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Modeling ground motion in Mexico City using artificial neural networks

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RESUMEN

A partir de los sismos de 1985 se ha instalado una gran cantidad de instrumentos de monitoreo en todo el valle de México. El registro de estos movimientos ha generado valiosa información con la que se está en posibilidad de desarrollar nuevos procedimientos analíticos basados en técnicas de aprendizaje.

Estos procedimientos se consideran aproximadores universales, por lo que se piensa son capaces de modelar todas las leyes mecánicas que describen un fenómeno. De acuerdo con esto, hace algunos años se inició una investigación con objeto de desarrollar una red neuronal artificial que modelara la respuesta sísmica de los depósitos de suelo de la ciudad de México. La red resultante, que permite el cálculo de la respuesta de los suelos arcillosos, se presenta y se discute en este trabajo. Se demuestra que las redes bien diseñadas representan una genuina alternativa a los métodos analíticos.

PALABRAS CLAVE: Movimientos de terreno, respuesta de sitio, inteligencia artificial, redes neuronales, modelado basado en aprendizaje.

ABSTRACT

After the September 1985 earthquakes in Mexico City, many strong motion instruments were laid down throughout the Valley of Mexico. Since then, a wealth of valuable information has been gathered. This has provided an excellent opportunity to develop new analytical procedures based on knowledge-based techniques.

An Artificial Neural Network (ANN) is a computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping. Accordingly, research aimed at developing an ANN to model the earthquake response of Mexico City soil deposits was initiated a few years ago. The resulting network that allows the computation of the response of the clayey ground is presented and discussed in this paper. It is shown that well designed networks represent a genuine alternative to analytical methods.

KEY WORDS: Ground motion, site response, artificial intelligence, neural networks, learning algorithms.

1. INTRODUCTION

Following the September 1985 Michoacan earthquakes, the authorities of the Federal District of Mexico sponsored many research projects aimed at understanding the nature of the ground motions developed within the Mexico City Metropolitan area, and to explain the damaging effects they inflicted on a significant number of modern buildings. Several of the studies included the installation of strong-motion instruments throughout the Valley of Mexico. Most of this equipment was laid down on the ground surface, several vertical arrays were set up within the clayey deposits, and some buildings were also instrumented. This practice has continued over the years and now there are more than 130 accelerometers installed. Accordingly, through the last 15 years a wealth of information on ground response and building behavior (including dynamic soil-structure interaction) has been gathered. These data have lent support to a series of pioneering investigations on soil behavior, wave propagation, building seismic behavior, and dynamic soil-structure interaction, among others. Many of the results from these studies have had an important impact on engineering practice and have been included, in recent reviews, in the Federal District Building Code.

In view of potential shortcomings of analytical modeling and considering the ever increasing bulk of information on earthquake-induced ground motions within the Valley of Mexico, knowledge-based procedures are being explored to develop alternate ways to analyze the response of Mexico City soil deposits. Modeling earthquake geotechnical problems by means of Artificial Neural Networks (ANNs), when these are trained on a comprehensive set of data, is very appealing because ANNs are capable of capturing and storing the related-phenomenon knowledge directly from the information that originates during the monitoring process.

In this paper, some of the results obtained using multilayer feedforward neural networks with a general regres-

sion learning paradigm are presented and discussed. The capabilities of the resulting network to carry out blind predictions are also highlighted. Herein, by a blind prediction it will be understood the reproduction of a recorded motion that has not been included in the database used in designing the ANN. Thus, in a sense, blind prediction and prediction capability will be used as synonymous throughout this paper.

2. ARTIFICIAL NEURAL NETWORKS

Neural networks (NNs) are computational models inspired from the biological structure of neurons that mimic the operation of the human brain. A NN is a nonlinear system consisting of a large number of highly interconnected processing units (processors). Each processor maintains only one piece of information (its current level of activation) and is capable of a few simple computations such as adding inputs, computing a new activation level, or performing threshold logical computations. The large number of processors, and even larger amount of interconnections, equivalent to the neuronal structure of human brain, give NNs their capability of knowledge representation. Furthermore, it is through self-organization (or learning) that a NN approximates some representation of a particular knowledge.

Contrary to traditional sequential programming techniques, NNs are trained with examples of the concepts they are trying to capture. The network then internally organizes itself to be able to reconstruct the presented examples. ANNs have the ability to produce correct, or nearly correct, responses when presented with partially incorrect or incomplete input data (stimuli). They also are able to generalize rules from the cases on which they are trained and apply these rules to new stimuli.

The main attributes of neural networks are their robustness to noise data and its ability to generalize to new (unseen) inputs. In other words, a trained network is capable of providing sensible output when presented with input data that have not been used during training, even if these data contain random noise. In general, it can be stated that as the uncertainty in the unseen input data increases, the predicting capabilities of the network are diminished to some degree. However it can still make reasonable predictions.

The operation of a processing unit in a NN computation is rather simple. The output of a processor, which is computed from its activation level, is sent to other (receiving) processors via the outgoing connections of the processor. Each connection from one processing unit to another one processes a numeric weight that represents the strength of the connection, which is a filter (in the form of multiplicative coefficient) of the output sent from one processor to another one. It may serve to increase, or decrease, the activation of the receiving processing unit. The activation level of each processor is computed on the basis of the sum of the products of connection strengths and outputs coming into the processor over its incoming connections, and then sends its output to other processors to which it has outgoing connections.

The propagation of activation in a NN can be feedforward, feedback, or both. In a feedforward network, the signal can be propagated only in a designated direction. In a feedback mechanism, the signal can flow in either direction or recursively. In multilayer feedforward networks with a certain type of learning rules, the amount of error defined as a measure of the difference between the computed output pattern and the expected output pattern is very much dependent on the weights of the connections between the processing units. Therefore, the definition of the computation is embodied within the connection strengths of a NN. It should be understood that the programming of a NN does not involve manually setting the numerical values of the connection strengths, but rather, involves training the network with many examples of cause-effect patterns and having it automatically modify the connections through the usage of learning rules.

This ability to modify its own weights, e.g., to self-organize, makes neural computing feasible. Also, self-organization leads to generalization. By modifying the connection strengths between processors, NNs can create internal features that might have not been apparent from the data and thus would have defined the manual setting of connection strengths. Likewise, they can be employed to produce correct, or nearly correct, cause-effect patterns not encountered before, but having similar internal features to those input patterns previously found.

Rumelhart *et al.* (1986) provided a description of the basic architecture of ANNs, consisting of the following basic concepts: 1) a set of processing units, 2) the state of activation of a processing unit, 3) the function utilized to compute the output of a processing unit, 4) the pattern of connectivity among the processors, 5) the rule of activation propagation, 6) the activation function, and 7) the rule of learning used. The network topology, and the form of the functions and rules are all learning variables that in neural network learning systems lead to a wide variety of network architectures.

Some of the well known types of NNs include the Competitive Learning (i.e., Grossberg, 1976); the Boltzman Machine (i.e., Hinton *et al.,* 1984); the Hopfield Network (Hopfield, 1982) the Kohonen Network (Kohonen, 1984);

the Adaptive Resonance Theory (ART) that evolved through various versions and contributed with a number of valuable properties with respect to other neural architectures, among which could be mentioned its on-line and self-organizing learning (i.e., Carpenter and Grossberg, 1987, 1991; Fernández-Delgado and Barro, 1998); and the Backpropagation neural networks (i.e., Rumelhart *et al.,* 1986) that learn by backpropagating the errors seen at the output nodes. Backpropagation networks and their variants, as a subset of Multilayer Feedforward Networks, MFN, despite their shortcomings, continue to be, currently, the most widely used networks in applications.

The networks developed in this research were designed using the MFN architecture, where the processing units are arranged in layers. Each network has an input layer, an output layer, and one or two hidden layers. Propagation takes place in a feedforward manner, from the input layer to the output layer. The pattern of connectivity and the number of processing units in each layer may vary with some constraints. No communication is permitted between the processing units within a layer. The processors in each layer may send their output to the processing units in higher layers. The specialized notation for architecture definition used in this study (*m*x*h*x*o*) is interpreted as follows: *m* is the number of input cells, *h* is the number of processing units in the hidden layer(s) and *o* represents the number of output cells.

At this stage it is important to define the input functions, learning rules and transfer functions that are used later on in this study.

Input Functions

Dot Product (DP). This input function is a weighted sum of inputs plus a bias value, which scales each of them according to its relative influence in increasing the net input to each node. It observes that the weights and inputs may take on negative values as well, so for inputs of roughly the same magnitude, the absolute value of weights corresponds to the relative importance of the inputs.

L1 Distance Input Function (L1). This calculates the distance between two vectors. Thus the processing element automatically obtains the distance to the input example. When the General Regression learning rule is used, each processing element on the hidden layer must have this distance processing element function.

Learning Rules

Back propagation (BP). This is a steepest descent algorithm that adjusts the weights of the net iteratively until the function error (difference between expected and computed values) is optimized. It has the advantage that it can be easily generalized but for large networks it converges slowly and may get stuck in a local minimum.

Quick Propagation (QP). This is a supervised learning algorithm, which provides several useful heuristics for minimizing the time required for finding a good set of weights. QP evaluates the trend of the weights and updates over time to determine when the step size can be optimized (Fahlman, 1998).

Conjugate Gradients (CG). This is a classical numerical method for minimizing arbitrary functions when derivative information is available. When applied to NN it becomes an excellent learning technique that can be used for batch mode training of feedforward networks. The CG algorithm uses the gradient of the weights to pick the initial direction for search. The proper choice of the new direction is a conjugate "non-interfering" direction. Of the several CG approaches the Heatness-Stiffel (Johansson *et al.,* 1990) method was selected for the implementation in the NN.

Levenberg-Marquard (LV). This algorithm contains a heuristic procedure that transitions smoothly between steepest descent method and the Gauss Newton procedure (Hagan and Menhaj, 1994). The Gauss Newton method converges to the minimum of a quadratic energy function in a single iteration of the algorithm. The LV algorithm is one of the fastest converging algorithms available for training small NN. However, is limited to only one output and the memory requirements are very high.

General Regression (GR). This is a memory-based learning rule based on the estimation of probability density functions. It features fast training times, can model nonlinear functions, and has been shown to perform well in noisy environments given enough data (Specht-Donald, 1991). The primary advantage to the GRNN is the speed at which the network can be trained. Training a GRNN is performed in one pass. The training data are simply copied into the hidden layers of the neural net. In a GR network, each node in the hidden layer contains one pattern from the training set. When presented with an unknown pattern, the distance between the unknown example and each node in the hidden layer (i.e., training set) is computed and passed through a kernel function. The output of the kernel function is an estimation of how likely the unknown pattern belongs to that distribution. Thus, the output layer is simply a weighted average of the target values close to the input pattern.

Transfer Functions

Sigmoid (sigm). This is the most popular transfer function. It compresses the input function when it takes on large

positive or negative values. Large positive values asymptotically approach 1, while large negative values are squashed to 0 or –1.

Hyperbolic Tangent (tanh). The tangent transfer function is also a "squashing" function, but has slower asymptotic convergence; it is useful as an alternative to the sigmoid when it is known large weights are necessary.

Hyperbolic Secant (sech). This is the hyperbolic counterpart to the gaussian function. It acts as a probabilistic output controller. Like the sigmoid function, the output response is normalized between 0 and 1. Gaussian and secant networks tend to learn quicker but can be prone to memorization. That is, being capable of repeating what they learn but unable to carry out blind predictions.

3. DATA BASE USED

To develop a knowledge-based modeling procedure, information about cause and effect is needed in the form of input vectors and corresponding outputs. Also, it is important to have a clear understanding of the phenomenon (intended to be modeled) to make adequate selections of the variables that should be included as input units. For the particular case of soil deposit response analyses, it was required to have information regarding the seismic environment of the site. Likewise one should posses sufficient data to characterize dynamically the soil deposits and to know the ground responses that result from the input earthquakes.

Previous investigations (e.g., Romo and Jaime, 1986; Romo and Seed, 1986) have shown that using the motions recorded at CU site as outcrop motions, the recorded responses within the urban area of Mexico City can be reproduced fairly well by a one dimensional-shear wave-propagation procedure. Thus, in this study, the excitation to the soil deposits is represented by the acceleration response spectra (5% damping) of the seismic movements recorded on the surface of the firm deposits (Hill zones, see Figures 1 and 2) outcropping towards the West of Mexico City. The general characteristics of the motions, their epicentral distances and geographic coordinates are given in Table 1. The location of the corresponding epicenters is shown in Figure 3.

The soil deposits included in this investigation were characterized dynamically by their elastic natural periods, defined from the pseudo-velocities spectra (2% damping) of the accelerograms recorded at the sites considered. The natural periods obtained are similar to those available in the form of iso-period contours for Mexico City (Federal District Construction Code, 1987). Natural periods and locations of the sites included in this study are given in Table 2 and Figure 2.

In order to interpret, to model and to represent properly the mapping problem, the seismic responses measured at the sites that were used as outputs in the ANN model development process, were selected on the basis that motions of the same seismic event were also recorded at CU site. The data base, used as input patterns, was constructed using the CU acceleration response spectra of the earthquakes included in Table 1, and the elastic natural period that characterizes each soil deposit. Natural periods were considered to classify the sites because they implicitly include the stiffness of the layering system and the geometry of the soil deposits. In fact, it is a key parameter in earthquake zonation. The acceleration response spectra of the seismic events recorded at the sites shown in Figure 2 were used as output patterns.

Response spectra were used to represent the ground movements because practicing engineers use them as input motions in seismic designs. Furthermore, the Construction

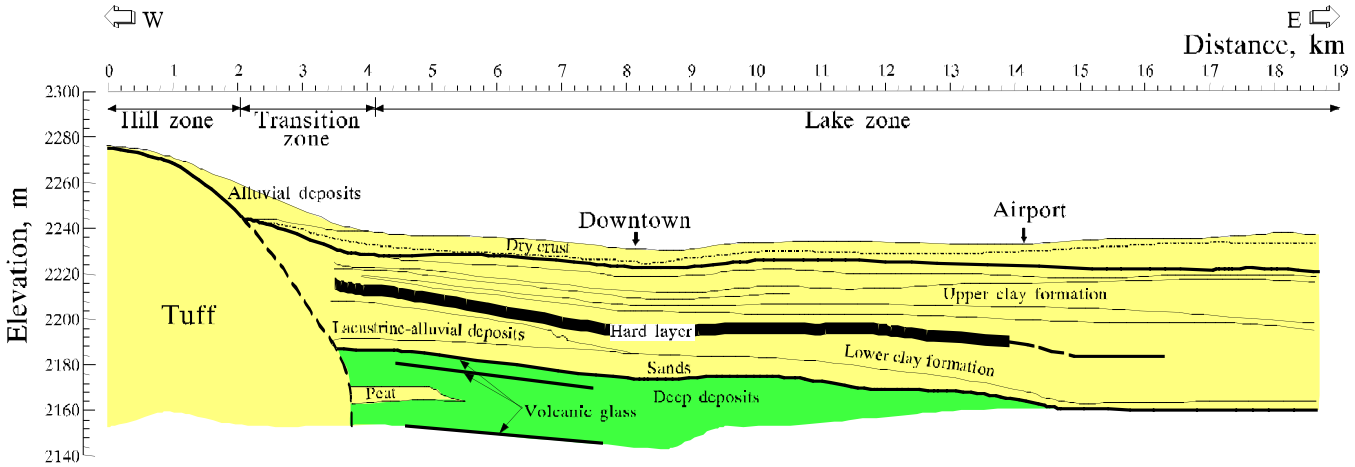

Fig. 1. Stratigraphic characteristics of Mexico City soil deposits (provided by TGC, Geotecnia).

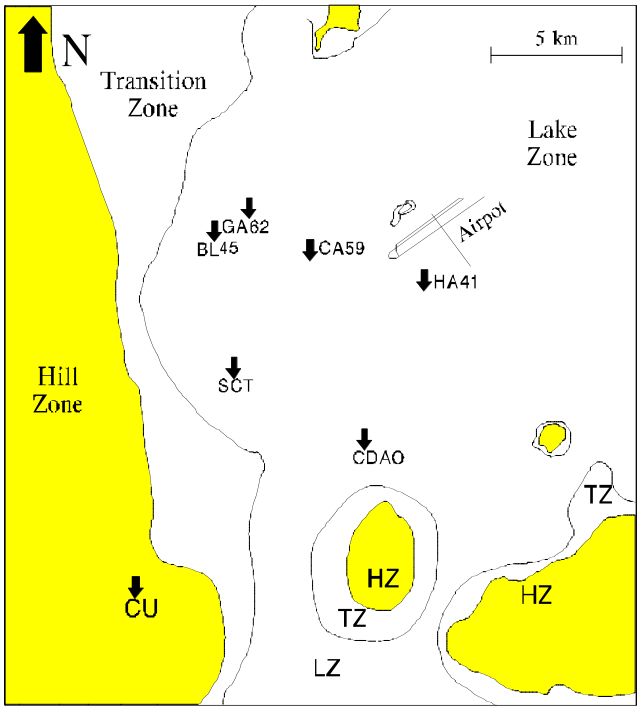

Fig 2. Site locations and Mexico City geotechnical zoning.

Code for the Federal District of Mexico specifies seismic excitations in terms of response spectra. Obviously, there are other means to represent ground motions such as time histories of accelerations, velocities, displacements, Fourier Spectra (should include amplitude and phase spectra), power spectral densities, and so on. Because of their jagged nature, Fourier spectra and time series are more difficult to reproduce than, say response spectra. Investigations are currently underway to develop networks that are able to make blind predictions of ground responses in terms of Fourier spectra and acceleration time histories.

After screening the bulk of available information, the resulting data base useful to design the ANN model includes eighteen earthquakes (represented by their 5% damping acceleration response spectra) with magnitudes M_s ranging between 5 and 8.1, and 23 soil sites having elastic natural periods varying from 2 to 4.2 sec. Due to space restrictions, this article only includes the results for six sites that, nonetheless, yield a clear picture of the capabilities of knowledge-based modeling. Seismic events identified by boldfaced numbers in Table 2, were used for testing the predicting capabilities of the network. All others were used for the net-learning stage.

Table 1

General characteristics of input seismic motions (CU site)

Date (yr/mo/dy)	Epicenter Lat N	Epicenter LongW	Epicentral Distance (km)	M_s (magnitude)	a_{max} (gals)
85/09/19	18.081	102.942	419	8.1	35.0
88/02/08	17.494	101.157	291	5.5	2.2
89/04/25	16.603	99.400	304	6.7	10.3
90/05/11	17.046	100.840	308	5.1	1.6
93/05/15	16.430	98.740	326	5.8	1.4
93/07/29	17.380	100.650	266	5.0	0.7
93/10/24	16.540	99.980	321	6.5	4.1
94/03/14	15.670	93.010	770	6.5	0.6
94/05/23	18.030	100.570	205	5.6	4.5
94/07/04	14.830	97.290	539	5.9	0.5
94/12/10	18.020	101.560	290	6.3	5.9
95/09/14	16.310	98.880	337	7.3	8.2
95/10/09	18.740	104.670	580	7.5	2.6
95/10/21	16.920	93.60	646	6.2	0.3
95/10/30	16.980	98.500	336	5.3	0.4
97/01/11	18.090	102.860	411	7.3	5.8
99/06/15	18.200	97.470	220	6.7	11.9
99/09/30	15.890	97.070	443	7.4	7.8

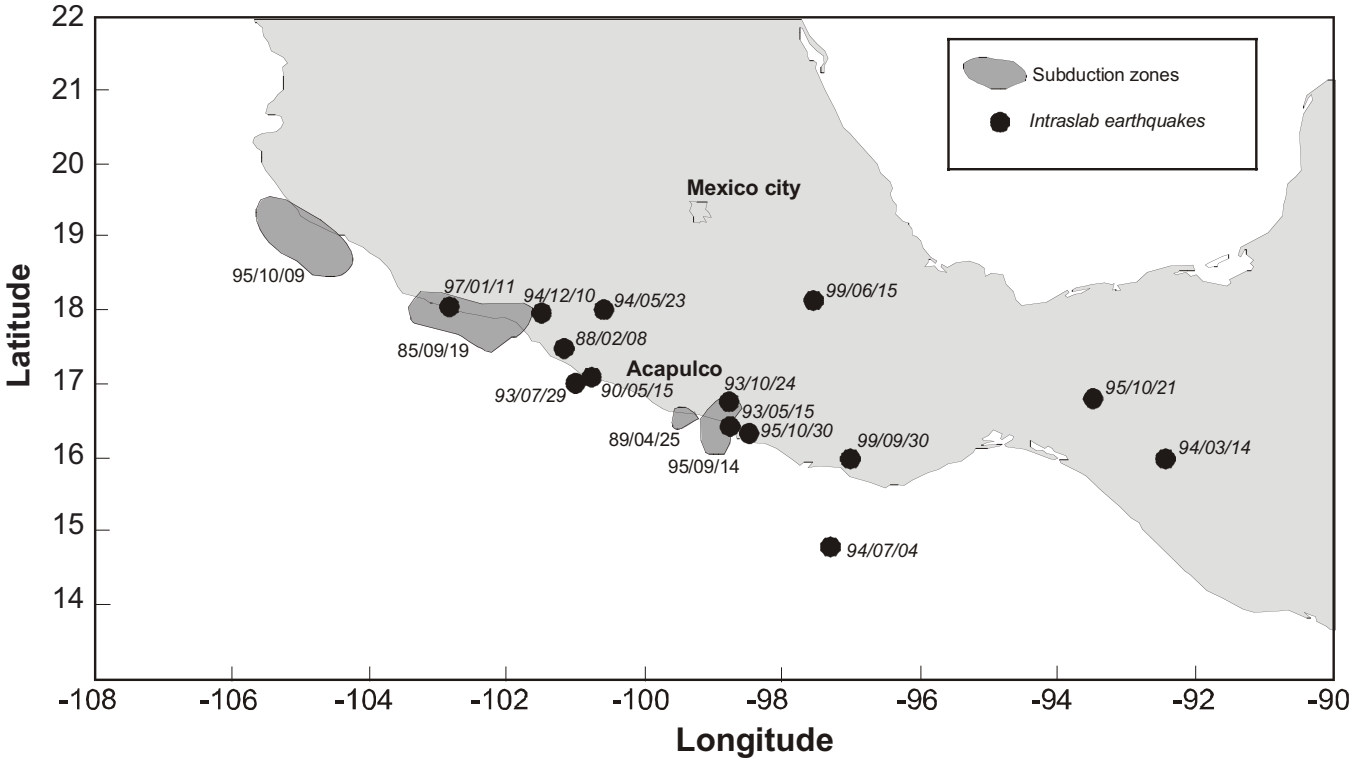

Fig. 3. Location of seismic events used in this study.

Table 2

Data base used in the ANN design

Site	SCT	Garibaldi (GA62)	Balderas (BL45)	Candelaria (CA59)	CDAO (CDAO)	Hangares (HA41)
Period, sec	2.1	2.2	2.4	3	3.5	4
Seismic events used in this study	90/05/11 94/05/23 94/12/10 93/10/24 89/04/25 95/09/14 97/01/11 95/10/09 85/09/19 99/06/15* 99/09/30*	93/07/29 94/05/23 94/07/04 94/12/10 94/03/14* 93/10/24 95/09/14 95/10/09	93/07/29 95/10/30 94/05/23 94/07/04 95/10/21 94/12/10 93/10/24* 94/03/14 95/09/14 95/10/09*	94/05/23* 95/10/21 94/12/10 93/10/24 94/03/14 95/09/14 95/10/09 95/10/30*	85/09/19 88/02/08 89/04/25* 90/05/11 95/09/14 97/01/11	94/05/23* 93/05/15 94/07/04 94/12/10 93/10/21 94/03/14 95/09/14 95/10/09*

**** Patterns used for testing***

4. NETWORK DEVELOPMENT

Given the variety of ANNs and the accuracy with which they reproduce specific behaviors, a number of possible designs including different transfer functions, learning rules and structures were evaluated with the purpose of optimizing the ANN architecture. The alternatives studied in this paper were discussed in section 2. In order to establish which of the dif-

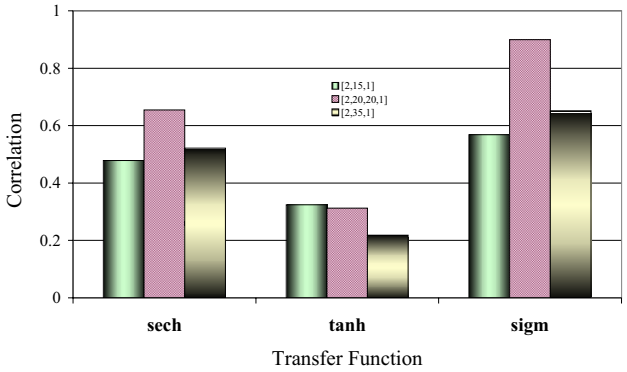

Fig. 4. Transfer function selection from QP-DP (Quick Propagation- Dot Product) topologies.

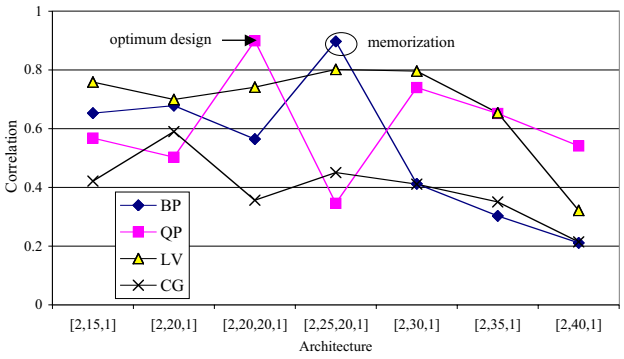

Fig. 5. Comparison between learning rules behaviors in the prediction stage.

ferent transfer functions meets better the conditions of the problem (input/output relationship), several topologies were tried. In Figure 4, the correlation reached for nine networks (using quick propagation as learning rule) with different transfer functions is shown. From these results, and other not included in this paper, it could be concluded that the sigmoid function and a network topology (2,20,20,1) yielded the highest training correlation. When it is used in other topologies (see Figure 4) the correlation attained decreases, but it is still higher than the correlations obtained with the sech and tanh functions.

To evaluate the learning and, most importantly, the predicting capabilities of the paradigms, seven networks were designed and tested using the data included in Table 2 for the SCT site. The input and output patterns were presented to the networks as vectors where the real-valued input vector describes a condition and the output vector the responses of the system. The natural period of the soil deposit was not considered as input variable because it was assumed that it remained constant within the nine-year period the earthquakes occurred (see Table 2). As it can be seen in Figure 5, the better-specialized function approximation network has 40 hidden nodes (20 nodes per layer), uses quick propagation as learning rule and dot product as input function (QP-DP). It is worth pointing out that the QP learning rule performs more slowly as compared with others such as LV and CG that use about 30 and 60% of the QP computation time. However, their generalization capabilities are much lower. Thus, the QP-DP was considered the most appropriate learning rule of all three. The entire learning process must be monitored to detect any memorization (lost of generalization capabilities) of the ANN. Memorization can be overcome by increasing the number of training patterns or decreasing the number of nodes in any or all of the hidden layers, as it is shown in Figure 5.

In this figure, the correlations for different architectures and learning rules have two prominent peaks. One corresponds to the optimum architecture and the other to a topology that memorizes. To tell whether an architecture is the optimum one or simply memorizes, different topologies (similar to the one in question) should be considered. If the correlations obtained with the new topologies decrease systematically, the network memorizes. If the correlation graph has a jagged configuration then the architecture that yields the maximum correlation value corresponds to the optimum design.

After a number of trials using networks with different topologies, it was realized that as the number of points used to define the input spectra increased, it became more difficult to differentiate the dynamic ranges of the variables assigned to the input processing units and their relationship with the output processors. Furthermore, when more sites are added to the data base, the representativeness of the soil deposit natural period faded out. It was also learnt that to overcome these shortcomings, it was necessary to increase significantly the size of the input vector (number of training patterns), as the number of points used to represent the input response spectrum grew. This led to a tremendous increase in computation time, since the number of operations per iteration increases exponentially with the amount of training patterns. These observations pointed out that the specialized function approximation and autocorrelation networks, commonly used in this type of problems, required to be coupled with specialized processing units (Masters, T. 1993).

When autocorrelation networks are used to model response spectra, many of their details are missed, particularly in the neighborhood of the site's natural period (where the maximum spectral ordinates usually develop), and spectral peaks that show up at higher frequencies. For the network to recognize sharp peaks it is necessary to use many computational resources. This slows down or even precludes network learning. However, after many trials, neural networks are capable of reproducing spectral shapes featuring large ordinate differences. An alternate procedure to overcome these

shortcomings is to use specialized neurons that focus on one region of the variable's domain as described in Nauck *et al*. (1997). Although this alternative leads to stable solutions, it has the drawback that the number of neurons and training patterns are increased.

Accordingly, new specialized function approximation neural networks were used in this study. There is a substantial amount of numerical evidence (e.g., García Benítez and Romo, 1999) that shows that for complex problems, like the one treated here, an alternative that can yield better results in approximating functions is the General Regression (GR) learning rule and distance processing element function (L1). To evaluate this alternative, the same case of SCT site was used and the corresponding architecture was developed. The results, in terms of acceleration response spectra, that depict the predicting capabilities of GR-L1 networks are included in Figure 6. This figure also includes the results obtained with two networks that use the QP learning rule and the response spectrum of the accelerogram recorded at the site during the 99/09/30 earthquake. From this information, it is clear that the GR algorithm is significantly more accurate. In fact, the spectrum predicted by the GR-L1 network falls on top of the actual spectrum practically throughout the range of periods considered in this analysis. Accordingly, the GR algorithm was used to compute the response at the additional sites those which are marked with asterisk in Table 2, where the events that were used for training and testing the ANN are indicated. Since the natural period of the soil deposit varies with the location of the site, this parameter was included in training the network. Thus the input variables were the period of soil deposits, the spectral ordinates (CU site) and the corresponding structural periods. The resulting network has only one hidden layer with 2050 processing units and one output unit (the ordinates of the spectral responses, for the same input structural periods, at each soil site).

The results obtained with this network are compared in Figure 7 with the actual spectra at six sites. It may be seen that the network reproduces with high accuracy the spectra of the measured acceleration time histories. In this figure, it is also included the blind prediction for SCT site using a random vibration (RV) procedure developed by Romo (1976). It can be seen that the ANN prediction is more accurate than the RV prediction. It should be mentioned that this RV method has been used extensively in Mexico City, and has shown its capabilities to reproduce with a good degree of accuracy the spectra of the motions recorded at many sites for different earthquakes, including the one recorded at SCT site during the September 19, 1985 earthquake (Romo and Jaime, 1986; Romo and Seed, 1986). These results support the argument raised in the introduction, regarding the predicting capabilities of neural networks versus conventional mathematically-based procedures.

The findings shown in this paper and other results presented elsewhere (Romo, 1999; Romo *et al*., 2000), that include additional sites in the lake and transition geotechnical zones, clearly indicate that knowledge-based procedures are capable of modeling accurately seismic problems which are inherently complex.

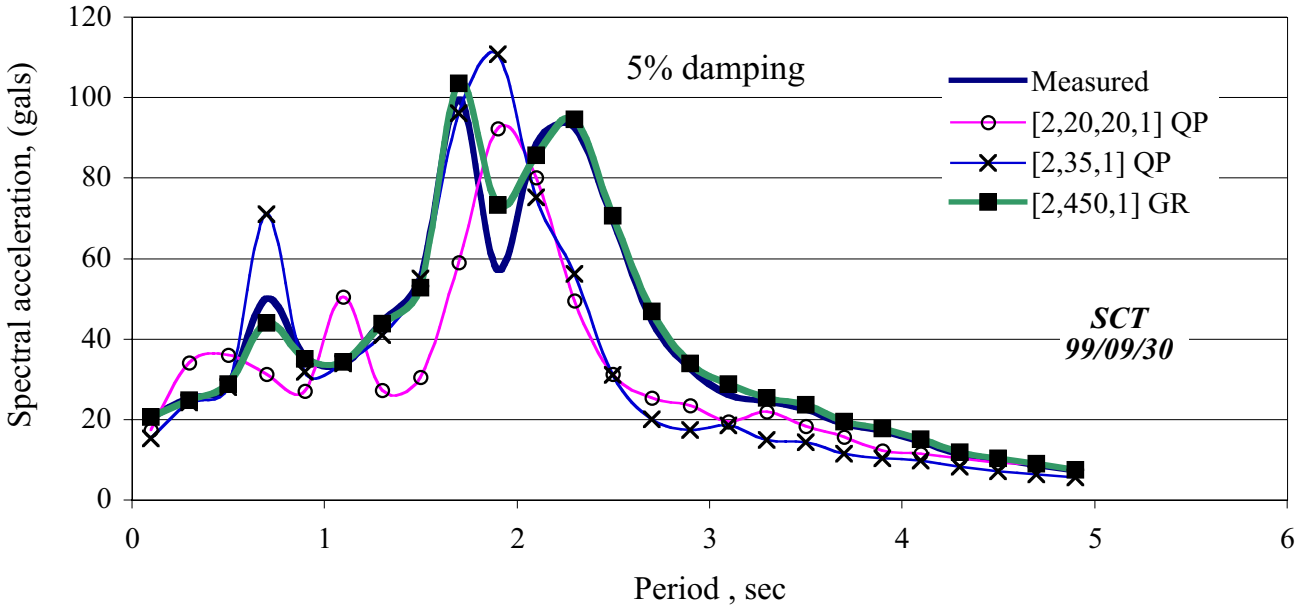

Fig. 6. Predicting capabilities of networks with QP (Quick Propagation) and GR (General Regression) learning rules.

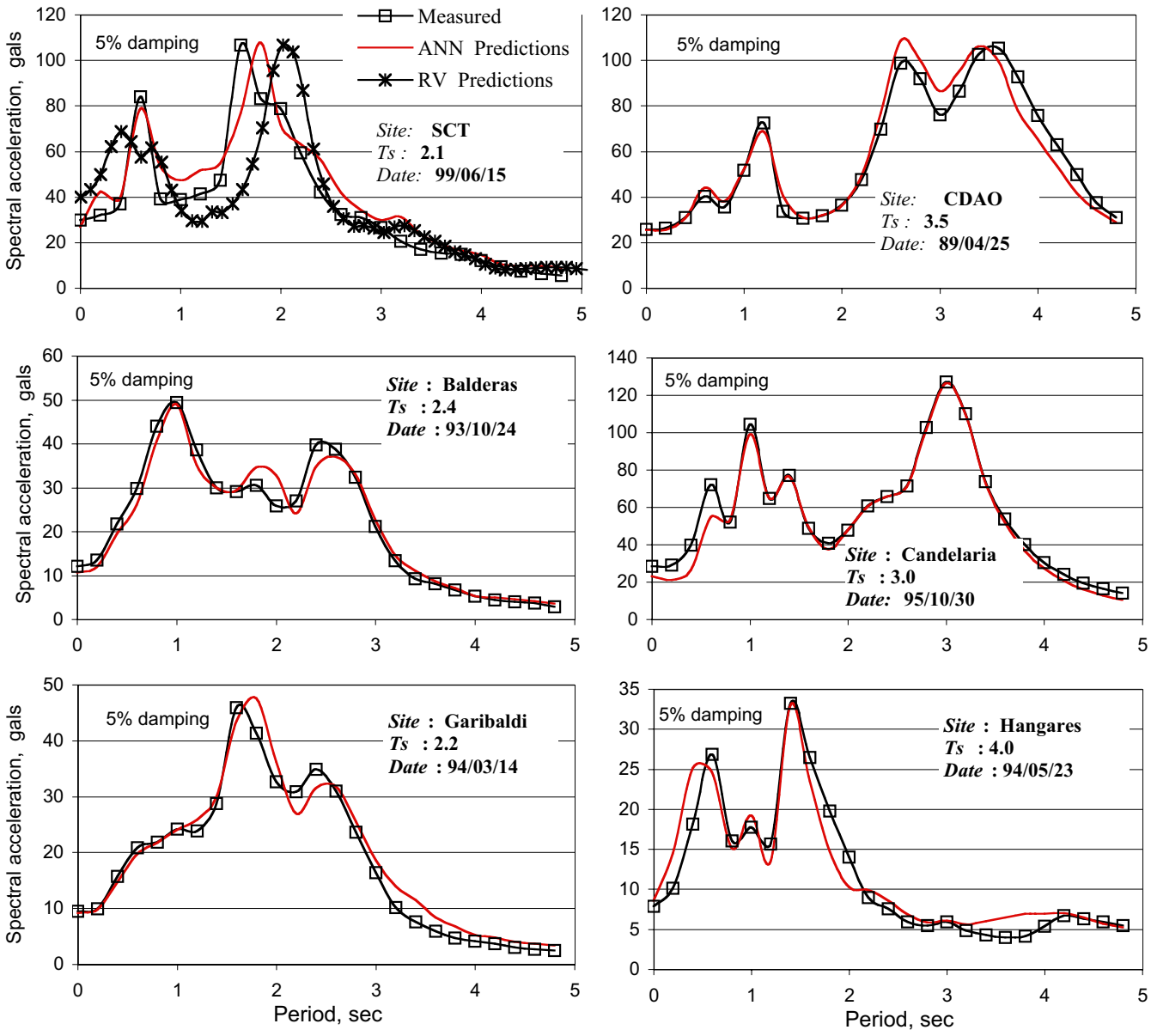

Fig. 7. Comparison of measured and ANN computed responses at six sites in Mexico City.

5. CONCLUSIONS AND FUTURE DEVELOPMENTS

The information given in this paper demonstrates that ANNs are able to predict with good approximation ground surface responses to seismic events that come from different earthquake sources, as indicated in Figure 3. The case of the Tehuacan seismic event (99/06/15) is particularly encouraging because procedures based on empirical relative transfer functions failed to produce reliable results (see Singh *et al.*, 1999). Similarly, the analytical tool used here for comparison purposes does not seem to predict accurately ground responses for intraslab earthquakes generated at mid distances from Mexico City.

After a significant number of trials using different combinations of input functions, learning rules and transfer functions, combined with one and two hidden layers and a variety of processing neurons in each layer, it was found that the architecture (2,2050,1) with GR-L1 learning rule, was the most accurate.

The various attempts to find the best ANN architecture presented in the previous pages evidence that a key point, regarding this knowledge-based technology, is to ensure its proper learning. An important factor to achieve this, is related to the level of understanding the designer has about the physics of the problem to be solved.

Although the GR network presented here yields very good results, some improvements are still possible. Natural systems are governed by numerous interacting variables (high dimensional problem) with drifting parameters in the presence of noise (internal and external perturbations). One promising approach for assessing such nondeterministic complexity is recurrence quantification analysis (RQA). This is a tool for the analysis of the experimental time-series data that transforms a single trajectory in a two dimensional representation (e.g, vectors into matrices).

Proper application and correct interpretation of this powerful discriminatory tool in the ANN model of the dynamical system can yield definitive clues for the qualitative assessment of time series. With RQA one can graphically detect hidden patterns and structural changes in data or see similarities in patterns across the time series under study. In this sense, the addition of RQA parameters would most likely improve the model proposed here because, it would be capable of identifying new patterns from different stratigraphies having equal natural periods. This would add power to the forecasting capabilities of the ANN because, as it is known, two soil deposits having equal natural period but different stratigraphy would behave differently under the same input motion.

Before the network developed in this study is used by the profession, the network has to go through a more intense period of testing. Once the reliability of the network is established beyond any doubt, friendly software or a chip for a computer can be developed, and thus released to be used by practitioners.

6. ACKNOWLEDGEMENTS

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