Seismic Attenuation for Medellin City-Colombia: A Neural Network Approach

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Abstract- Considering the artificial neural networks techniques and incorporating the information contained in strong motion database, of the Local Accelerographs Network of Medellin Colombia, cognitive models were identified for computing the duration of the intense part of seismic shaking, the horizontal peak ground acceleration, and the acceleration response spectra with 5% damping. These neural models were obtained by means of algorithmic transformations of parameters that characterize seismic source, wave trajectory and site effects at a particular location. A set of 278 accelerograms was used for training the neuronal networks and verification of their generalization capabilities. The results achieved the demostrate potential of the artificial neural network to model non-linear problems and phenomena that are not well understood yet.

Index Term- Attenuation laws, Ground motion parameters, Neural network, Response spectral.

I. INTRODUCTION

The instrumental measurement of earthquakes has provided valuable information for development of analytical procedures and quantitative assessment of the seismic movement because it contains a source-station configuration. This has represented a major advance in the understanding of the seismic response, its effects and scope of their influence. Thus the seismic records and its associated response spectra, show the influence of the earthquake source, wave propagation path, and local effects.

Several dynamic parameters have been proposed to characterize the amplitude, frequency content and duration of the phase intense shaking. Of all the parameters, the most widely recognized, and the ones better reflecting seismic changes and their effects on structures, correspond to the displacement, velocity and acceleration, in terms of maximum values or spectral ordinates, and a criterion defining an accelerogram portion during which the strong movement takes place.

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Ground motion attenuation relationships may be established either empirically or theoretically. Some researchers have resorted to multiple regression analysis. Other investigators make use of seismological models that link the main parameters of ground movements with the characteristics of the seismic source, the focal path and local site conditions. There is a large number of technical literature where these two approaches have been documented [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13]. Many more references on this subject may be found in state-of-the-art-papers [14], [15].

Most existing theoretical models are useful in practice because they consider global analyses with cortex general models. The main drawback of these models is the evaluation of the physical parameters involved such as: shear wave velocity β, density of the path medium ρ, quality factor Q, and the azimuthal effects. Although proper knowledge of all these qualities is important, the last one seems to be of paramount importance in the predicting capabilities of theoretical models [16].

In the search for overcoming the difficulties of seismological models and taking advantage of the existence of reliable data sets, we look into the use of alternative procedures based on Artificial Neural Networks, (ANNs). These knowledge-based techniques have the advantage that conditions of independence of the variables are not required to model the non-linear problem. Furthermore, they are capable of handling data noise and some uncertainties inherent to the data set. In this paper it is shown how ANNs can be used as an alternative procedure to develop generalized attenuation functions [22].

II. SEISMIC ACTIVITY

The whole western coast of South American is an active subduction zone. Colombia as part of this area, is located in the northwestern corner of the South American continent. In this particular location, the Nazca oceanic plate, the continental South America plate, and the Caribbean oceanic plate, converge producing thereby a very complex tectonic framework in the Colombian territory. The convergence of plates has provided the dominant forces in the development of the geological structures of Colombia, whose architecture is described as made up of individual fragments of overlapping plates, withheld to as tectonic terrains [17]. Each terrain is characterised by having its own lithology, stratigraphy, structural style, and geological history.

The tectonic terrains are separated by faults with a predominant N-S to NE-SW direction. In the majority of the seismic events there is a spatial correspondence between the distribution of intensities and the regional structures, witnessing the anisotropic allocation of attenuation. The iso-seismal major axis coincides with the straight of the fault systems and the geological bodies. This tendency evidences the important effect of geological environment in the attenuation of seismic movements.

Medellin is a city that has an area of ~ 110 km^2 and has been developed on the alluvial plain of the Medellín River and in the peripheral areas, which consist of steep slopes surrounding the valley and which are made up of igneous and metamorphic rocks, such as quartz-diorites, gabbros, amphibolites, dunites, and gneiss. All with different of weathering degrees, producing distinct types of residual soils and a great diversity of geotechnical conditions.

The seismic activity to which the city can be subject comes from a complex geodynamic frame of interactions within the territory between the tectonic plates mentioned above, more particular the Panama microplate and the Andean Block. Thus generating a high seismicity in the Pacific coast, within the Benioff zone, and active geologic faults inside the tectonic plate. During its history, Medellin has been disturbed by earthquakes of moderate intensity.

III. SEISMIC RECORD MEDELLIN DATABASE

The database used in this research was the acceleration time-history provided by the Accelerographs Network of Medellin (RAM).The seismic network is made of 24 recording stations, two of which have been installed at depth in the rocky basement. The record stations are distributed in the urban area of the city and their location covers a large part of the present geologic formations, as shown in figure 1. The RAM is considered the second most important local network of Latin America after the Mexico City one. The RAM began to operate in November 1996, under the responsibility of EAFIT University [18].

To design the topology of the ANNs that allow to calculate the seismic movement, a set of 278 accelerograms was used. On the basis of quality of these records, which met the necessary conditions for the recording of seismic events. Both at the source and within Medellin City (cause-effect), 26 earthquakes were finally used in the development of the ANNs. Both horizontal components of each seismic event were considered. Thus in all, 556 records were used. However, valuable information to define the input parameters was extracted from 278 seismic events [24]. The earthquake source locations and the corresponding magnitudes, as well as, the date of their occurrence are given in Table I.

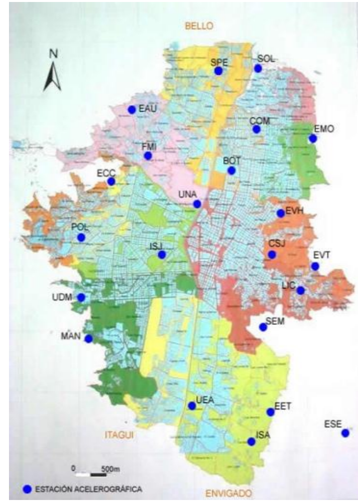

Fig. 1. Location of Accelerographs Network stations of Medellin

TABLE I
Seismic events used in the ANNs designs

Location source	Date	Latitude	Longitude	Mw	Record
Camposeco	22/11/1996	6.16	74.28	4.7	5
Villanueva	01/01/1997	6.73	73.18	6.2	5
Sipí	19/02/1997	4.62	76.58	6.0	12
Zapatoca	07/03/1997	6.76	73.23	5.8	15
Villanueva	11/05/1997	6.74	73.18	5.8	14
Cepita	11/06/1997	6.81	72.96	6.0	12
Santos	11/06/1197	6.84	73.09	6.1	14
Zapatoca	24/06/1997	6.87	73.23	5.5	5
Roncesvalle	02/09/1997	3.93	75.68	6.5	16
Génova	11/12/1997	4.00	75.95	6.8	19
Cimitarra	06/03/1998	6.28	73.89	5.4	16
Cimitarra	08/03/1998	6.30	73.88	5.4	15
Cimitarra	27/03/1998	6.37	73.95	4.5	8
Bu/ga	30/03/1998	6.70	72.93	4.5	5
Abriaqui	13/07/1998	6.56	76.05	3.8	15
San Andrés	26/10/1998	6.85	72.90	5.7	4
Los Santos	04/12/1998	6.8	73.18	5.6	10
Los Santos	10/12/1998	6.81	73.18	5.4	3
Córdoba	25/01/1999	4.40	75.71	6.0	14
Zaragazo	10/02/1999	7.52	74.88	4.6	13
Los Santos	14/04/1999	6.78	73.08	6.1	11
Sativasur	17/07/1999	6.07	72.75	5.5	7
Urrao	18/09/1999	6.50	76.16	4.7	8
Piedecuesta	08/11/1999	6.93	73.07	6.7	15
Betania	16/01/2000	5.74	76.06	6.2	11
Nido Bu/ga	05/02/2000	6.76	72.93	4.8	6

VI. ARTIFICIAL NEURAL NETWORKS

The artificial neural network ANNs, are a new generation of information processing systems that are deliberately constructed to make use of some of the organization principles that characterize the human brain. Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions that: (1) information processing occurs at many simple elements called neurons, (2) signals are passed between neurons over connection links, (3) each connection link has an associated weight, which in a typical neural net, multiplies the signal transmitted and, (4) each neural applies an activation function, usually non-linear, to its net input (sum of weighted input signals) to determine its output signal[19].

Thus, models of neural networks are specified by three basic entities: models of the processing element themselves, models of interconnections and structures or network topology, and the learning rules or the way information is stored in the network.

Each node, in a neural network, collects the values from all its input connections, performs a predefined mathematical operation, and produces a single output value. The information processing of a node can be viewed as consisting of two parts, input and output. Associated with the input of a node is an integration function which serves to combine information or activation from an external source or other nodes into a net input to the node. A second action of each node is to output an activation value as a function of its net input through an activation function which is usually non-linear. Each connection has an associated weight that determines the effect of the incoming data on the activation level of the node. The weights may be excitatory or inhibitory. The connection weights store the information, and the value of the connection weights is often determined by a neural network learning procedure. It is through adjustment of the connection weights that the neural network is able to learn.

In a neural network, each node output is connected through weights, to other nodes or to itself. Hence, the structure that organizes these nodes and the connection geometry among them should be specified for a neural network. Inputs can be connected to many nodes with various weights, resulting in a series of outputs, one per node. This result is a single-layer feedforward network. Further, several layers can interconnected to form a multiplayer feedforward network. The layer that receives input is called the input layer and typically performs no computation other than buffering of the input signal. The outputs of the network are generated from the out layer. Any layer between the input and the output layers is called a hidden layer because it is internal to the network and has no direct contact with the external environment. There may be from zero to several hidden layers in a neural network. The types of networks feed-forward since no node output is an input to a node in the same layer or preceding layer. When outputs are directed back as inputs to same – or preceding-layer nodes, the network is a feedback. This network that has closed loops is called a recurrent network.

The third important element in specifying a neural network is the learning scheme. Broadly, there are two kinds of learning in neural networks parameter learning, which concerns the updating of the connection weights in a neural network, and structure learning, which focuses on the change in the network structure, including the number of nodes and their connection types. These two kinds of learning can be performed simultaneously or separately. The kind of learning can be supervised, reinforced, and unsupervised.

The capacity of generalization of the neural network is the more salient characteristic; ANNs can sensibly interpolate input patterns that are new to the network. From a statistical point of view, this can fit the desired function in such a way that has the ability to generalize a situation that is different from the collected training data [19].

There is no a clear-cut procedure to define the best ANN topology. The optimum architecture is obtained when the error function is minimized, i.e., the sum of the patterns of the squared differences between the actual and desired outputs is minimum. The accuracy with which they reproduce the actual values of the parameters for the testing (predicting) stage, are given in Table II. It may be seen that the correlation achieved in all three networks is not very high, but quite acceptable for professional practice. This is mainly due to the complexity of the problem and the great scatter found in the values of the parameters used as input data for each case. It must be stressed that there are so many variables involved in the seismic movement problem, that the selection of the parameters that have more influence on the phenomenon are not clearly known yet [22]. Thus the input parameters listed in Table III are the dominant parameters, to yield the most accurate predictions for the network architectures indicated in Table IV.

TABLE II
Artificial networks statistical approximations

Model	Mean error Learning	Mean error Testing	Correlation (%) Learning	Correlation (%) Testing
DIF	0.210	0.460	0.95.9	0.827
PGA	0.270	0.340	0.972	0.906
Sa	0.328	0.505	0.958	0.829

The approach pursued to define the input parameters was based purely on the recorded evidence and on the support provided by the studies that have been carried out to understand the seismological phenomenon [14], [15]. The selected parameters connect three of the dominant aspects of the surface ground response phenomena: source parameters, wave path and local site effects. The listing of these parameters, which were used as vector inputs for the three ANNs, are shown in Table IV. All three networks yield as output the natural logarithm of the variable of interest [23]. The attenuation factor Q was defined following Aki's proposal reported in [13].

TABLE III
Input parameters for the ANNs

Model	Input variables	Output variables
DFI	Magnitude, Mw;, source-to-site distance R; soil type, S; predominant period of the site (receiver),Tp; frequency and period attenuation factors Q(f) and Q(T). Where, $Q=(29.4)\left(1+\left(\frac{f}{0.3}\right)^{2.9}\right)\div\left(\frac{f}{0.3}\right)^{2}$	Ln (DFI)
PGA	Magnitude, Mw; focal depth,h; source-to-site distance, R; soil type, S; Arias' intensity, Ia; duration of the intense phase of the accelerogram at the source, DFI.	Ln (PGA)
Sa	Magnitude, Mw; source-to-site distance, R; focal depth,h; fundamental frequency of the accelerogram at the site, fp; attenuation factors Q(f) and Q(T); duration of the intense phase of the accelerogram at the site, DFI; Arias' intensity, IA; soil deposit period at recording station, T; peak ground acceleration at recording station, PGA.	Ln (Sa)

TABLE IV
Characteristics of the ANNs

Neural network	Duration of the intense part (DIF)	Peak ground motion (PAG)	Spectral acceleration (Sa)
Architecture	Cascade	Multilayer full feed forward	Cascade
Number of input cells	Six	Six	Ten
Processing function	Normalize	Normalize	Normalize
Processing elements in hidden layer	Three	Three	Fourteen
Learning algorithm	Quick propagation	Quick propagation	Quick propagation
Input function	Dot product	Dot product	Dot product
Transfer function	Sigmoid	Sigmoid	Sigmoid
Error type	Mean square	Mean square	Mean square
Output	Ln (DIF)	Ln (PAG)	Ln (Sa)

The vagueness with which many of the seismological parameters are defined compels the use of neurofuzzy techniques to develop models to study the problem of seismic intensity attenuation as the earthquake waves draw away from the source and azimuthal effects. The theory of fuzzy logic is a useful tool in problems involving a particular type of uncertainty. Currently its applications cover very diverse areas of knowledge. Fuzzy logic in civil engineering has been applied in studies such as: risk assessment of soil liquefaction, safety assessment of earth dams, design of tunnels and underground excavations, environmental impact, and wastewater treatment.

V. RESULTS

The results computed with the ANNs developed for purposes of seismic attenuation studies in Medellin, are presented in the following graphs: in figure 2 the duration of the strong shaking are compared to those predicted by the neural network, whereas in figure 3 the maximum ground accelerations recorded during some seismic events, are compared to those predicted by the neural network at several sites within Medellin city.

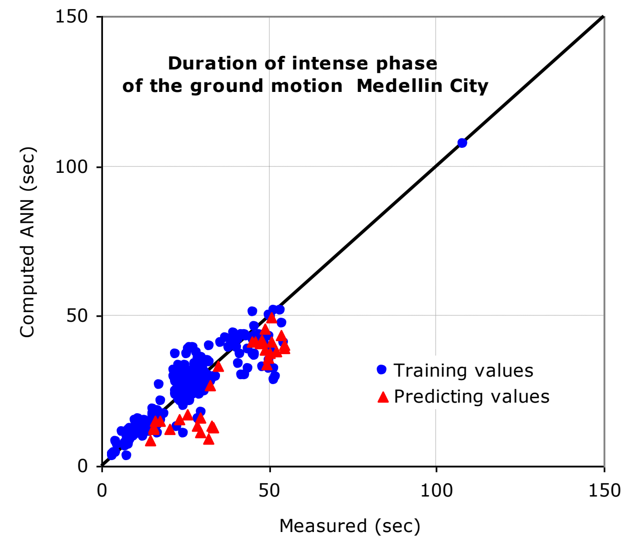

Fig. 2. Comparison between measured duration of the intense motion phase and ANNs-predicted

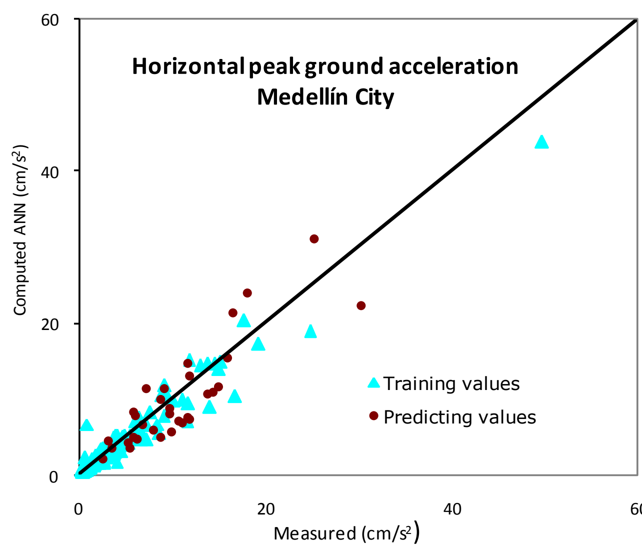

Fig. 3. Comparison between measured PGA and ANNs-predicted

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Figure 4 compares the acceleration response spectra (5% damping) computed with the network and those obtained from recorded motions, for several recording stations in two seismic events. It is seen that the spectral shapes are adequately reproduced for all cases shown and the prediction accuracy of spectral amplitudes varies from extremely good to fair. This unequal matching indicates that there are some additional parameters, between source and site (receiver) that ought to be included in the input vector of the ANN. This graph allows a direct comparison that highlights the forecasting ability of the neural system. In general, the predictions may be considered good enough for practical applications.

Estimations obtained with the networks show relatively low scatter and its predictions are more accurate than those forecasted by the other two procedures [15].

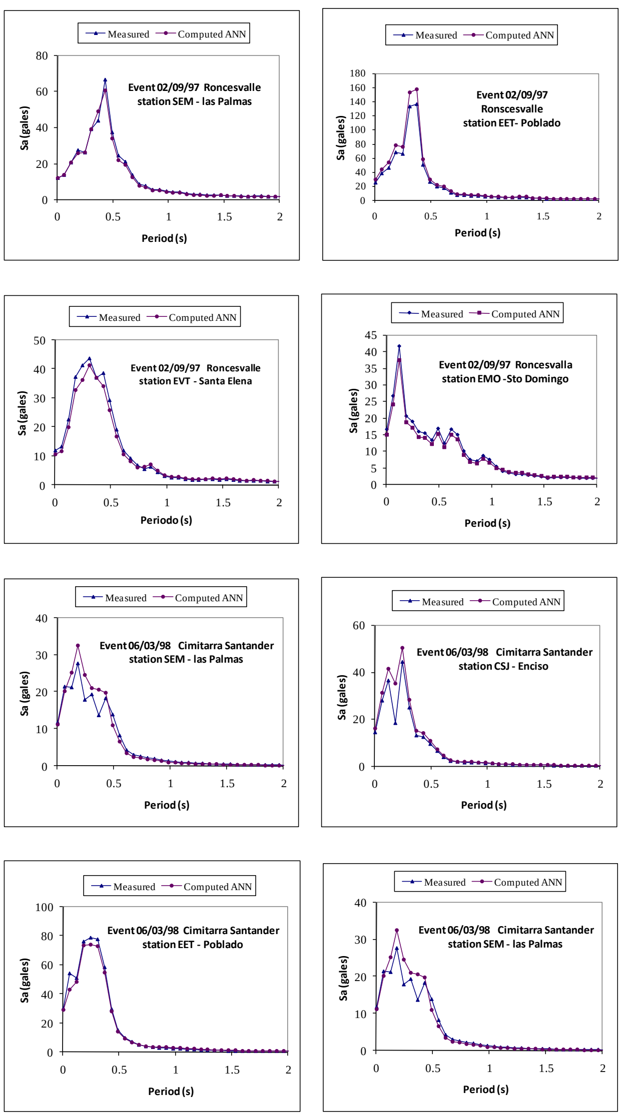

Fig. 4. Comparison between measured and ANN-predicted response spectral

VI. CONCLUSIONS

This paper shows the applicability of ANNs to the solution of seismological problems. The architecture of three networks were developed to forecast the maximum ground acceleration, 5% damping acceleration response spectra and lasting of the intense part of ground motions. Through comparisons with actual values, it was shown that ANNs can be considered as a feasible technique to analyze the earthquake attenuation problem and thus to be of used in seismic hazard evaluations. An advantage of this alternative is that it allows individual analysis between the seismic source and the receptor site of the movement (seismic intensity), providing more realistic conditions for seismic hazard assessment.

Although artificial neural systems do not solve the problem with mathematical rigor, the approximate solutions achieved are valuable because they do no require a prescribed rule and independence of the variables, and obviate the problem of non-linearity in complex systems, as is the case of this research.

In order to perform quantitative analysis concerning the sensitivity of the parameters that make up the input vector of artificial neural networks, it is recommended to examine the space of the synapse considering the inverse model via the concept of bidirectional associative memory.

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