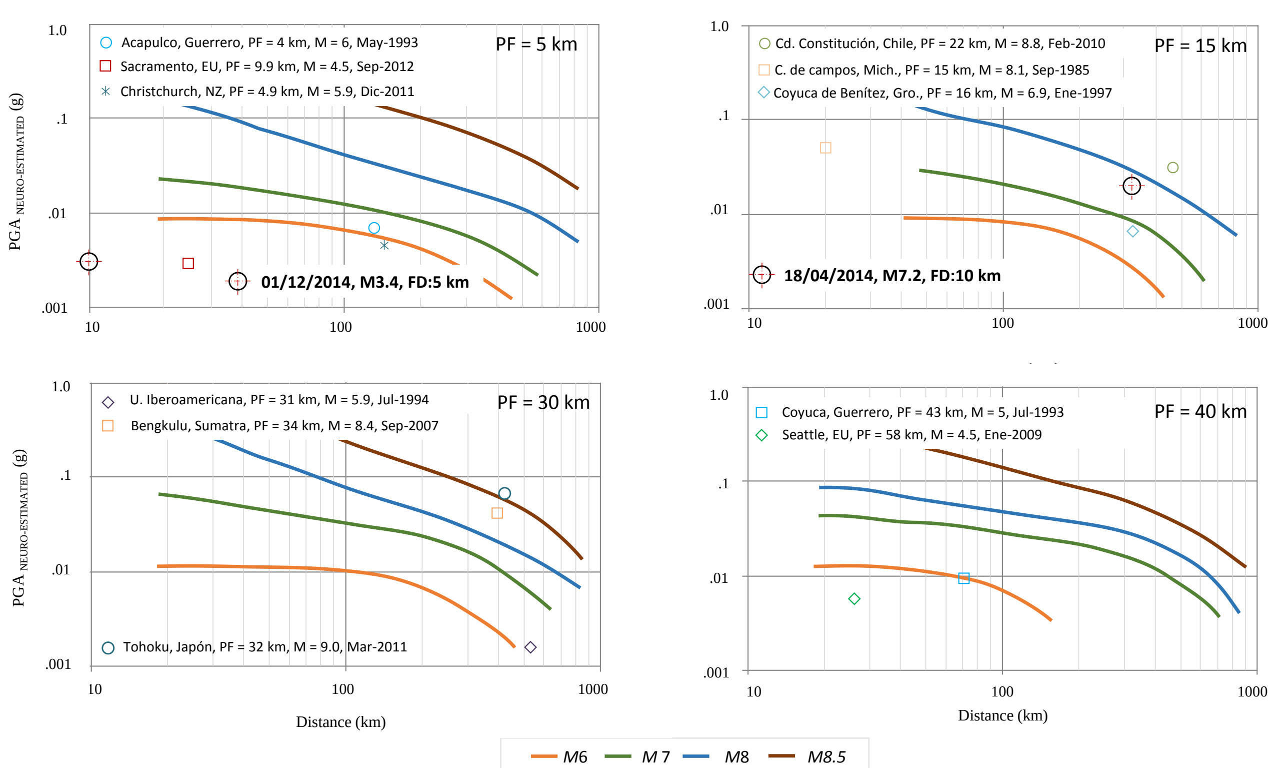

Fig. 7 – Some examples of PGA's predictions

In Figs. 6 and 7, it appears that some authors underpredicted the rock responses at close distances. This might suggest that nonlinearity is stronger than that assumed in the regressions.

The most relevant measure of any empirical regression result is how accurately it models the database that it purports to represent. With the large database available in this updating effort, we were able to develop a more comprehensive analysis than has been given in any previous regression studies for Mexican subduction-zone earthquakes. We conclude that there is a significant tendency to lower variability for higher magnitudes (M>7) and for higher frequencies, in agreement with the findings of Youngs et al. [35]. The more important reason for the differences (minimum) lies in the increased database that we were able to employ: we had 12 more years of records, representing an order-of magnitude increase in database size, particularly more inslab events could be added. This enables us to better distinguish differences in the amplitudes and distance dependence of in-slab and interface events, as well as to improve the modeling of other effects such as the magnitude, path, directivity, seismogenic zone dependence of attenuation and rock response.

Fig. 8 includes the horizontal PGA values for Chilean thrust earthquakes of the indicated magnitude and soil type. Thus, for the magnitude M7.8, the Central Chile, March 3, 1985 earthquake PGA data are included. From Fig. 8, it is appreciated that Youngs et al., [35] formula does not reproduce Chile earthquake data on rock and hard soil. For the design magnitude (Ms8.5), estimated values remain very low with respect to Chile expected values. For a Chile service thrust earthquake (Ms7.8), Youngs et al. [35] formula gives values 50% less than expected values. Youngs et al., [35] and Saragoni and Ruiz [36] formulas only give similar values for magnitude less than 7.2. Similar comparisons were done for hard rock with magnitudes M8.5 and M7.8. In this last case it can be appreciated that practically all the horizontal PGA recorded for the Central Chile earthquake of 1985/03/03 are higher than proposed by Youngs et al., [35], being the Saragoni and Ruiz [36] attenuation formula and the NN_{h2} predictions the closer to the recordings. This situation is inverted for M<6, where Youngs and Saragoni curves overestimate the available data PGA values. On the other hand the formula proposed by Atkinson and Boore [34] for soil type C of NEHRP is shown in Fig. 8, which is almost 10 times less than Chile formula and 13 times for NN-curve, for the design earthquake (M>7.8). In analogous experiments the Atkinson formula for soil type B of NEHRP is 5 times less than Chilean formula and 7 times the NN values. The Atkinson formula remains practically always under all horizontal recorded PGA values.

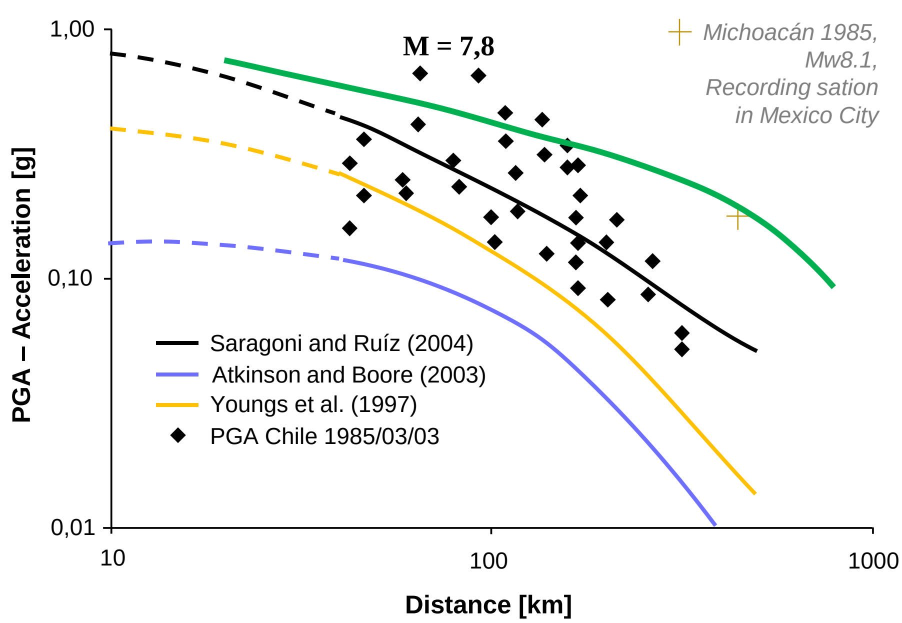

Fig. 8 – Comparison with some GMPEs for subduction zones (*modified from Saragoni and Ruiz [36]*)

Just an example of the GMPEs used in seismic hazard assessment in Mexico, the neural curves were compared with the obtained by Ordaz et al., [37], Arroyo et al., [38] and Rodríguez-Pérez [39]. As can be seen in Fig.9 the PGA predictions of the conventional equations, were considerably lower than the ones registered.

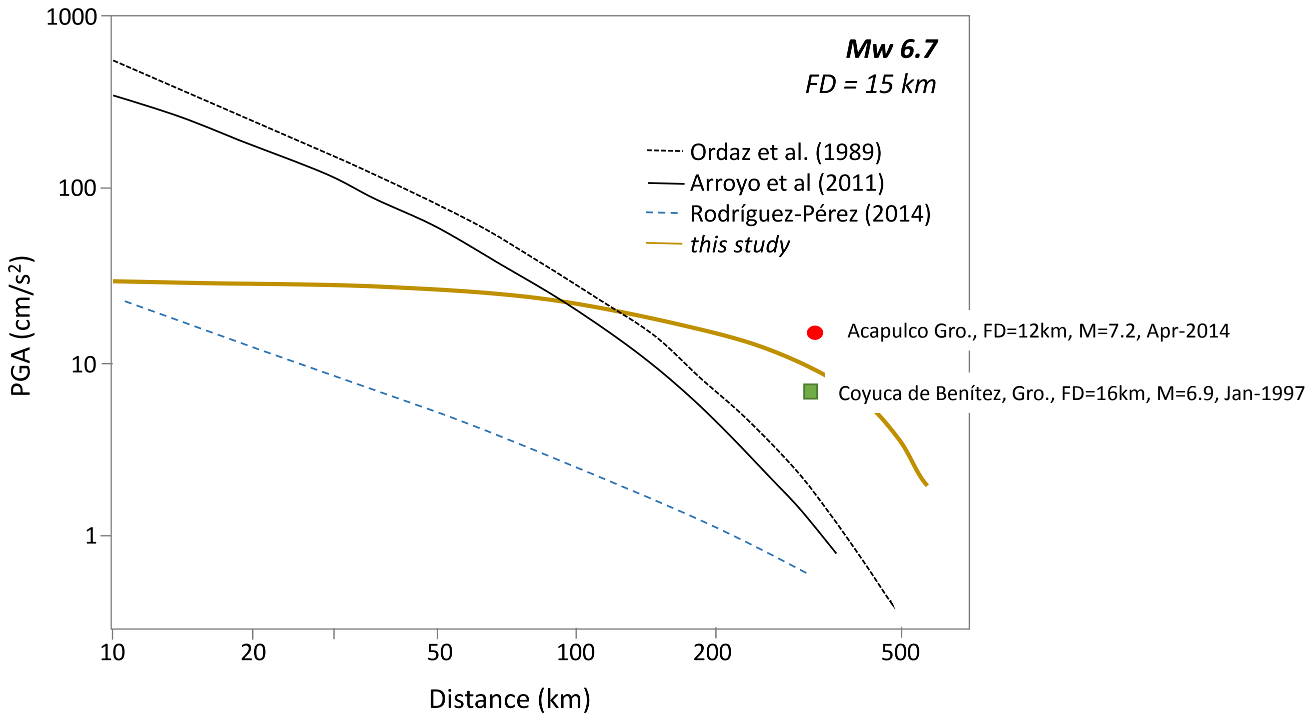

Fig. 9 – Comparison of the attenuation curves from the results of this study and some other studies for interplate earthquakes in central Mexico

5. Conclusions

This paper presents the application of neural network models to estimate horizontal and vertical PGA at rock sites for Mexican Subduction Earthquakes. The importance of this parameter is that PGA is a natural simple design parameter that can be related to a force and for simple design this can be introduced to model a building (to resist a certain horizontal force), also PGA is a good index to hazard for short buildings, up to about 7 stories [40].

The neural models were developed from a set of known parameters (i.e. Mw, ED and FD). Comparisons shown that NN is capable of predicting the recorded values collected from the Mexican subduction zone. Furthermore, the experimental knowledge-based method is able to forecast the peak ground acceleration of events not even included in the database and registered in other world subduction zones. It is worthwhile to notice the powerful prediction capabilities of neural models developed network modules for practical applications that with a limited number of parameters would be able to describe the trends observed in measured peak ground accelerations. The validation of the NN is achieved by comparing neural-calculations with those obtained by some classical GMPEs for subduction earthquakes. The results of the comparison show that the updated NN model performs better than the GMPEs most commonly used, even for sites in other subduction zones. This raises the question of regional dependence of ground-motion which is a highly debated issue. One of the reasons why the network has this effective functioning may be for the inclusion of entries in the form of class for ED and FD. It is believed that the model developed in this research is a good alternative to classical GMPEs and could be used in seismic hazard assessment studies.

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