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ANN SIMULATOR FOR DETERMINATION OF SOIL CHARACTERISTICS USING EARTHQUAKE SPECTRA

Mohsen TEHRANIZADEH[1] Mohammad SAFI[2] and

SUMMARY

A committee of Artificial Neural Networks (ANN) has been designed and employed for determination of soil characteristics based on the analysis of earthquake records. This committee contains competitive neural networks which uses the unsupervised learning procedure for classification of the records and back error propagation neural networks for estimation of shear wave velocity in soil media. The shear wave velocity ranges for various soil types and velocity values have been obtained and compared to the seismic codes and experimental results. It has been shown that the method is potentially capable of predicting shear wave velocity in soil media and soil type for standard design in engineering applications in a simple and effective manner.

INTRODUCTION

Accelerograms are considered to contain the most direct engineering information of the earthquake and are capable of measuring strong motion excitations of major earthquakes. Peak ground velocities are recognized to be related strongly to structural damages. The ultimate displacement demand of a structure has also been recognized as a key parameter governing the seismic behavior of structures. One can use time history analyses to obtain the response of the structure using these various records [1]. However, the most practical means to evaluate earthquake effects on a structure are spectra.

Spectrum analyses use acceleration, velocity and displacement spectra that are obtained using earthquake records. The design spectra proposed by seismic codes are based on statistical analysis of the response spectra for an ensemble of ground motions. The design spectrum is obtained for different sites or soil characteristics, near field or far field ground motions and moderate or high intensity earthquakes. Thus, the primary step to obtain a design spectrum is to classify existing ground motion records according to their characteristics. This classification job has been performed here using the application of artificial neural networks. Different researchers have applied the artificial intelligence phenomena in order to construct artificial acceleration time histories, estimating the fault motions and process earthquake data [2,

[1] Professor, Department of Civil Engineering, Amirkabir University of Technology, Tehran, I.R. Iran, Email: tehz@committee.or.ir

[2] Faculty Member, Power & Water Institute of Technology, Tehran, I.R. Iran, Email: msafi@pwit.ac.ir

3]. To the authors best knowledge it is the first time that the neural networks are being used for constructing design spectra.

In the first part of the paper, the response spectrum concept and the required corrections for the accelerograms have been briefly reviewed. In the second part, the theory of self-organizing networks has been considered. Iranian ground motion records are primarily selected and have been classified through a multi steps procedure. The committee of competitive and back propagation neural networks have then been introduced and used to obtain the final categories for the calculation of the design spectra. The results obtained from classification method have been verified comparing to the available experimental investigations [4, 5, and 6]. Finally the obtained acceleration and displacement design spectra have been compared to the existing national and international seismic codes and the advantages and disadvantages of the method has been investigated.

DESIGN SPECTRA REQUIREMENTS

Generally, there are two basic sources for acceleration time histories, first selecting a group of past recorded earthquake ground motions, and second synthetically developing or modifying one or more ground motions. In order to prepare a site specific earthquake spectrum it is needed to classify the accelerograms according to the site characteristics. If the design spectrum is being modified the intent is to cover the valleys of the spectrum produced by one record, which fall significantly below the site-specific design response spectrum. It is also necessary that the spectra produced by the new records not significantly exceed the site-specific design response spectrum. In this paper the first procedure, explained above, has been selected to obtain the design earthquake spectra for Iran. More than 2000 accelerogram recorded in different stations and related to various earthquakes have been processed to obtain the appropriate design spectra for the defined soil types. This process consisted of three phases as a) general classification, b) correction and c) intelligent classification that are discussed in the following subsections.

Selection of Ground Motion Correction Method

In the measurement of long period wave components in an accelerogram, resolutions are generally poor due to the low acceleration levels. Thus, the recorded accelerations often require corrections when the terminal velocity or displacement obtained by integration of the acceleration data turns out to be non-zero. The simplest form of corrections in the time domain is by applying a short rectangular pulse at the beginning of the record or by baseline correction. The correction pulse can be calibrated to result in a zero terminal velocity by forcing a stepped change in the velocity at the beginning of the record. Alternatively, the baseline of the accelerogram is uniformly shifted to result in a zero terminal velocity. Further, a parabolic baseline correction can be calibrated to result in a zero terminal velocity as well as a reasonable value of terminal displacement. However, the parabola is often very close to a straight line. Corrections can also be applied in the frequency domain by filtering high and/or low frequency components in the accelerogram. The zero frequency components in the accelerogram represent uniform acceleration lasting the duration of the record. Such uniform acceleration results in a linear increase in velocity and a parabolic increase in displacement with time. Discretionary judgment is needed to decide the roll-off frequency of the filter.

There is not a general consensus among seismic designers regarding the methods and procedures used for correction of accelerograms. There is also a lack of knowledge among seismologists in correcting the strong motion records especially in long period region for filtering the long period noise. However in this study the base line correction in the time domain has been employed to modify the records for further processes.

Record Classification Method

In the context of spectrum preparation, earthquake record classification is primarily based on site characteristics and soil types. Soil types are roughly classified according to the shear wave propagation velocity, V_s in the soil media. The effective strong motion duration of an accelerogram can also be used as a basis for further classification. This duration refers to the time interval based on the 5% to 95% energy fraction [7]. Some representative acceleration time histories for each soil type have been shown in figure 1. These accelerograms have been selected using the classification method introduced in the following sections.

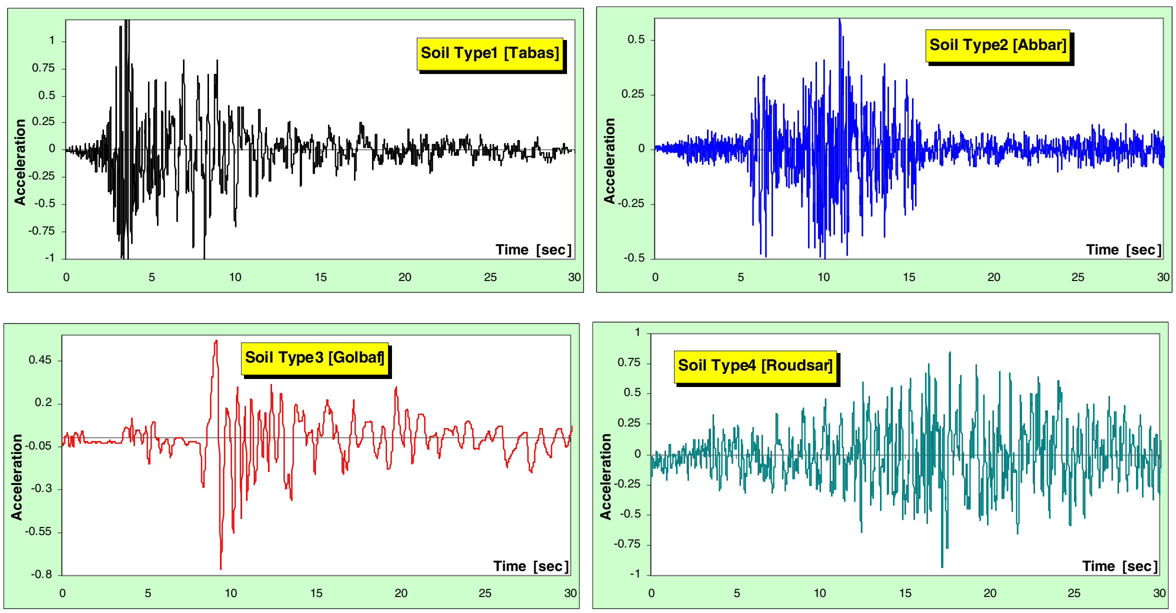

Figure 1– Sample accelerograms of different soil types

RECORD CLASSIFICATION USING ARTIFICIAL INTELLIGENCE

In this part of the paper the idea of artificial intelligence, here neural networks, has been employed for the problem of earthquake record classification. The most appropriate networks for classification problems are self-organizing networks that benefit the unsupervised learning method. In unsupervised learning, the designer does not explicitly specify mappings to be learned. The training sets are no longer pairs of input desired output, but simply patterns. Typically, such networks then cluster the patterns in certain ways. The designer in turn, can interpret the clusters as categories. A simple form of non-supervised networks is competitive schemes, which are a kind of self-organizing maps. The principal goal of the self-organizing map is to transform an incoming signal pattern of arbitrary dimension into one or two-dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion [8]. In such network each neuron is fully connected to all the source nodes in the input layer. This network represents a feed forward structure with a single computational layer consisting of neurons arranged in rows and columns. The algorithm of the self-organizing map proceeds first by initialization of the synaptic weights in the network, which can be done by assigning them small values, picked from random number generators. The most anonymous networks that can be formed in this manner are the Competitive Neural Networks (CNN).

Competitive Neural Network Model

Consider the architecture for a competitive network shown in fig. 2. The output nodes in this network compete for the activation, once they have an advantage; they inhibit the other nodes in the layer through the negative connections and activate themselves through positive connections. In general the nodes in the output layer are all connected to one another by negative inhibitory connections. The self-connections are positive excitatory. After a certain time only one node in the output layer will be active and all the others inactive. Such a network layer is called a winner-take-all network. The purpose of such a network is to categorize an input vector. A node in the output layer gives the category. The point is that the network has to cluster or categorize inputs such that similar inputs lead to the same categorization [9].

In the simplest case, the input nodes are connected to the output layer with excitatory connections or weights $w_{ij} \geq 0$. Assuming a network with inputs x_j, the winner is normally the unit with the largest input h_i defined as [10],

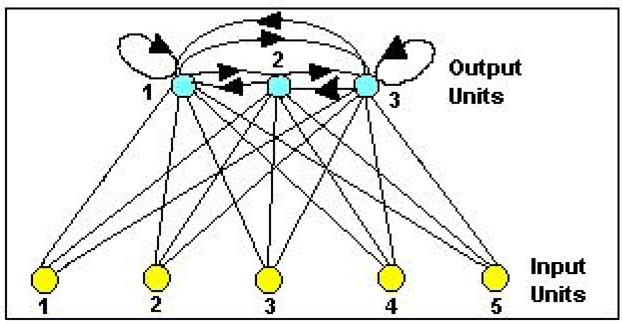

Figure 2- Sample competitive learning network

$$h_i = \sum_j w_{ij}.x_j = \boldsymbol{w}_i.\boldsymbol{x} \tag{1}$$

If i^* is the winning unit, for any value of i we must have,

$$\boldsymbol{w}_{i^*}.\boldsymbol{x} \geq \boldsymbol{w}_i.\boldsymbol{x} \tag{2}$$

If the weights for each output unit are normalized, $|w_i| = 1$, i.e. if the sum of the weights leading to output unit o_i sum to 1, for all i, this is equivalent to,

$$|\boldsymbol{w}_{i^*} - \boldsymbol{x}| \leq |\boldsymbol{w}_i - \boldsymbol{x}| \tag{3}$$

In brief, the winner is the unit for which the normalized weight vector w is most similar to the input vector x. How the winner is determined is actually irrelevant. It can either be found by following the network dynamics, simply using the propagation rule for the activation. After a number of steps only one output unit will be active. Alternatively, simply h_i is calculated for all output units and the maximum is taken. If the network is winner-take-all, the node with the largest h_i is certain to win.

Learning Rule for Self Organizing Maps

The problem of finding the appropriate weight vectors such that clusters can be found in the input layer can be achieved by applying the competitive learning rule through the following steps,

- Start with small random values for the weights w_{ij}. It is important to start with random weights because there must be differences in the output layer for the method to work. The fancier way of stating this is to say that the symmetry must be broken.
- A set of input patterns $x_.$ is applied to the input layer in random order.
- For each input $x_.$ find the winner i* in the output layer by the method described above.
- Update the weights $w_{i^* j}$ for the winning unit only using the following rule,

$$\Delta w_{i^* j} = \eta \left(\frac{x_j}{\sum_{k=1}^{n} x_k} - w_{i^* j} \right) \tag{4}$$

in which η is the learning rate. This rule has the effect that the weight vector is moved closer to the input vector. This in turn has the effect that next time around, if a similar stimulus is presented, node i* has an increased chance of being activated. If the inputs are pre-normalized, the following rule, the so-called standard competitive learning rule can be used,

$$\Delta w_{i^* j} = \eta \left(x_j - w_{i^* j} \right) \tag{5}$$

In the above equation it can be directly seen that the weight vector is moved in the direction of the input vector. Note that the learning rules only apply to the winner node. The weights of the other nodes are not changed. If we have binary output units, then for the winner node i* we have $o_{i^*} = 1$, and for all the others $o_i = 0, i \neq i^*$. Thus, we can rewrite (5) as,

$$\Delta w_{i\ j} = \eta . o_i \left(\xi_j - w_{i\ j} \right) \tag{6}$$

which looks very much like a Hebbian rule with a decay term.

The mathematical interpretation of competitive learning may also be described based on Euclidean distance minimization. Let n denote the dimension of the input data space. Let an input pattern vector selected at random from the input space be denoted by [9],

$$X = [x_1, x_2, ..., x_n]^T \tag{7}$$

The synaptic weight vector of each neuron in the network has the same dimension as the input space. Let the synaptic weight vector of neuron j be denoted by,

$$W_j = [w_{j1}, w_{j2}, ..., w_{jn}]^T, \qquad j = 1,2,...,l \tag{8}$$

where l is the total number of neurons in the network. To find the best match of the input vector X with the synaptic weight vector W_j , compare the inner products $W_j^T.X$ for $j = 1,2,...,l$ and select the largest. This assumes that the same threshold is applied to all the neurons. This assumes that the same threshold is applied to all the neurons, which is negative of the bias. Thus, by selecting the neuron with the largest inner product $W_j^T.X$ we will have in effect determined the location where the topological neighborhood of the excited neurons is to be centered. If all biases are zero, the maximum net input a neuron can have is 0. This occurs when the input vector equals that neuron's weight vector. The competitive transfer function accepts a net input vector for a layer and returns neuron outputs of 0 for all neurons except for the winner, the neuron associated with the most positive element of net input. The winner's output is 1. If all biases are 0, then the neuron whose weight vector is closest to the input vector has the least negative net input and, therefore, wins the competition to output a 1.

As the best matching criterion, based on maximizing the inner products $W_j^T.X$ is mathematically equivalent to minimizing the Euclidean distance between the vectors X and W_j. If we use the index $I(x)$ to identify the neuron that best matches the input vector X, we may then determine $I(x)$ by applying the following condition,

$$I(x) = Arg \min_{\mathrm{j}} \left\| X - W_j \right\|, \quad \mathrm{j} = 1,2,...,1 \tag{9}$$

which sums up the essence of the competition process among the neurons. $I(x)$ is the subject of attention because we want to identify of neuron i. The particular neuron i that satisfies this condition is called the best matching or winning neuron of the input vector X. Thus a continuous input space of activation patterns is mapped to a discrete output space of neurons by a process of competition among the neurons in the network. The neurons in a competitive layer distribute themselves to recognize frequently presented input vectors.

Depending on the application of interest, the response of the network could be either the index of winning neuron, or the synaptic weight vector that is closest to the input vector in the Euclidean sense. The remaining parts of the paper discuss the application of the introduced network in classification of earthquake records and preparation of design spectra.

Neural Network Committee

For final classification of ground motions a committee of competitive and back propagation neural networks has been used. The records have first been classified by competitive neural network and the classification results have then been verified using back error propagation network. The theory of back error propagation networks has been summarized in appendix A. As batching of concurrent inputs is computationally more efficient than sequential inputs the total computation of errors for every epoch has been used here, with parameters introduced in Appendix A,

$$E_{epoch} = \frac{1}{n_{epoch}} \sum_{n=1}^{n_{epoch}} \sum_{u=1}^{U} (t_u - y_u)^2 \tag{10}$$

In order to improve the network training with limited number of training data, the method proposed in [11] has been used. In this methodology more training cycles are generated from the existing data. In the random generation used herein a number of selected vectors of epochs have been chosen to be different to the previous ones. This has increased the speed of the network convergence rate. The online weight updating which was performed after the presentation of each exemplar will act as a random source of perturbation to the gradient descent and help the network to get away from stuck in a local minimum and converge to the absolute minima. In order to increase the ability of network in extrapolation the test and training data were also overlapped.

NUMERICAL ANALYSES

In This section the numerical procedure to obtain the acceleration and displacement design spectra for Iran earthquakes has been presented. This job has been fulfilled in the following two steps. First the classification of the records according to the soil type using the competitive neural network and verifying the classification results using back propagation neural network and second the calculation of the design spectra. In the first subsection the efficiency of the intelligent classification method (neural network committee model) is investigated comparing to the experimental site classification methods and existing data for Iran earthquake. In the second subsection the acceleration and displacement design spectra are calculated using the results obtained from the first step. These spectra are then compared to the existing code spectra.

Record Classification Based on Soil Type

For the purpose of efficiency analysis, the horizontal components of ground motion records of Iran, which have been selected base on the criteria in section two, were used for the classification process by the network. 303 records with pick ground acceleration of more than 0.4g were finally selected and the acceleration and displacement response spectra for each were calculated. These vectors were classified in four categories using the unsupervised competitive neural network. The obtained network architecture has been shown in fig. 3. This network has 303 input and four output neurons indicating the soil types. The network outputs for all categories have been shown in fig. 4 for the Kohonen learning ratio of 0.10. Parametric studies were also performed for network parameters and it was seen that the most sensitive parameter was the Kohonen learning rate. The increase in the network learning rate resulted in more errors in the classification process compared to the existing methods. Figure 5 shows the network weight vectors of acceleration spectra of the four categories for different categories. These vectors called as the leading patterns may also show an average representative for each category.

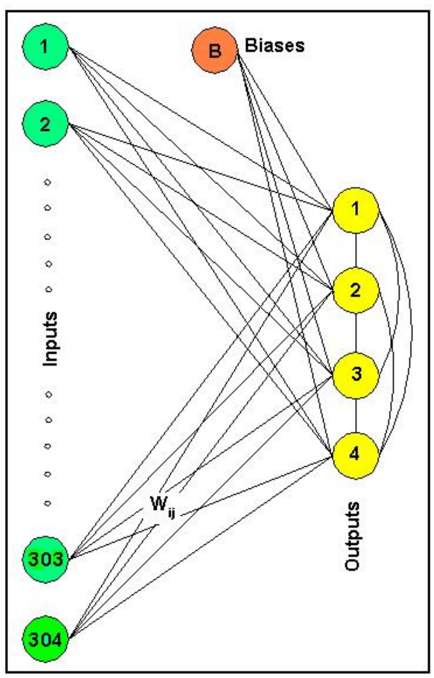

Figure 3– Competitive Network architecture for data classification

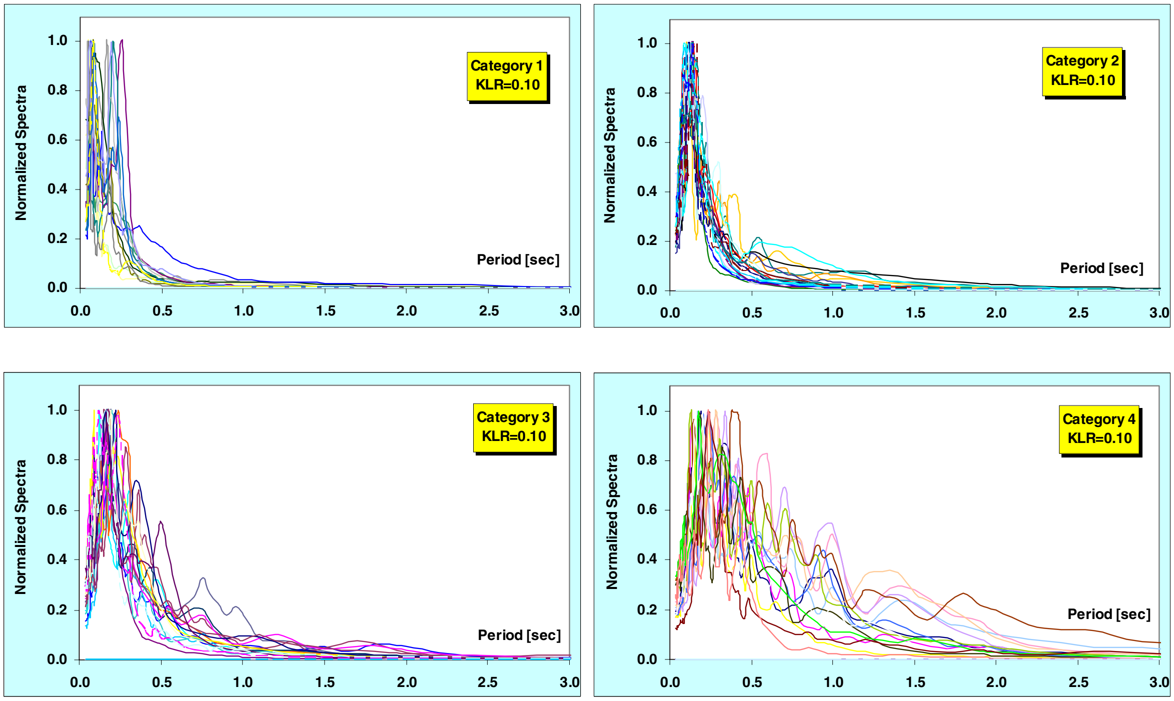

Figure 4- Classification results of S_a for Kohonen learning rate of 0.10

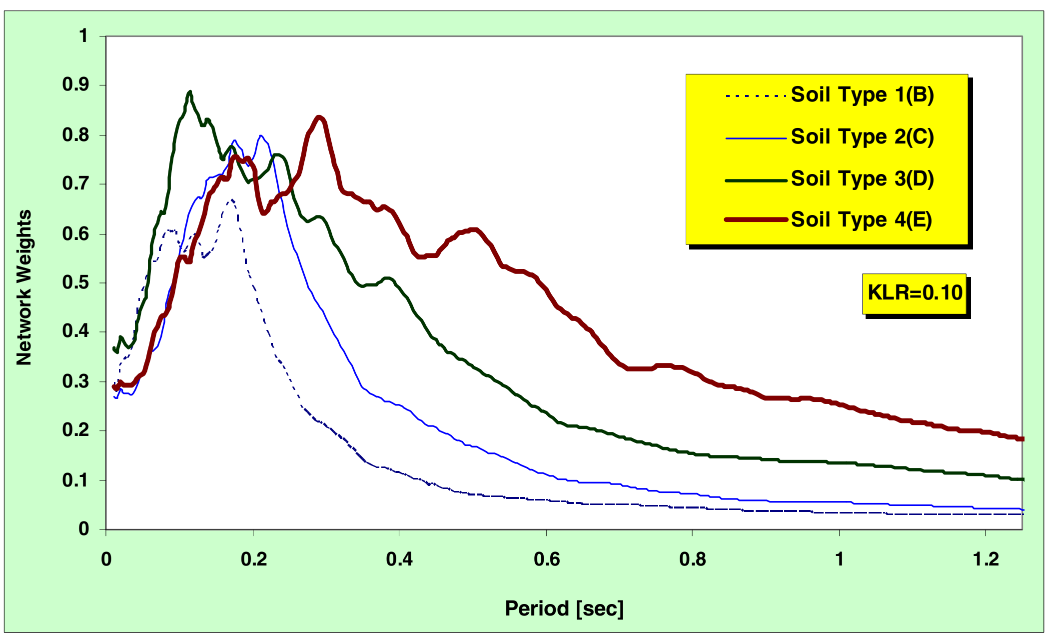

Figure 5- Network weights for different categories

Table 1 shows the shear wave speed ranges obtained from competitive neural network compared to the code ranges [12] and reference [5]. The results have been compared to experimental and analytical results based on wave velocity values in soil media for different network parameters and an average variation error of 13 percents were obtained. These results have been showcased for 16 stations in table 2 and fig. 6. The wave velocities form references [4] and [5] have been presented in columns 3 and 4. Columns 5 and 6 show the presented soil types from references [4] and [5] respectively while the next two columns show the results based on column 3 and 4 using table 1. In the last column the results obtained from the presented method have been given.

Table 1- Comparison of shear wave velocities

Soil Type	Soil Shear Wave Velocity, Vs [m/sec]			
	Iran [16]	Ref. [3]	UBC	CNN
1 (B)	750<Vs	700<Vs	750<Vs<1500	715<Vs
2 (C)	375<Vs<750	500<Vs<700	360<Vs<750	460<Vs<715
3 (D)	175<Vs<375	300<Vs<500	180<Vs<360	215<Vs<460
4 (E)	Vs<175	Vs<300	Vs<180	Vs<215

As shown in the table and figure a good adaptation of the results have been obtained noting that the presented method offers a huge reduction in time and cost for classification. Similar outputs for displacement spectra have been shown in fig. 7 and 8. The coincidence of the classification results for acceleration and displacement based classification have been computed for all categories and gave an average value of 89 percents. Comparing the errors obtained form classification using acceleration and displacement spectra it was seen that there is no considerable difference between the results of the methods of classification.

Table 2- Soil type determination for different earthquakes

No.	Station	Magnitude	Vs [m/s]		Soil Type [Iran 2800 Code [13]]				
			Ref.[4]	Ref.[3]	Ref.[4]	Ref.[3]	Vs [4]	Vs [3]	CNN
1	Zarrat	5.9	491	704	1(B)	1(B)	2(C)	2(C)	1(B)
2	Firuzabad	5.5	853	478	1(B)	3(D)	1(B)	2(C)	1(B)
3	Dayhook	6.7	799	826	1(B)	1(B)	1(B)	1(B)	1(B)
4	Naghan	6.1	646	768	2(C)	1(B)	2(C)	1(B)	2(C)
5	Tabas	7.3	731	715	2(C)	1(B)	2(C)	2(C)	2(C)
6	Ghaen	6.8	787	867	1(B)	1(B)	1(B)	1(B)	2(C)
7	Zanjiran	5.9	884	672	2(C)	2(C)	1(B)	2(C)	2(C)
8	Manjil	4.8	557	589	2(C)	2(C)	2(C)	2(C)	2(C)
9	Rudbar	5.0	595	339	1(B)	3(D)	2(C)	3(D)	2(C)
10	Vandik	4.7	497	597	2(C)	2(C)	2(C)	2(C)	2(C)
11	Tonekabon	7.7	238	209	3(D)	4(E)	3(D)	3(D)	3(D)
12	Abbar	4.5	636	621	2(C)	1(B)	2(C)	2(C)	3(D)
13	Gholbaf	7.0	352	439	3(D)	3(D)	3(D)	3(D)	3(D)
14	Lahijan	5.1	220	264	3(D)	4(E)	3(D)	3(D)	3(D)
15	Abhar	7.7	270	263	3(D)	4(E)	3(D)	3(D)	4(E)
16	Rudsar	7.7	213	215	4(E)	4(E)	3(D)	3(D)	4(E)

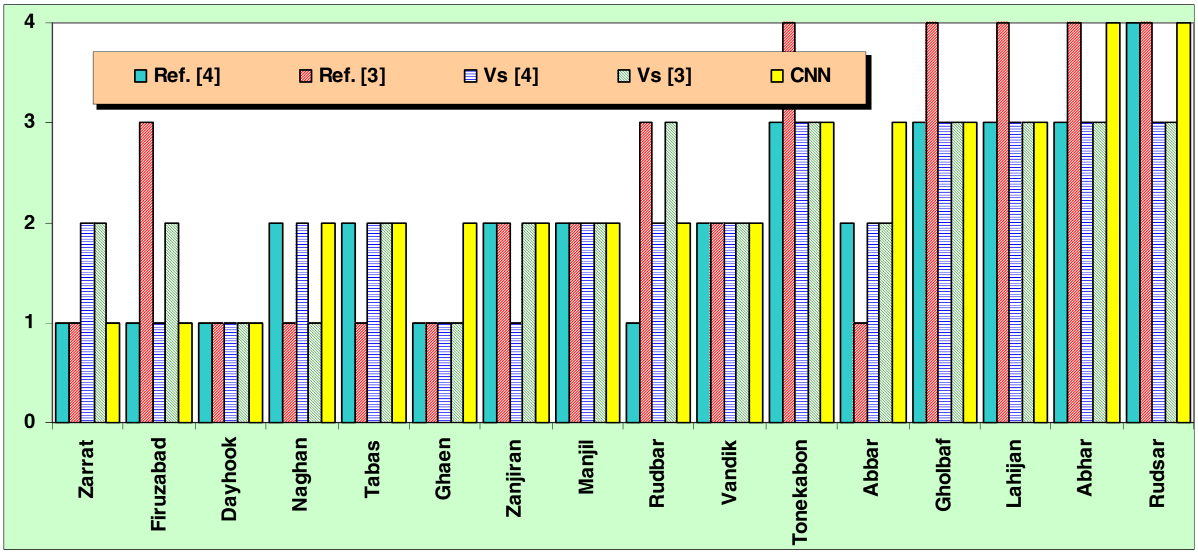

Figure 6- Comparison of soil type determination form different methods

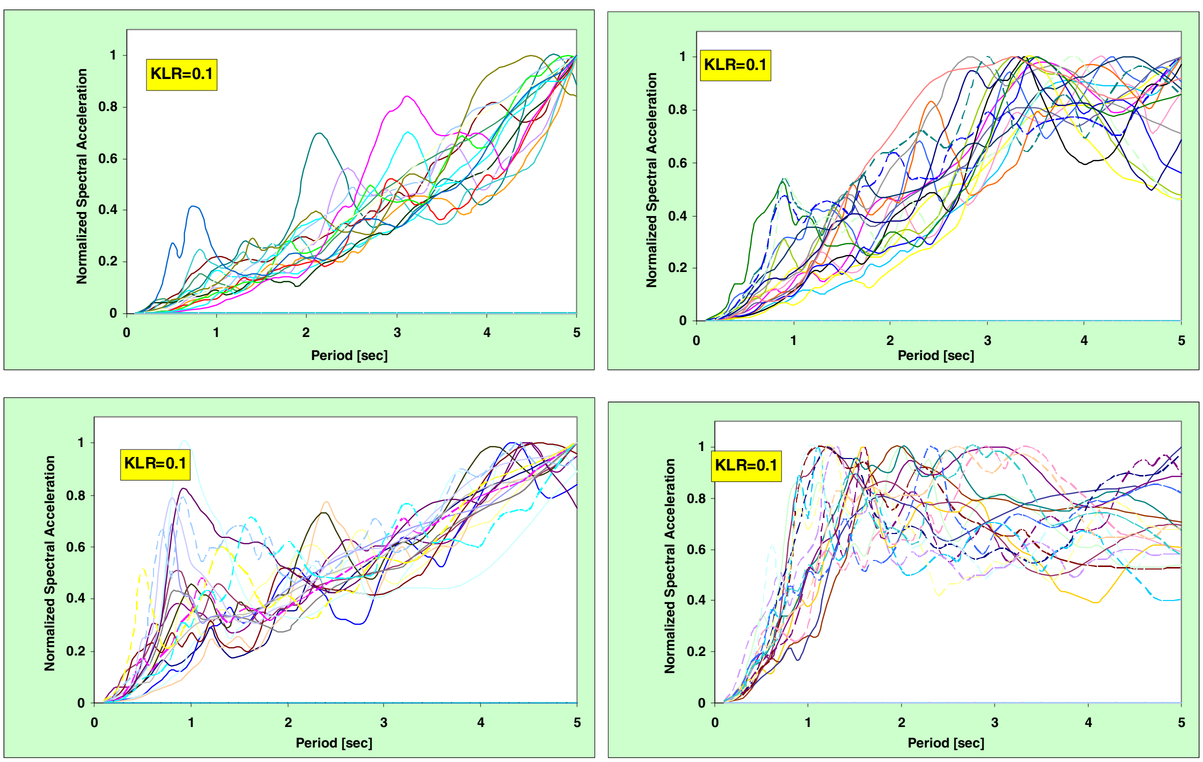

Figure 7- Classification results of S_d for learning rate of 0.1

In order to refine the classification results obtained from competitive network a back propagation network is added to form a neural network committee. The back propagation network shown in figure 9 consists of

85 input neurons for input vector that define each spectrum and two output neurons indicating soil type and shear wave velocity of each spectrum. For 98 records of the total 303 records the soil type and shear wave velocity were obtained from experimental investigations [5]. These data have been used in 10 vector epochs for training process. The final architecture of the network has been presented in figure 9. This network consists of two hidden layer and 46 hidden neurons in each layer. The neural network committee reduced the error from 13 to 10 percents noting that the training data seemed not to be sufficient to meet the expected convergence rate.

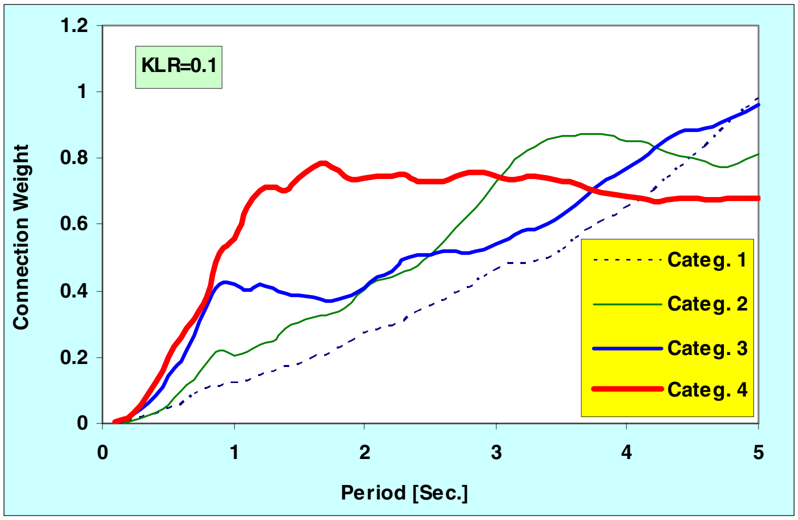

Figure 8- Leading patterns of displacement spectra for KLR=0.1

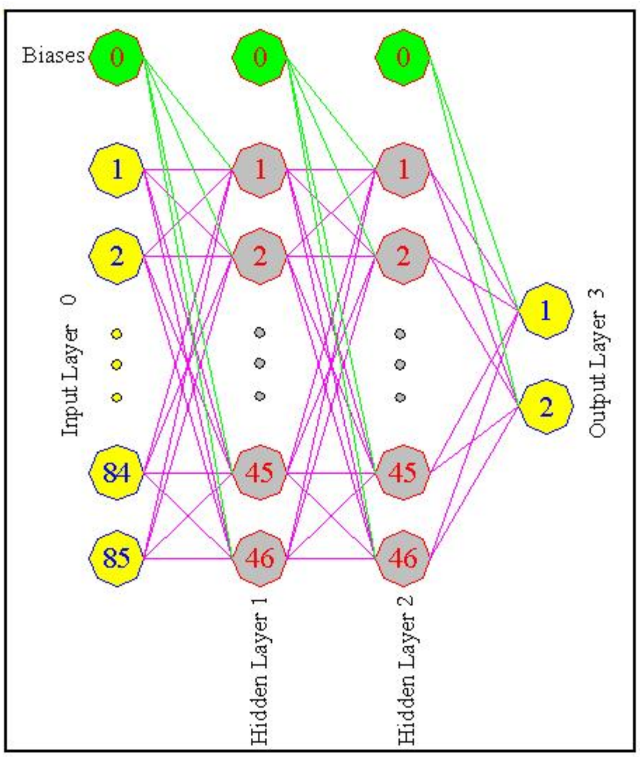

Figure 9– Back propagation Network architecture

The results obtained from back propagation neural network for estimation of shear wave velocity for the stations where experimental investigations had been performed, have been presented in figure 10. As the available experimental data for training the network were not sufficient the network did not efficiently converged. Despite this weak convergence the simulation results were generally acceptable. Therefore the method is potentially capable of predicting shear wave velocity in soil media for engineering applications in a simple and effective manner.

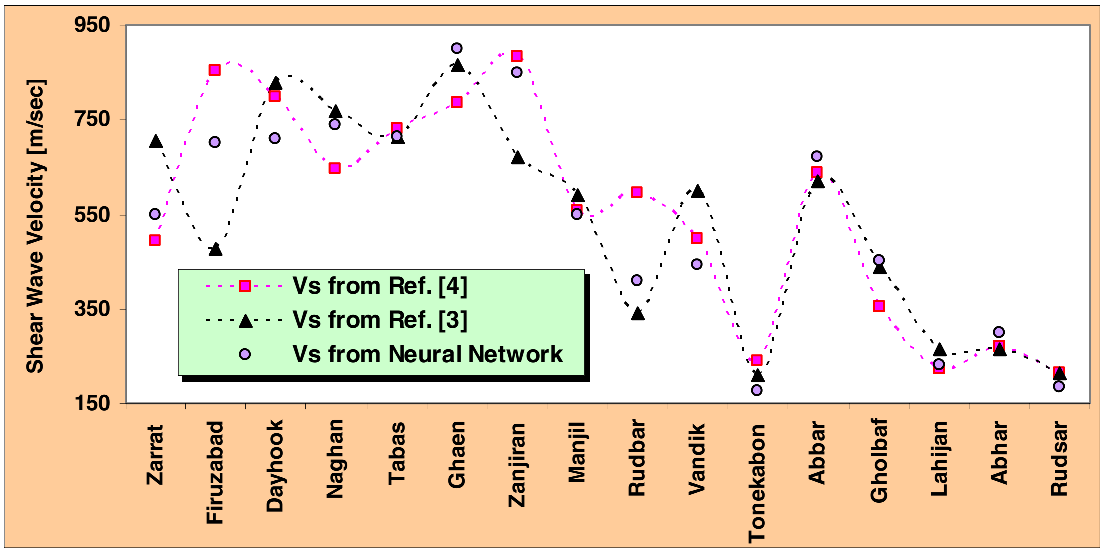

Figure 10– Estimation of shear wave velocity by neural network committee

COMMENTS AND CONCLUSIONS

A new method for the classification of earthquake records was presented using a committee of competitive neural networks which uses unsupervised learning procedure and back error propagation neural networks. The classification was based on earthquake acceleration and displacement spectra rather than earthquake acceleration time histories. In this paper the moderate to high intensity earthquake were selected to construct the design spectra for Iran. The records and spectra were modified for further processes to obtain design spectra using deterministic approach. It is currently held that the deterministic approach of modeling seismic hazard is more suited to high seismicity regions, where detailed information of the potential fault sources is available from which to simulate earthquake ground motions specific to certain site and source. The results may be used to determine the soil characteristics and range of variation of shear wave propagation speed in the soil media. As this method of determination of shear wave ranges is based on spectrum shape and thus soil characteristics it should be considered together with the existing theoretical and possibly conventional experimental methods. In competitive networks, four winning categories were selected to comply with the seismic code categories. In order to refine the classification results obtained from competitive network a back propagation network is added to form a neural network committee. For 98 records of the total 303 ground motions, the soil type and shear wave velocity were obtained from experimental investigations and used for training process.

The adaptation of the obtained results for determination of soil types and shear wave velocity comparing to the available experimental investigations was also excellent. On the other hand using this intelligent classification one can easily classify any quantity of earthquake records at a very short time and produce an appropriate input to obtain the design spectra. It was also considered that although the classification results from the acceleration and displacement spectra were almost the same, they would not necessarily result in the same design spectra and should be used at the same time. The changes in the network parameters, for example the learning rate in competitive networks, had also little effects on the classification results.

The calculated design spectra for different soil sites were compared to the existing national and international code design spectra and showed a global adaptation. Finally it was concluded that the presented method for preparing design spectra had good robustness, efficiency and also considerable reduction in time and computer effort comparing to the conventional methods. It must also be noted in order to take into account the effect of strong motion duration to construct the design spectra it is better to use hysteretic energy spectra rather than elastic or inelastic response spectra. This issue is the subject of our future work.

APPENDIX A. BACK PROPAGATION NETWORK SUMMARY

Back Error Propagation Network Algorithm

Set all weights, biases weight modifiers and bias modifiers to random values in the desired ranges.
Scale and present input vector to the input layer.
Calculate input vector of the hidden layers:

$$Y_u^{in} = v_u + \sum_{h=1}^{H} x_h . w_{hu}$$

Determine output vector using the transfer function:

$$Y_u^{out} = f(Y_u^{in})$$

Continue the procedure for all layers to obtain output vector.
Calculate the error vector and total error to check for convergence:

$$\delta_u = (t_u - y_u).f'(Y_u^{in})$$

$$E = \frac{1}{2}\sum_{u=1}^{U}(t_u - y_u)^2$$

Calculate weight and bias modifiers:

$$\Delta v_{hu} = \alpha.\delta_u \qquad \Delta w_{hu} = \alpha.\delta_u.y_h$$

Modify weights and biases in the output layer:

$$v_{hu}^{new} = v_{hu}^{old} + \Delta v_{hu} \qquad w_{hu}^{new} = w_{hu}^{old} + \Delta w_{hu}$$

Back propagate error in the hidden layers of the network, modify weights, biases, weight modifiers and bias modifiers and go to step 3.
The procedure is continued until the convergence criteria are met.
Nomenclature:
$X = (x_1, x_2, ..., x_I)$: Input vector with I members.
$T = (t_1, t_2, ..., t_U)$: Target vector with U members.
α : Learning rate
v : Biases
Y : Input or output of the H hidden and K output layers
W : Weights
δ : Error in the layers

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NOTATIONS

Symbol	Definition
C_e	Elastic seismic coefficient
g	Acceleration of gravity
I	Importance factor
h_i	Network unit input
m	System mass
o_i	Network unit output
R	Seismic reduction factor
S_a	Spectral acceleration
S_d	Spectral displacement
S_v	Spectral velocity
t	Time
T_{eff}	Effective period
T_i	Initial natural period
u	Displacement vector
v	Velocity vector
V_s	Shear wave propagation speed in soil media
W	Network weight vector
X	Network input vector
Z	Seismic risk factor
ω	Angular frequency
ξ	Damping ratio
η	Unsupervised learning rate

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