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A neural-attenuation model before Mexican extreme events

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Abstract. The most recent shaking experiences have demonstrated that the predictions of the seismic models are not always in agreement with the registered responses, especially in the face of extreme earthquakes. Records collected from 1960 to 2011 at a rock-like site are used to develop a neural network that permits to estimate peak ground accelerations via the magnitude, the focal depth, the site-source distance and a seismogenic zone. The neural model is applied to the 8th and 19th September 2017 events that hit Mexican territory and the obtained results show that the network is flexible enough to work appropriately to various conditions of intensity and sites-sources with remarkably predictive capacity. The neural-attenuation curves are compared with those obtained from Ground Motion Prediction Equations and their performance is assessed for events, in addition to the devastating Mexican events, from Japan, Taiwan, Chile and USA.

Keywords: neural networks; attenuation laws; peak ground acceleration; September 19th 2017 earthquake

1. Introduction

A central parameter for assessing the earthquake effects at a given location is the peak ground acceleration 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, empirical GMPEs (ground motion prediction equations) are usually employed. These equations relate PGA to earthquake and site parameters through a physical model. The development of such equations requires large database of recorded responses and associated metadata on earthquakes and sites (Stewart *et al.* 2012, Lussou *et al.* 2001, Ambraseys and Douglas 2003, Atkinson 2008, Atkinson and Boore 2006, 2011, Zhao *et al.* 2006).

In spite of the frequent earthquakes that strike the western coast of the American continent (due to subduction of Pacific Juan de Fuca, Rivera, Cocos and Nazca plates with North, Caribbean and South American plates), the number of available accelerograms is rather scarce, being the most important records of subduction, for the earthquake engineering, those from Chile and Mexico.

In this paper an empirical neural network NN formulation that uses information about magnitude M, site-source distance D, and focal depth FD from pre-classified subduction-zones to predict PGAs at rock-like sites (rock, very dense soil or soft rock) is presented. The NN model was trained using information compiled in the Mexican strong motion database (BMDSF-SMIS 2000) from 1960 to 2011. The obtained results indicate that the proposed NN is able to capture the overall trend of the recorded PGA´s. Actually the neural attenuation curves were tested, to prove its applicability to extreme events, with the destructive earthquakes that hit Mexican territory the 8th (M8.2) and 19th (M7.1) September, 2017.

2. Neural networks

The artificial neural networks (or simply neural networks NNs) together with the fuzzy logic and genetic algorithms, conform the symbolic methods of intelligent calculations and data processing that are labeled as soft computing. A NN is an information processing paradigm that is inspired by the way biological nervous systems (the human brain) process information (Fig. 1). The fundamental element of this paradigm is that is composed of a large number of highly interconnected processing elements (neurons) congruently working to solve specific tasks. This interconnected system has many simple processing elements operating in parallel (the neuron functioning is determined by network structure) through connection strengths. A NN mimics the brain because the knowledge is acquired by the network through a learning process (examples presentation) and the interneuron connections (the called synaptic weights) are used to save this knowledge (Haykin 1999).

The NNs development and application emerge from the desire of creating an artificial "intelligent" system for data calculation and processing. A NN and a biological neural network have similar structure, functions, and methodology of calculation and response. This artificial model of learning is a simplified mathematical model that can simulate the basic characteristics of the biological nerve system. The NNs are capable of gathering, memorizing and

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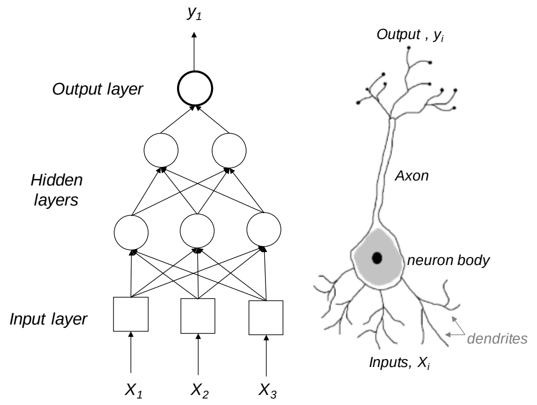

Fig. 1 A simplified scheme of biological and artificial neural networks (modified from Fasel 2003)

processing numerous data, they analyze large number of data in order to learn from them and to derive solutions to complex problems.

Once a neural network is trained, it serves as an analytical tool for efficient forecasts (or responses) for any input set of data which were not included in the learning process of the network. The neural control is reasonably simple and easy and the results can become very correct and precise. The remarkable ability of NNs to derive meaning from complicated or imprecise data is very attractive to implement them to extract patterns and detect trends that are almost impossible to be detected by humans or conventional computer techniques, however, neural networks and conventional algorithmic computers are not in competition but complement each other. Other NN advantages include: adaptive learning, self-organization, real time operation and fault tolerance via redundant information coding (Csáji 2001).

In the following a brief explanation of the NN basics is presented in order to make this paper self-contained. For the interested reader, detailed explanations and algorithmic demonstrations of the tool can be found in the referred readings (Cybenco 1989, Hornik 1991, Hassoun 1995, Haykin 1999, Csáji 2001).

2.1 Architecture of neural networks

In general, the artificial neuron receives the input signals and generates the output signals; data from the surrounding or output from other neurons can be used as input signal. An NN is composed of numerous mutually connected processing units grouped in layers: the input (first), the output (last) layer and as many as necessary hidden layers (Fig. 1). The input layer receives data from the surroundings and sends the information to the hidden layers where is processed. This intermediate layer is connected to the output layer. The NN results are the outputs of the last network layer and that is considered the solution or prediction for the considered set of inputs.

The different networks are because of the number of layers (one layered and multi layered networks), the connection type between neurons (layered, fully connected and cellular), the learning process (feed forward and feedback), the data type (binary and continuous networks), the course of information spreading (supervised, partly supervised and unsupervised networks), etc. (Bose 1996). But the characteristic common to any of the different types of networks is their ability of discovering patterns inside complex data and that they generate outputs even though the input data are not completed or contaminated.

In this investigation the training process of the neural models consists of data conduction through the network and comparison of the received input values with the expected ones (supervised training). In order to minimize the difference between expected and evaluated values, weights adjustment (modification of the neuron connections) has to be made. By adjusting the weights, the desired output of a NN, for specific inputs, can be obtained in a process that is known as learning. 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 (Rumelhart and McClelland 1986), will be explained. It is one of the most common and applied method used in successful NN applications (Shahin *et al*. 2008, 2009, Moreshwar 2013) and also it is the one adopted in this investigation.

2.2 The backpropagation algorithm

Despite its publication in the 70´s, the backpropagation algorithm BP was respected until the 1986 presentation of Rumelhart and McClelland (1986) where was shown how a NN trained with BP works far faster than earlier approaches, making it possible to solve problems that had been considered impenetrable. The BP algorithm is used in layered feedforward NNs and supervised learning, which means that the modeler specifies the task with examples of the inputs and their corresponding outputs. Backpropagation as an optimization technique, uses gradient descent to minimize error in the predictions calculating the gradient of the error function of any given error function.

The procedure begins with random weights that are adjusted 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})

$$A_j\left(\overline{X},\overline{W}\right)=\sum_{i=0}^{n} X_i W_{ji} \tag{1}$$

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. In this investigation is used the most common output function, the sigmoidal

$$O_j\left(\overline{X},\overline{W}\right)=\frac{1}{1+e^{A_j\left(\overline{X},\overline{W}\right)}} \tag{2}$$

The aim 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

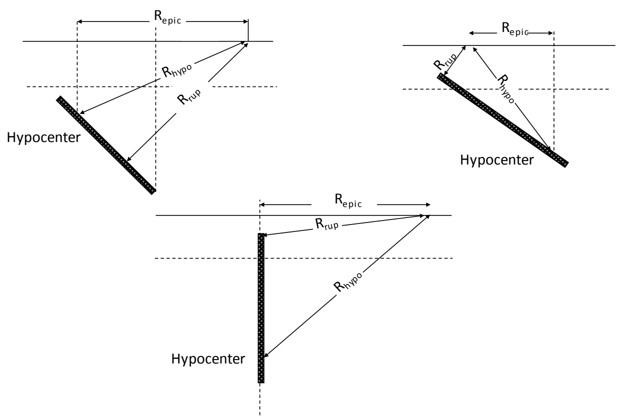

Fig. 2 Illustration of various measures of distance to fault rupture plane for dipping and vertical faults (modified from Gupta 2006)

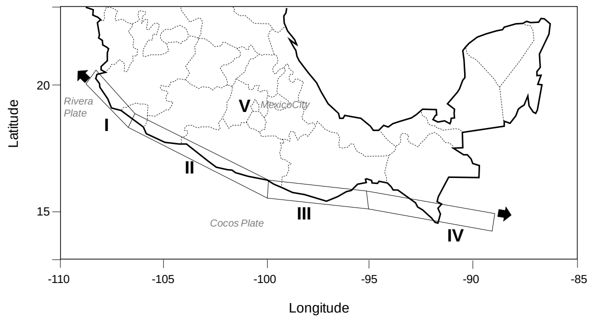

Fig. 3 Predefined seismic environments for Mexican subduction (modified from Ordaz and Reyes 1999)

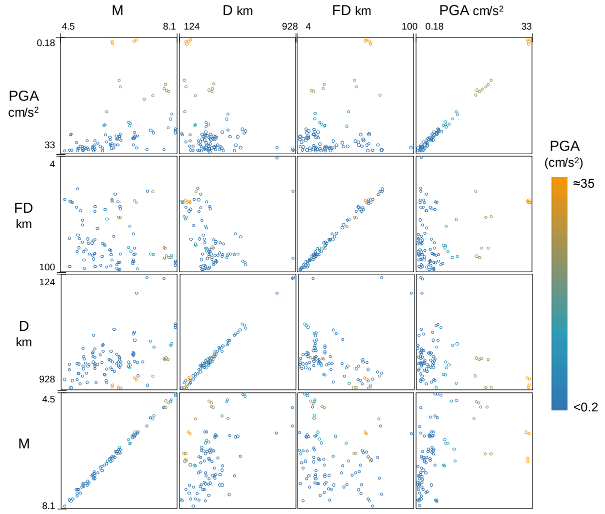

Fig. 4 Dynamic range of M, D and FD related to the PGA values

error depends on the weights. The error function for the output of each neuron is defined as

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

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

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

A complete explanation of the backpropagation algorithm can be checked in the suggested reading (Werbos 1994, Jeremias *et al.* 2014).

3. Data set

The database used in this study is an updated version of those used by other researchers (Ordaz *et al.* 1989, Arroyo *et al.* 2010, Rodríguez-Pérez 2014) to develop attenuation models for México. The selected events were recorded at rock-like sites in accordance with the availability of records from predefined seismic environments for subduction region. Episodes dates range from 1960 to 2011 and the recordings poorly defined (in magnitude, focal mechanism, or site-source distances) were removed from the set. To assess the predicting capabilities of the neuronal model, 20% of all records was excluded from the data set, of this percentage 10% was used to test and the remaining 10% to validate the model. While training, the evolution of the testing errors is used to calibrate the learning process whereas the validation cases are applied to qualify the NN performance as a completed model.

One of the most exceptional testing cases (separated from the records used to build the network) was the 19th September 1985 (M8.1) Mexican earthquake, allowing assess the potential of the model to predict responses to extreme events.

The moment magnitude Mw was selected as the magnitude scale 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 (2006) can be used. In this document it will be used merely M to refer to this parameter. The site-source distance, D (in km) is the smallest value between i) the hypocenter distance R_{hypo}, ii) the epicenter distance R_{epic} and iii) the closest distance to fault rupture plane R_{rup} (Cambell 1981) (Fig. 2). This selection criteria has the best effect on predictions for extreme earthquakes (Gupta 2006). The parameters that complete the set of independent inputs of the model are the FD (in km) and the membership of one of the five-subduction regions predefined in (Ordaz and Reyes 1999) (see Fig. 3).

The dynamic range of these variables is depicted in Fig. 4. The interval of M goes from 3 to 8.1 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.

4. Development of the attenuation model

The NN proposed here is a feed-forward back-propagation (FFBP) with total connection. The inputs are the source-site parameters, previously defined, and the output is PGA (Fig. 5). The starting hidden structure of the neural network follows the recommendations given by

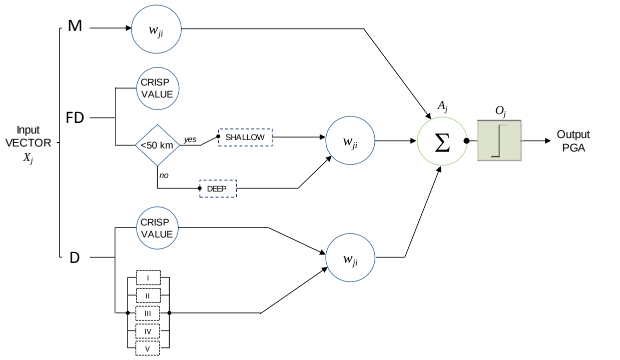

Fig. 5 NN structure: 3 inputs (two of them are a double-node), 1 hidden layer and 1 output

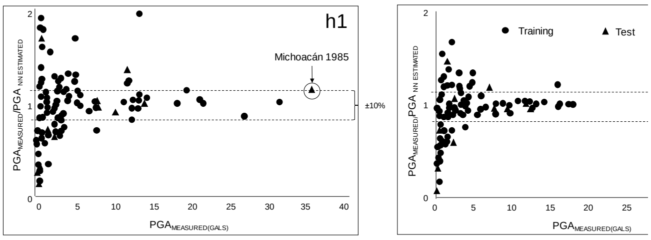

Fig. 6 Measured and Calculated PGA's, training and testing cases (triangle symbol points to the devastating earthquake of 1985, which is a test case)

Seung and Sang (2002). The minimum number of epochs is set to 5000 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 while linear function is used for the output layer. As criterion of completion of the training stage the best MSE (the mean squared error) between the PGAs calculated and those registered is set to 0.1 cm/s^2.

Many topologies (changing the number of nodes and hidden layers) were ran to determine which structure better described the data. The neural attenuation model is qualified by validation analyses comparing neural predictions with those PGAs excluded from the original database. In Fig. 6 the residuals of the neural model of PGA are shown, any noticeable bias with distance, magnitude, or depth is observed. These graphs indicate that the topology selected as optimal (three inputs, 120 nodes in 1 hidden layer, one output) behaves consistently within the full range of inputs, even in extrapolation. Note that the extreme earthquake of 19th September 1985 is a well-predicted testing case.

The inclusion of *D* as a crisp value and the membership of one of the five subduction regions (*a seismogenic class*) substantially improved the fit, mainly at close distances. Another parameter included as a pair of nodes is the focal depth. It was found that for inslab events large errors were obtained for deep and intermediate *FD*, which forced the introduction of support node. Then *FD* is a double input, the crisp value (depth in km) and a category (*shallow* for FD<50 km and *deep-focus* for FD>50 km).

Fig. 7 shows neural-attenuation curves constructed for M 5, 6, 7, 8 and 9. Each graph represents 10, 15, 30 and 50 km focal depths and zones II and III, respectively. The paths expose that the estimated horizontal PGA is mainly dependent on the M. Although deep-focus instances represent a minimum percentage of cases in the training set, the addition of the two nodes allowed them to be sufficiently representative to generate useful curves; the differences between classes are evident. As illustrated in Fig. 7, deeper events has a response behavior that is closely linked to the seismogenic class while for more superficial events the term that seems to have the greatest effect on PGAs is the distance site-source.

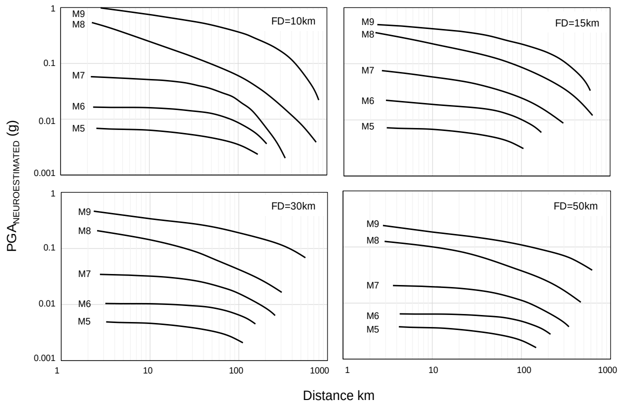

Fig. 7 Neural-attenuation curves for subduction Zone II (left) and Zone III (right).

In Fig. 8 the NN predictions for a set of Mexican sites, not included as training cases, are presented. For the full range of site-source distances, the neural forecasts are accurate enough. It is recalled that none of these stations is contained in the database with which the neural network was built. The curves closely follow the behaviors recorded at stations on the coast and at other points in the area of rock deposits in the capital.

To demonstrate the advantage of this tool, the results of the neuronal model and curves obtained with the Ground Motion Prediction Equations published by other authors (normally used in seismic hazard assessment in Mexico), are compared. As can be seen in Fig. 9 the results obtained (Ordaz *et al.* (1989), Arroyo *et al.* (2010), Rodríguez-Pérez (2014)) are considerably lower than the PGAs registered while the neural predictions are very close to the trend of the measurements.

In Fig. 11 the horizontal PGA values for Chilean earthquakes of the indicated magnitude are placed on their respective neural curves. The NN curves are graphed and compared with those obtained using conventional attenuation models. It is considered that the Chilean events belong the seismogenic class IV. While Youngs *et al.* (1997) formula does not reproduce Chile earthquake data properly (estimated values remain very low with respect to Chile expected PGA), Saragoni and Concha (2004) curves are nearer to the recordings. However this attenuation model has problems with closer distances and M<6 (it overestimates the data). Observe how the neural network behaves very well to all the events indicated by showing great flexibility to adapt to the combination of input parameters.

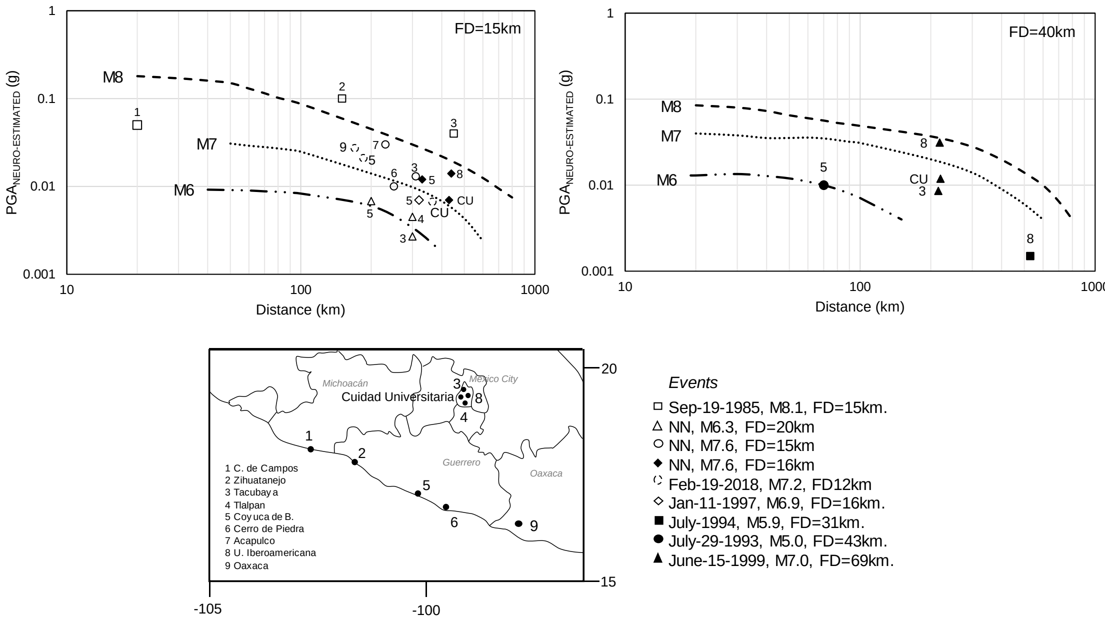

Fig. 8 Neural attenuation curves and a set of rock-like sites, validation cases

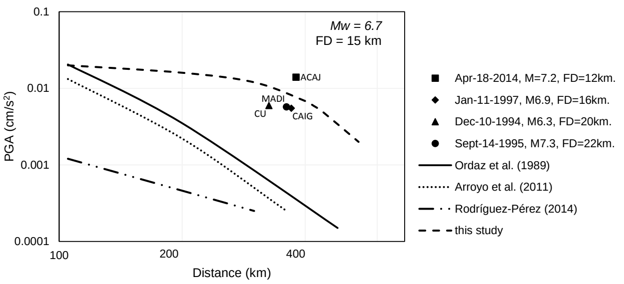

Fig. 9 Comparison of the attenuation curves from this study and some other for interplate earthquakes in central Mexico

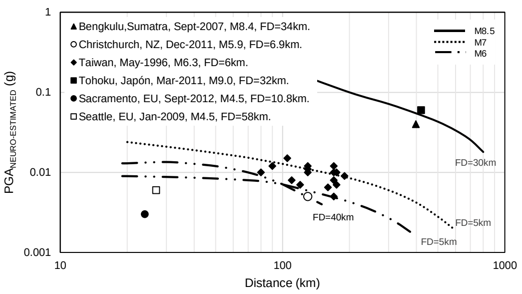

Fig. 10 Some values of PGAs registered in the world, Asia-Pacific Zone, on neuronal curves

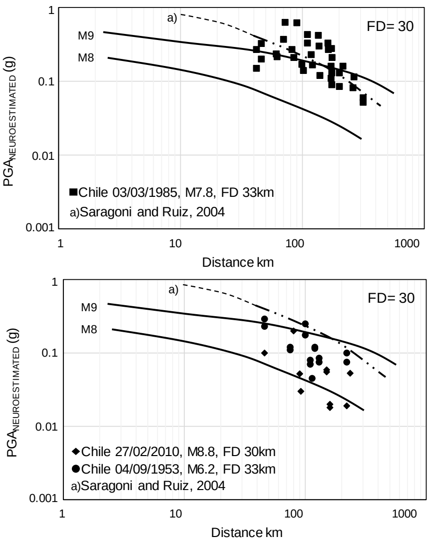

Fig. 11 Comparison between Chilean GMPE and the NN attenuation curves

5. Extreme Mexican events of 2017

Using some previously published attenuation curves (García *et al*. 2017), constructed with the model presented here, the neural performance before the extreme earthquakes that recently struck the Mexican territory, is shown.

On 8th September, 2017, the Servicio Sismológico Nacional (National Seismological Service of Mexico) reported an earthquake M8.2 (Mw) with epicenter located in the vicinity of Pijijiapan, state of Chiapas and focal depth of 58 km (Fig. 12). The mechanism was a normal fault, characteristic of the Mexican intraplate earthquakes where the Cocos plate is subducting below the North America plate. This event was also the second strongest recorded in the country's history, behind the magnitude 8.6 earthquake in 1787 (Núñez-Cornú *et al*. (2008)) and the most intense recorded globally in 2017 (USGS 2018).

Twelve days later, on 19th September, central Mexico was struck by an earthquake M7.1 (Mw) with epicenter between the states of Puebla and Morelos (at 12 km southeast of Axochiapan, Morelos and 120 km from Mexico City). The focal depth was 57 km in a hypocentral section perpendicular to the Mesoamerican trench. The hypocenter of the earthquake occurred just below the continental plate, in the Cocos plate (Fig. 13). It is not uncommon the occurrence of earthquakes between the states of Puebla and

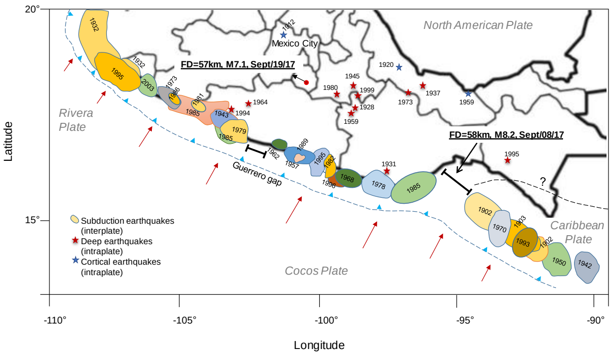

Fig. 12 Seismicity in Mexico (modified from Vladimir and Pacheco 1999)

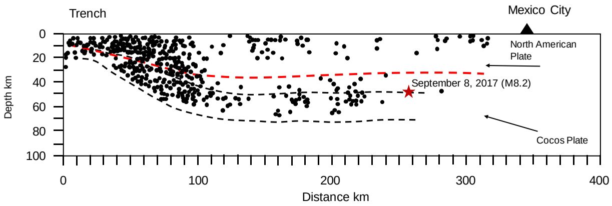

Fig. 13 Plate tectonics subduction (SSN-UNAM 2017)

Morelos, see the Fig. 12 where the epicenter of the earthquake of 19th September 2017 and other events of magnitude greater than M7 are shown. The most recent of considerable magnitude (occurred on 24th October 1980, M7.1) was located 19 km west of Acatlán de Osorio, Puebla.

For exploring the generalization capabilities of this neural model, in 2016 the attenuation curves for two magnitude intervals (M7.8- M8.2 and M5.8 - M6.2) were constructed (García *et al*. 2017). In that publication, it was proved that the proposed attenuation law was sufficiently useful for practical purposes, the predictions agree well with the general trend. The PGA recorded in Ciudad Universitaria CU-station (rock-like site) during the 8th September event is placed in that graph (Fig. 14). As can be seen the NN approach own great flexibility as it is demonstrated by the good agreement between estimations and data recording. The results shown that the neural network can extrapolate beyond the range of available data, even before extreme values of magnitude and distance source-site.

Two weeks after the M8.2 earthquake a new extreme event struck the country. The 19th September 2017 earthquake caused damage in the Mexican states of Puebla and Morelos and in the Greater Mexico City area, including the collapse of more than 44 buildings. 370 people were killed by the related building collapses, including 228 in Mexico City, and more than 6,000 were injured. The event occurred at an intermediate depth of 57 km within the Cocos plate with an intraplate-normal-faulting mechanism. The epicenter was located at 12 km southeast of Axochiapan, Morelos, and about 120 km from Mexico City. The closest distance from Mexico City to the rupture zone is approximately 105 km (SSN-UNAM 2017, Cruz *et al.* 2017).

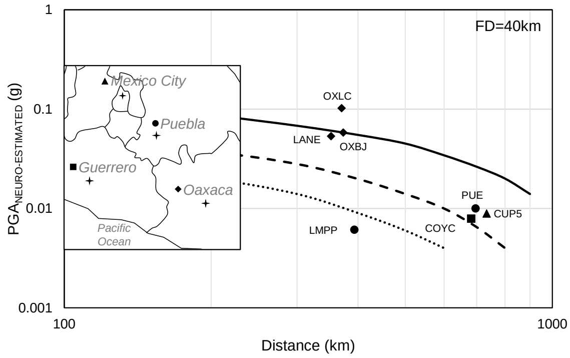

Fig. 14 Some registered PGAs during the September 8th 2017 event, the highest curve is for M8.5, the middle one is for M8 and the lowest is for M7.5

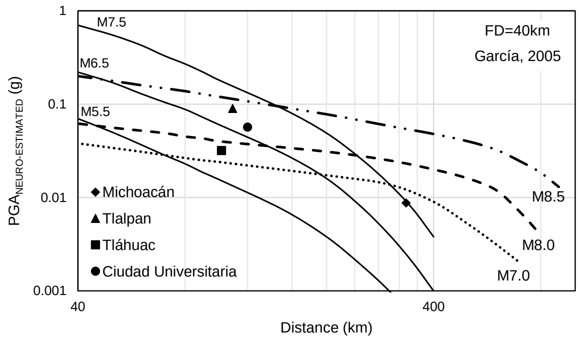

Fig. 15 Recordings during the September 19th 2017 event, comparison between the neural curves (dotted lines) and a GMPE (García *et al*. 2005) (continuous lines)

The greatest acceleration recorded in Mexico City was in the Culhuacán station (Lake Zone, very-soft clays deposit) with a PGA =226 gals and a maximum spectral acceleration of 1548 cm/s^2 for a period of 1.42 sec. During the devastating event of 1985, in CU station the PGA registered was 30 gals (1 gal =1 cm/s^2), while in 2017 the maximum acceleration was 57 gals. That is to say that the deposits in the area near CU experienced a shock twice as much as in 1985. If this registered information is collocated in the space where neural-curves for M7.0 and M7.5 (seismogenic class V) were constructed the notable NN-abilities are revealed (Fig. 15). As can be verified, the estimated curves are very close to the trend of the measured PGA (the registered acceleration is closer to the M7.5 than to the M7 curve). These results prove that the model is capturing the physical attenuation mechanisms of the Mexican subduction zone.

Despite the good results shown and the exceptional capabilities of the neuronal attenuation model, it should be noted that the validity of any kind of GMPE (even one constructed with artificial intelligence, particularly with NNs) derived from the data of tectonic setup used for developing the equation; it is therefore recommended that the results shown here as well as the neural instrument itself be used with caution. For employing a GMPE in any region of the world, the designer or analyst should first test it against the data that are present in that region which and then decide about the applicability of the GMPE.

6. Conclusions

This paper presents the application of neural networks to estimate PGA at rock sites for Mexican subduction earthquakes. The results show that the NN is capable of predicting the acceleration values with useful accuracy. Even though the records from deep-focus, large magnitudes and distant events are scarce, paths about PGA evolution with increasing focal depth and with those magnitudes and distances that are critical for estimating seismic hazard, are well followed by the neural model.

Unlike the regression models that has an obvious dependence on completeness and quality of data, the neural approximation interpolates and extrapolates adequately despite lack large magnitude and far-field data. Exactness in the location of an epicenter has a through influence in the calculation of the distance and depth inputs for any attenuation equation. In this study, the election of the closest distance plus the election of a predefined subduction region, and the accompaniment of focal depth with a class, was enough to make the precise earthquake location should be not so important. The appropriate performance of the network is tested before extreme events, being remarkable the results for 19th September 1985 (M8.1), and those for 8th (M8.2) and 19th September, 2017 (M7.1).

The NN is straightforward to use and to implement in practice and can be adjusted almost in real time with direct feed from the accelerographic stations. This aspect is very important since it is evident that the NN needs as many training cases as possible. For phenomena such as seismic in which the absence of data is a constant, overfitting is a prohibitive danger and this should be avoided (as in any other model or GMPE) by systematically facing test cases and making the necessary modifications.

As in other stages of history, in terms of science and technology, communities are faced with the use and exploitation of tools (as the NNs) that challenge traditional approaches. Derived from its black box nature, the interpretation of the internal behavior of the network is very difficult and this is a limitation to achieve acceptance among professionals involved in the subject but it is in the hands of the developers to present the results and the investigations themselves in a solid and sufficiently attractive manner so that positive changes are generated in the state of the art and practice.

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