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SOFT COMPUTING APPLICATION IN SOIL CLASSIFICATION ANALYSIS

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Abstract. *This paper deals with a new application of soft computing methods in soil classification procedure that is technically easy to use and does not require complex mathematical definitions for the model components. Two types of radial-basis neural networks, namely, probabilistic neural networks and generalized regression neural networks were used in this study. The proposed quick-automatic soil classification methods are implemented to analysis number of ground-motion stations located at North-West of Iran. The efficiency of proposed methodologies is compared with soil classification results based on measurement of the average shear wave velocity at a subsurface depth of 30 m. In addition, the results from neural network-based soil classification system were evaluated and compared with two empirical schemes which are based on the spectral shape of normalized response spectra and the average horizontal to vertical spectral rations of ground motions. The results revealed the acceptable ability of proposed methods to predict the soil class in the study area.*

1 INTRODUCTION

The previous destructive earthquakes experiences indicated that the local subsoil conditions can extensively influence the seismic demands and structural damages pattern which should be considered properly in seismic performance evaluation of the structures. The amplitude and frequency content of seismic motions could significantly be influenced by the soil response which is controlled by the mechanical properties of the soil. In fact, reliable design of the structures due to earthquakes will not be possible without considering local site effects.

In many countries like Iran, Turkey and Mexico, there is a lack of detailed information of the site conditions at most of the existing strong motion stations. Site classification based on borehole data or interpretation of geologic maps and geomorphologic data could not be done. For this reason, empirical methods have been developed by various researchers for site classification based on analysis of recorded strong ground motion data. These methods are generally quick and inexpensive in comparison with other schemes which are based on measurement of shear wave velocity. Standard Spectral Ratio, SSR, [1] and the horizontal-to-vertical spectral ratio technique, H/V or HVSR, [2] are most popular and widely used techniques for estimating site conditions. SSR is defined as the ratio between the Fourier spectrum calculated on the horizontal (or vertical) component recorded at a site of interest and the Fourier spectrum of the same component recorded at the outcropping rock. H/V technique is another simple and effective tool used widely for site effect analyses which does not require the presence of a reference rock station. The basic assumption of this method is that the vertical component of the ground motions is almost free from the amplification effects of soil. Applications of H/V method in soil response evaluation have been extensive [3-8].

The feasibility of using of two effective type of radial basis function neural networks named probabilistic neural networks (PNN) and generalized regression neural networks (GRNN) is examined in this paper for soil classification purpose. The efficiency of proposed soft computing methodologies is compared with soil classification results based on measurement of shear wave velocity. In addition, the results from neural network-based soil classification system was evaluated and compared with two other schemes which are based on the spectral shape of normalized response spectra and the average horizontal to vertical spectral rations of ground motions.

2 IMPLEMENTATION OF NEURAL NETWORK CAPABILITY IN SITE CLASSIFICATION

Soft computing techniques have been successfully used for solving pattern recognition and classification problems in the past. Artificial neural networks (ANNs) as one of widely used computational models consist of an assembling of connected processing units called neurons. The nonlinear nature of artificial neural network and their ability to learn in a complex environment while different factors influence the results of prediction, render it the capability of site classification. The theory, design and application of artificial neural networks as a powerful tool have been advancing broadly during the past decade for solving complicated problems in different fields including seismology, earthquake engineering, construction engineering, geotechnical engineering and geosciences. The use of two types of radial basis function (RBF) neural networks, namely, probabilistic neural networks (PNN) and generalized regression neural networks (GRNN) were proposed by Yaghmaei-Sabegh and Tsang [7]. The following features of PNN and GRNN rendering them the suitable tools in classification analysis:

i) no learning rule is required
ii) no pre-defined convergence criterion is needed

iii) removes design-decisions about the number of layers and also the number of neurons in hidden layer

iv) the simplicity in design

A typical structure of PNN consists of four layers, namely, input, pattern (first hidden layer), summation (second hidden layer), and output layers. Fig 1 shows structure of a typical PNN. The input variables X are each assigned to a node in the input layer and then conveyed directly to the hidden layer without weights. Each unit in the pattern layer implements a RBF by computing the Gaussian kernel of the Euclidean distance between the existing input vector and the training pattern. It is generally expressed in an exponential form as Equation (1):

$$\phi(X) = \exp\left[-\frac{(X - Y_i)^T (X - Y_i)}{2\sigma^2}\right] \tag{1}$$

where X is the input set to be classified; σ is the smoothing parameter or bandwidth; Y_i is the i^{th} training pattern and the superscript T denotes the transpose of a vector.

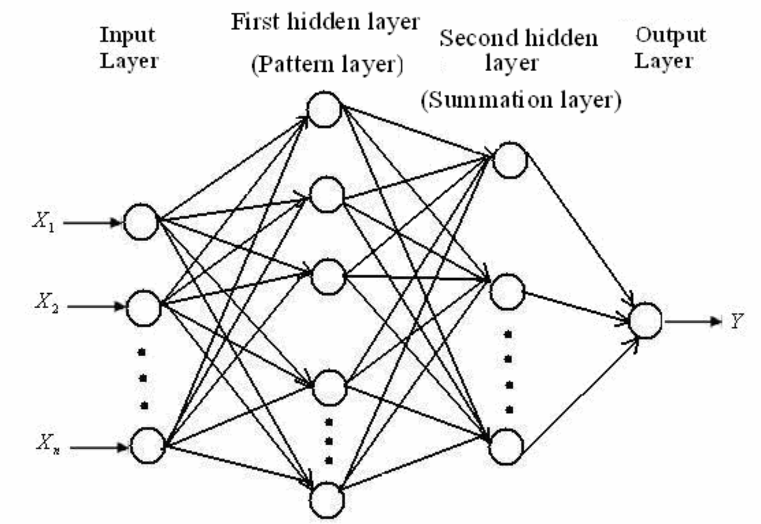

Figure 1: A typical structure of probabilistic neural network (PNN).

The GRNN, which is an alternative type of RBF neural network, approximates a function between input and output vectors based on a standard statistical technique called kernel regression. GRNN consists of four layers as of PNN. The pattern layer as the first hidden layer has one neuron for each case of the training data set and computes the Euclidean distance of the test case from the center point of a neuron and then applies the RBF kernel function. The next hidden layer in the network is the summation layer that represents the major difference between PNN and GRNN. The summation layer consists of two neurons only, namely, S-summation neuron and D-summation neuron. The S-summation neuron computes the sum of the weighted outputs from the pattern layer, while the D-summation neuron calculates the unweighted outputs from the pattern layer. The summation layer and output layer together produce a normalization of output set.

3 RESULTS AND DISCUSSIONS

Among 73 stations which have been triggered in 2012 Ahar-Varzaghan doublet events at North-West of Iran, 44 station with known Vs30 measures have been used in the analysis.

The uncorrected accelerometer records were corrected for the instrument response and baseline. Then a high-pass 4'th order Butterworth filtering was used as a conventional filtering method to remove noise from all raw time series. Finally, the average spectral values of horizontal components have been considered in evaluation process.

PNN and GRNN models have been processed for each station and a continuous value ranging from 1 to 4 is assigned to each station. The basic procedure starts with a selected set of representative horizontal to vertical spectral ratio (HVSR) curves for four site classes. A set of four reference HVSR curves has been collected according to Yaghmaei-Sabegh and Tsang [7].

Finally, the reference patterns and the input data are compared through the pattern recognize analysis with designed PNN and GRNN. The prediction results of two empirical methods proposed by Phung et al., [9] and Zhao et al. [8] are used in comparisons as well. Phung et al., [9] have proposed a technique for site condition using strong-motion dataset in Taiwan based on the spectral shape of normalized response spectra. In 2006, an empirical site-classification method was proposed by Zhao et al. [8] for strong-motion stations in Japan using H/V response spectral ratio. In fact, they have designed a classification scheme based on new site classification index (*SI*) as follow:

$$SI_k = \frac{2}{n}\sum_{i=1}^{n} F(-abs[\ln(\mu_i) - \ln(\bar{\mu}_{ki})]) \tag{2}$$

where k and n are the site class number and the total number of periods, respectively. As well, F( ) is the normal cumulative distribution function, μ_i is the mean response spectral ratios of the horizontal and vertical components (H/V) for the site of interest in the *i*th period, and $\bar{\mu}_{ki}$ is the mean H/V ratio for the *k*th site class averaged over all sites of the database for the *i*th period.

The results of classification based on PNN and GRNN neural networks along with Phuang et al. [9] and Zhao et al. [8] sites class have been presented in Table 1. Vs30-based site classes have been superimposed into Table 1 to give a clear image about different empirical methods used in the analysis.

The site classification criteria in Iranian seismic design code [10] are based on average shear wave velocity in the top 30 m soil layers. Four different site classes are defined in this code as a rock site, very dense soil and soft rock site, stiff soil site, and soft soil site (named as soil type 1 to 4). Shear wave velocity (Vs30) values have been adopted from Mousavi et al [11] for selected sites of current study. As seen in Table 1, the classification results of GRNN are consistence with those obtained based on the averaged shear-wave velocity (Vs30) as a widely used site description variable. It is worth nothing that, the classification method of Phung et al. [9] could be used for classifying a site into either rock (R) or soil (S).

4 CONCLUSIONS

Nowadays, soft-computing based methods have been developed increasingly in engineering fields by the growth of computer processors. In this regards, the high capability of PNN and GRNN models for soil classification has been validated in this paper using the dataset of 2012 Varzaghna-Ahar earthquake ground motions records. Unlike of multi-layer feed-forward networks that commonly take a large number of iteration to converge to the preferred values, the time process of designed GRNN and PNN is very short. GRNN gives a continuous (more precise) output value as a site class. Analysis showed the consistency of site classification of GRNN with VS30 measurements. The proposed procedure is considered particularly useful for regions where geotechnical, geologic and geomorphologic data are not available, which indeed represent the majority of areas in the world.

Station	Phung et al. (2006) Site Class	Zhao et al. (2006) Site Class	Yaghmaei-Sabegh and Tsang (2011) Site Class		Measured Vs30 (m/s)	Vs30-based Site Class
			PNN	GRNN		
Varzeghan	R	4	4	*2.75*	275	3
Khajeh	R	2	*2*	*1.75*	450	2
Kalaybar	R	1	*1*	*1.62*	850	1
Haris	R	2	*3*	*2.04*	530	2
Damirchi	R	1	*2*	*1.59*	1241	1
Hoorand	R	1	*1*	*1.4*	500	2
Meshkin Shahr	R	4	*1*	*2.34*	500	2
Hadi Shahr	R	2	*2*	*1.79*	475	2
Basmanj	S	4	*4*	*3.57*	564	2
Soofiyan	R	2	*3*	*2.27*	707	2
Khomarloo	R	1	*1*	*1.44*	921	1
Zanjireh	R	1	*2*	*1.7*	919	1
Shabestar	R	2	*2*	*1.55*	922	1
Ziveh	R	2	*2*	*1.8*	304	3
Amand	R	1	*2*	*1.78*	743	1
Sharabiyan	R	2	*2*	*2.2*	484	2
Lahrood	R	1	*2*	*1.6*	981	1
Tasooj	R	1	*3*	*2*	709	2
Marand	R	1	*2*	*1.65*	546	2
Sarab	R	2	2	*2.07*	406	2
Ajab Shir	R	2	*3*	*2.4*	657	2
Naghadeh	S	4	*3*	*3.12*	275	3
Torkmanchay	R	3	*2*	*1.67*	542	2
Avin	R	4	*3*	*2.46*		
Yekan Kahriz	R	1	*1*	*1.26*	738	1
Qara geshlakh	S	2	*3*	*2.89*	275	3
Hashrood	S	3	*3*	*2.58*	681	2
Band	R	4	*3*	*3*	275	3

Sharafkhaneh	R	4	*3*	*3*	466	2
Karigh	R	1	*1*	*1.28*	589	2
Germi	S	3	*4*	*3.8*	712	2
Nir	S	2	*3*	*1.89*	541	2
Oldoo	R	2	*2*	*1.79*	445	2
Taleb Qeshlaghi	R	1	*1*	*1.75*	978	1
Azarshahr	R	4	*4*	*2.85*	660	2
Kooraeim	R	2	*1*	*1.74*	787	1
Rashkan	R	3	*2*	*1.814*	275	3
Astara	S	3	*3*	*2.8*	189	3
Helabad	R	3	*4*	*3*	387	2
Namin	R	2	*1*	*1.6*	1236	1
Ardebil 2	S	3	*3*	*2.84*	275	3
Talesh	S	2	*1*	*1.45*	559	2

Table 1: Site classification results based on different empirical methods; PNN, GRNN, Phung et al. (2006) and Zhao et al. (2006) methods

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