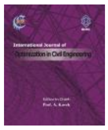
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2019; 9(3):395-410



PREDICTIVE MODELS OF THE DOMINANT PERIOD OF SITE USING ARTIFICIAL NEURAL NETWORK AND MICROTREMOR MEASUREMENTS: APPLICATION TO URMIA, IRAN

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ABSTRACT

Direct drilling method and the use of microtremor studies are among the most commonly used available methods utilized to estimate dynamic parameters for a site. One of the most important parameters is the dominant period of the site whose estimation plays a pivotal role in seismic hazard mitigation. The conventional models obtained are not capable of estimating the parameters that govern the seismic response of a site. Therefore, Artificial Neural Networks (ANNs) are reliable and practical estimation methods that can be used to analyze comprehensive measurements such as dominant period of a site, and improve the data. In this paper, the performance of ANNs has been investigated on calculation of the dominant period for a site. Three different models, namely BP, RBF and ANFIS, have been compared to determine the best model that provides the most accurate estimation for the dominant period. The input parameters have been chosen to be alluvial layer thickness, grain size, specific gravity, effective stress, shear wave velocity, standard penetration number, Atterberg limits. Each of the three models has been trained and tested for these input parameters and a unique output which is the dominant period of the site. The results showed that ANNs successfully model complex relationships between soil parameters and seismic parameters of the site, and provide a robust tool to accurately estimate the dominant period of a site. The accurate estimations can be then used for engineering applications including damage assessment and structural health monitoring. In addition, The obtained emulator of RBF model shows the least model error in estimation of dominant period and has been found to be superior to the other evaluated methods.

Keywords: artificial neural network; dominant period; microtremor; geotechnical boreholes.

Received: 12 October 2018; Accepted: 15 February 2019

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1. INTRODUCTION

Earthquakes cause a vast variety of extreme events including ground shakes, structural damages, liquefaction, landslides, failure of retaining structures, damages to vital arterials, vortex hazards, and sea and oceanic seismic waves [1,2]. Seismic waves are generated from fault movements within the ground and propagate through the hard shell of the earth. In the vicinity of the earth, their vibrational nature changes as they hit the soil layers of the earth [1]. Since the effects of site and in particular the properties of the soil layers can vary dramatically, different seismic responses may be observed in different locations. Therefore, the local condition of a site can impose significant effects on important properties of the ground motions such as amplitude, period and duration [3]. The rate of its influence on each of these parameters depends on the geometry and topography of the site, the input ground motion, and the properties of geomaterials in the ground subsurface layers [4]. Direct drilling method and the use of microtremor studies are among two available methods utilized to estimate the dynamic characteristics of subsurface layers [5]. The direct borehole drilling is the most reliable and accurate method, assessment of which leads to high resolution data for dynamic properties of subsurface layers [5,6]. To obtain the characteristics of subsurface layers for a vast area, one requires to drill significant number of boreholes with high density. Therefore, this method requires significant human resources, time, and huge cost, and cannot be commonly used as an engineering method [7]. To overcome the limitations of direct drilling method, another approach has been extended to simply obtain the dynamic characteristics of subsurface layers with low cost and by performing simple field operations [8]. This technique employs the microtremor studies and has been accepted by academic researchers and engineers. Microtremor studies can be used to obtain the resonance period, magnifying amplitude, liquefaction potential by calculating the vulnerability index, peak ground amplitude (PGA), thickness of alluvial layer, effects of topography on site response, lateral spreading, etc [9-14]. Site effects assessment is an important method for evaluation of seismic hazards for the area under study [15]. In this regard, dominant period is an important factor that must be utilized to analyze the earthquake hazard (such as resonance phenomena occurs in structural elements). Despite the extensive developments in computational methods and advances in computer sciences, seismic analysis requires more accuracy in terms of engineering applications. In other words, the conventional models obtained based on elastic and plastic theories cannot simulate the behavior of geomaterials properly [16]. This is partially due to their complex formulations, idealization of material behavior, and existence of too many experimental parameters required. Artificial Intelligence (AI) is a branch of science that employs the capability of computers in solving complicated algorithms to overcome the limitations of closed-form solutions. Recently, AI attracted the researchers in geotechnics and served as a strong tool to solve a wide variety of geotechnical problems. For example, optimization algorithms are used to optimize the construction of geotechnical structures [17,18]. Image processing techniques are employed to intelligently obtain microscopic features of soil fabric [19-21]. Artificial Neural networks ANNs and different types of regression analysis are performed to estimate the dynamic properties of geomaterials [9,7,6,22-25] Researchers proposed ANNs as a practical and reliable method to model the hysteric and monotonic behavior of geomaterials. Based on the performance of ANNs, methodologies are developed to estimate the geotechnical destructive phenomena such as resonance and liquefaction, or soil characteristics such as preconsolidation pressure, shear strength and stress history [26]. ANNs are strong tools that obtain physical relationships between input and output pairs by using the measured available dataset, whereas the basic unknown relationships or physical concepts of the problem might be very complex and vague. Since the early 1990s, ANNs have been successfully used for many geotechnical engineering problems [16,27]. Meanwhile, regarding the high costs associated to field studies and laboratory tests and measurements, it is important to find an model that shows the best performance for this specific problem. As a border city and due to its commercial and economic location, Urmia city underwent a quick and sharp developments during the recent years which indicates an urgent need for comprehensive studies to develop constructions and insure safe structures. Since the city is located close to the Lake Urmia and development of the population and infrastructure on sedimentary layers of soil and an area with high seismic potential, it is necessary to assess natural hazard threaten the city. To perform proper constructions (design and implementation), comprehensive studies should be carried out on seismic, geotechnical and geological characteristics of the region, and the data should be used to make more efficient decisions. Neural network models (ANNs) have recently been used in different areas of civil engineering, including the geotechnical engineering, to model complex relationships between inputs and outputs [28-31]. Neural networks are able to simulate the behavior of complex systems [32]. In the present study, ANNs are used to obtain a reliable and practical estimation method to provide more accurate information for the dominant period of the site. The field measurements and experiments that were conducted on a general scale microzonation studies are used. These microzonation studies data is categorized into geotechnical studies (such as layers' thickness, specific gravity, shear wave velocity, effective stress and Atterberg limits) and microtremor studies (dominant period and resonant factor). There are several types of neural network models that have been used to predict geotechnical parameters such as the dominant period of a site, however, the literature lacks a study to obtain the best model for seismic problems which requires more investigation [33]. In this regard, three models of BP, RBF, and ANFIS neural networks are used to determine the most suitable neural network model. With this in mind, neural networks can be used as a validation tool for improvement of data and reliability for future engineering designs. The purpose of this study was to determine the best ANNs model for estimating the natural period of the site using multiple regressions and comparing the ability to predict models. The final achievement can be used for the same sublayer in other areas.

2. SEISMOLOGY AND GEOLOGY OF URMIA CITY

According to Fig. 1, Urmia city is located at northwest of Iran, west of Urmia lack and close to the border of Iran and Turkey. The region follows the seismic features of Van State in Turkey and Central Iran. The area of the study is a radial region with a radii of 100 Km centered on Urmia City. There are different faults in this region and each of them follows different mechanisms. All of the faults are extended from northwest to the southeast and resulted from pressures imposed from subduction of Saudi Arabia tectonic plate into Iran tectonic plate. The maximum pressure direction of this subduction movement is perpendicular to the structural axis of the region. Within this structural zone, Permian deposits are driven by low-slip faults on other units and their base is eliminated by these faults. Fig. 1 shows the location, magnitude of earthquakes, faults and their mechanisms and distance from Urmia City.

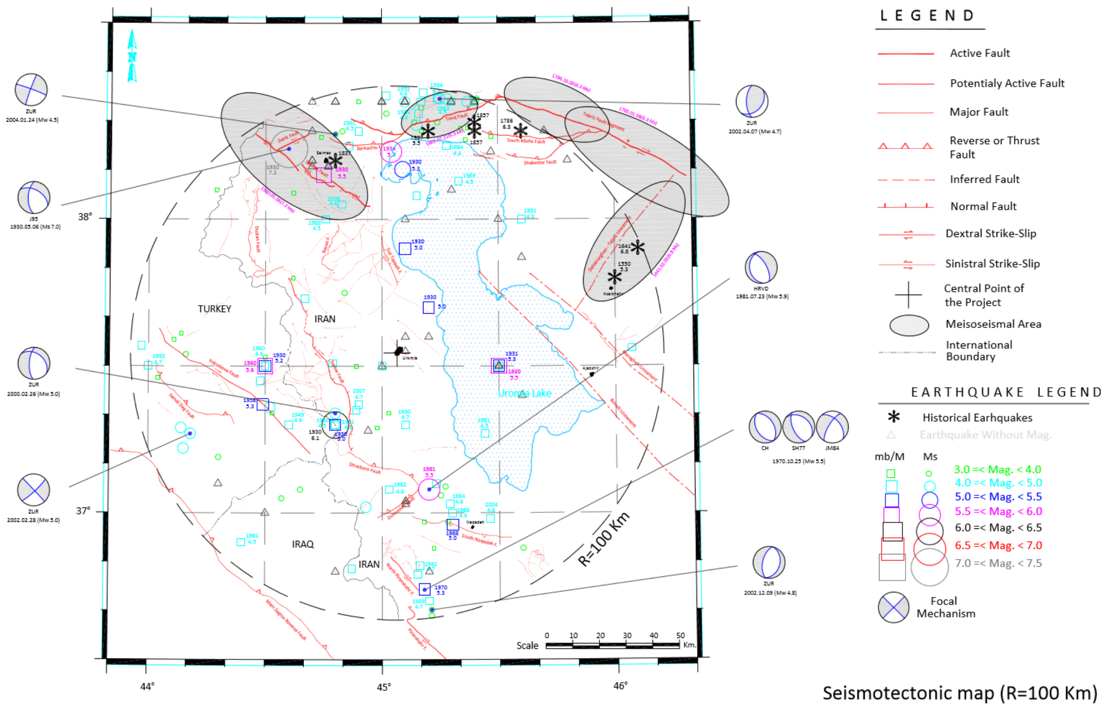

Figure 1. Distribution and center of earthquakes within 100 Km from Urmia City

3. DATA AND MICROTREMOR MEASUREMENTS

Ambient noises or microtremors are defined as elastic vibrations in ground surface resulted from natural resources such as sea tides, collision of sea waves with beach, and wind and the local and regional weather, and also urban resources such as transportation industrial machines and daily activities of residents which cause permanent vibrations of ground with amplitudes limited to microns. Generally, the range of amplitude for Microtremors is from 0.1 to 1 micron and their period varies from 0.3 to 10 seconds. The dominant period and amplification function of a site can be obtained by measuring the microtremors and using Nakamura method (spectral ratio or H/V method). The Seismographs used in this study are three dimensional (Two horizontal and one vertical component) instruments of the type Guralp CMG-6TD that have period response of the range 0.033 to 50 Hertz. In each Seismography station the environmental vibrations have been continuously recorded. The period of recording was 100 records per second. Although the high duration of recordings increases the field studies duration, it allows the evaluation of probable low-resonance periods, and provides sufficient information for data analysis even after elimination of probable transient noises. Despite the high constructions density and crowded districts especially within the downtown of the city, it has been tried to eliminate the transient noises and follow the requirements described in codes and standards. For this purpose, a quiet spot far from the main streets, arterials and highways has been chosen for each recording point. In addition, the results have been controlled with SESAME guidance (Site Effect Assessment using Ambient Excitations). Fig. 2 shows the experimental setup for evaluation of microtremors and geotechnical borehole drillings.

(a) (b)

Figure 2. Field study equipment; (a) Seismograph of the type Guralp CMG-6TD (b) Drilling setup

Due to the presence of soft and thick sediments, and due to continuous earthquakes occur in the area, it is necessary for Urmia city to be assessed for the site conditions. Therefore, the number of microtremor evaluation points is as high as 900 points. Fig. 3 shows the location of microtremor recording stations and geotechnical boreholes performed in the city. The locations of microtremor recording stations and geotechnical boreholes are shown with green and yellow circles, respectively. The exact coordinates of each borehole and station have been determined at site using GPS technology. The location of boreholes and stations have been selected in way that it covers the whole city. The criterion for determining the depth or drilling for all boreholes in geotechnical studies is the depth that engineering bedrock with modified standard penetration number (N60) greater than 50 is observed.

Figure 3. Location of microtremor recordings and geotechnical boreholes

In general, the site effects are assessed by determining the response of the soil mass to the motion of the bedrock underneath the soil mass. Assuming the linear method and homogeneous soil for subsurface layer with damping characteristic, the value of the dominant period of the site depends only on the thickness and the shear wave velocity of the soil. For such a case, one can calculate dominant period by using equation (1) [1].

$$T_s = \frac{4H}{V_s} \tag{1}$$

H and Vs are the thickness of alluvium and shear wave velocity of the layer, respectively. Although the monolayer homogenous elastic models are useful for explaining the effect of soil condition on different soil characteristics, they are rarely useful for engineering and practical evaluation and analysis of ground response to seismic stimulations. The real ground response problems include more than one ground layers with different stiffness, and mechanical and damping characteristics, which requires additional parameters for layers to estimate the dominant period of a site. Fig. 4 schematically illustrates the subsurface layers along with their geotechnical characteristics such as layer thickness, specific gravity, and shear wave velocity. To determine the true response of the ground, the linear methods should be modified or nonlinear methods must be utilized. The important issues are the inaccuracy of the results obtained based on nonlinear methods, and complexity of the nonlinear methods which are also time consuming and costly. Therefore, geophysical studies and neural networks can be employed to find a correlation between the results of the tests and field measurements, and the governing physical theories. This integrated method is an efficient way to reduce the cost and time, and increase the accuracy of the estimations.

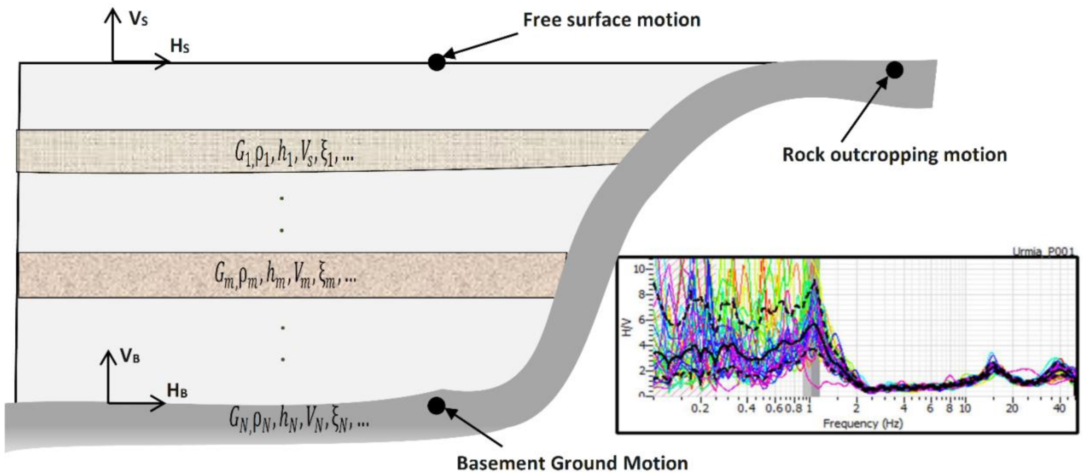

Figure 4. Schematic shape of Underlying layers and Fourier spectral amplitudes involved: horizontal and vertical components of the motion at the surface and at the bottom of the layer (Vs, Hs, VB, HB) in Nakamura TechniqueNakamura [34]

It is worth noting that the microtremor measurements and its performance in evaluating the site effects are examined by equivalent linear models.

4. RESULTS OF NEURAL NETWORK ANALYSIS

Nowadays, the performance of Neural Networks in the engineering world is well investigated and acknowledged. Among the different types of function estimation tools, ANNs provides a framework that can be trained to mimic the behavior of a system. The most important features of neural networks are flexibility and the ability to learn and create complex relationships between input and output data. In this study, it has been tried to employ ANNs techniques and find a relationship between geotechnical parameters of subsurface layers and dominant period obtained from microtremor measurements. Two series of analysis have been performed in this study. The first analysis consists of 8 input parameters including layer thickness, soil type, specific gravity, effective stress, shear wave velocity, modified standard penetration number, liquid limit and plastic index of the soil. In the second analysis in order to evaluate the number of effective parameters in estimation power of dominant period of a site, only two input parameters including alluvium thickness and average shear wave velocity have been utilized in the analysis. Dominant period is the only output parameter for both series of analysis. The data are normalized before being trained to neural network models. The input data consists of 73 individual sets, 85 (61 individual sets) and 15 (11 individual sets) percent of which is used for training and test of the networks, respectively. The key problem in the training phase of ANNs is to choose the most suitable input variables to obtain the most reliable results with least errors. Fig. 5 shows the distribution of dominant periods obtained from all the boreholes by microtremor.

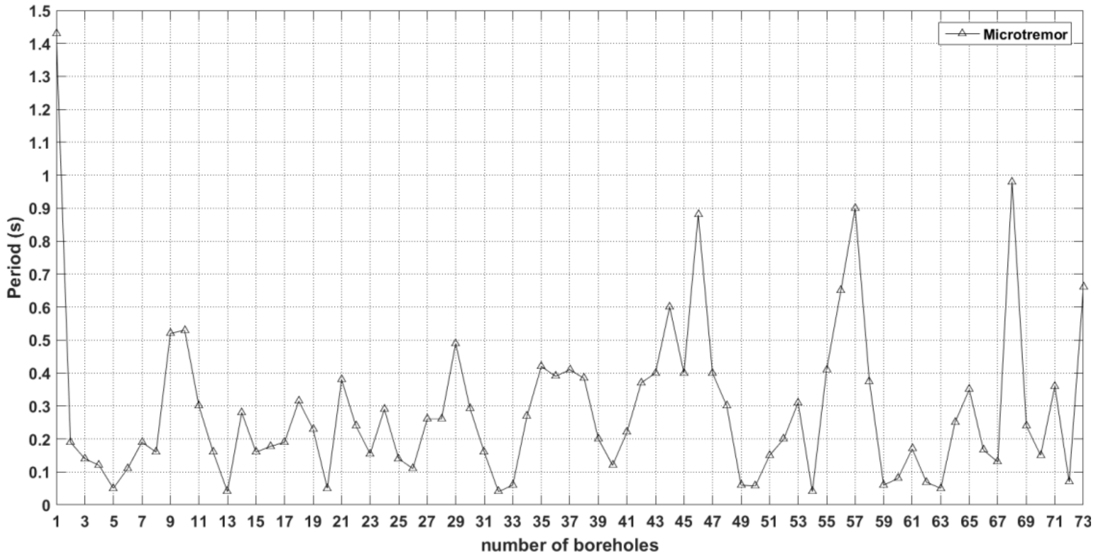

Figure 5. Dominant periods obtained from all the boreholes by microtremor

The results of second series of analysis which only employed two input parameters (i.e. alluvium thickness and average shear wave velocity) showed significant errors and weak estimations for dominant period of the site for all ANNs. Therefore, the output of the second series of analysis will not be presented in this work. The results for the first series of analysis are presented in the following sections.

5. NEURAL NETWORK ANALYSIS WITH BP MODEL

BP is a feed-forward generated neural network. Feed-forward neural networks are among the most popular neural networks used in engineering problems. In this study, using trial and error method, six neurons are assigned for input layer and one neuron is determined for output layer. A hyperbolic tangent sigmoid transfer function, and tansig transfer function have been utilized between input and hidden layer, and between hidden and output layer, respectively. The highest obtained coefficient of correlation was 0.969 which indicates a R-square value of 0.94 ($R^2 = 0.94$). Fig. 6 shows the comparison between the values of dominant period obtained from microtremor and estimated by neural networks. It is clear from Fig. 7 that the BP neural network provides highly accurate results in estimation of dominant period.

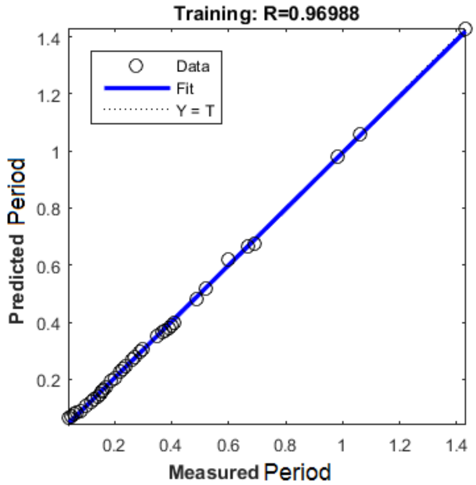

Figure 6. The comparison between the values of dominant period obtained from microtremor and estimated by neural networks.

Fig. 7 shows the graph for the data obtained from microtremor, 62 individual set in training and 11 individual set in the test phase, along with the estimations of BP ANNs. The estimation of ANNs is different from real value at three points. The mean error is also presented in Fig. 7, whose value is calculated from equation 2.

$$Mean\ error\ (\%) = \left|\frac{M_i - P_i}{M_i}\right| \times 100 \qquad (2)$$

In equation 2, Mi and Pi are the measured and estimated value of the dominant period for i[th] data point, respectively. The mean error obtained for BP ANNs is equal to 34.7%.

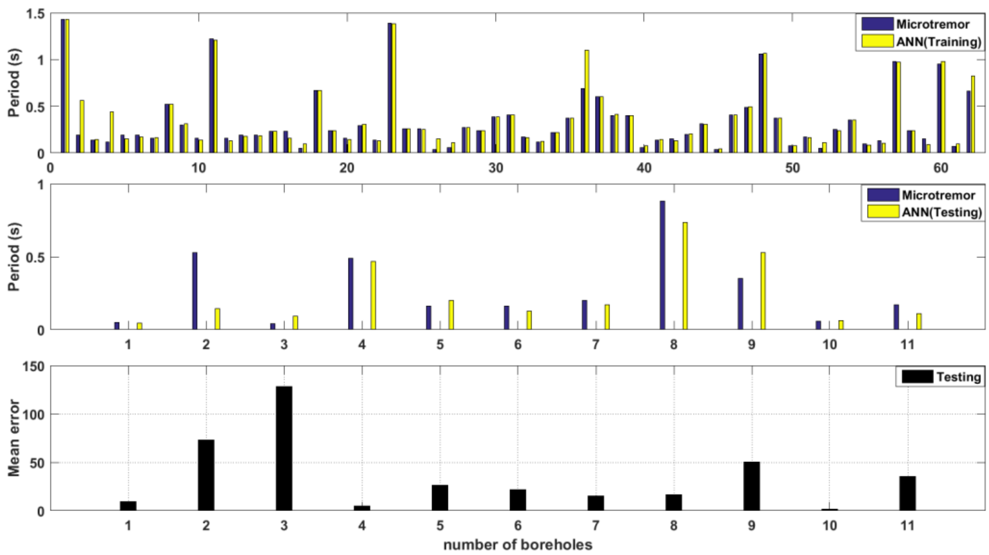

Figure 7. Evaluation of dominant period by using microtremor and estimation of BP neural networks along with mean error

6. NEURAL NETWORK ANALYSIS WITH RBF MODEL

Fig. 8 shows the graph for the data obtained from microtremor and the estimations of RBF ANNs. There is only one point that the estimation of ANNs is different from real value of dominant period. The mean error obtained using this neural network is less than 10%.

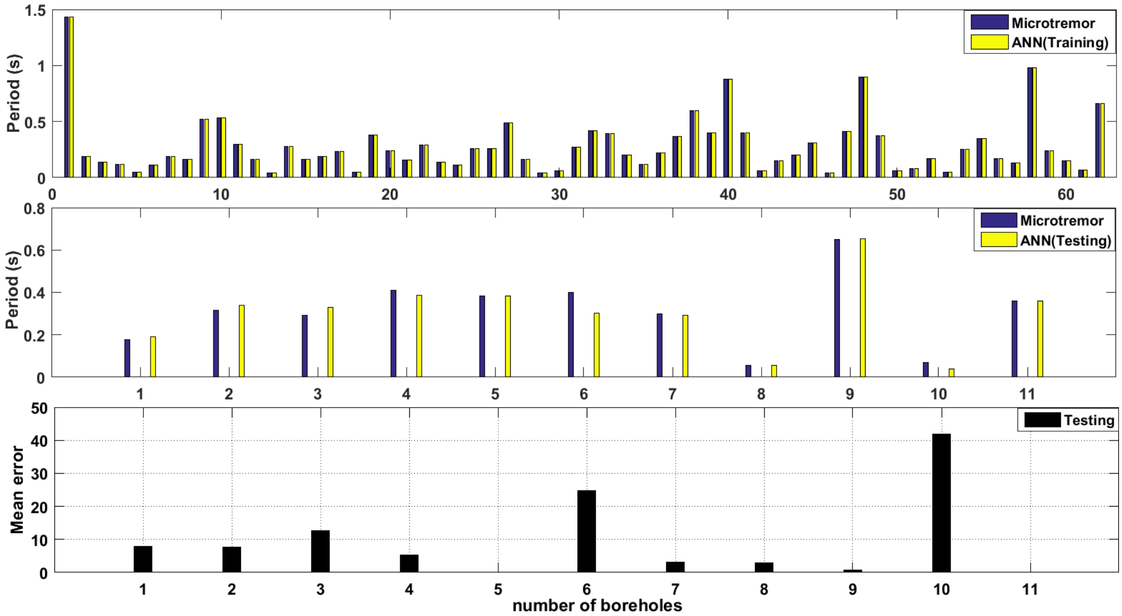

Figure 8. Evaluation of dominant period by using microtremor and estimation of RBF neural networks along with mean error

7. NEURAL NETWORK ANALYSIS WITH ANFIS MODEL

ANFIS uses a hybrid learning algorithm to tune the parameters of a Sugeno-type fuzzy inference system (FIS). The algorithm uses a combination of the least-squares and back-propagation gradient descent methods to model a training data set. ANFIS also validates models using a checking data set to test for overfitting of the training data.

Fig. 9 shows the graph for the data obtained from microtremor and the estimations of ANFIS ANNs. Almost for all points there is a significant difference between the measured and estimated values of dominant period. The mean error obtained using this neural network is more than 289%.

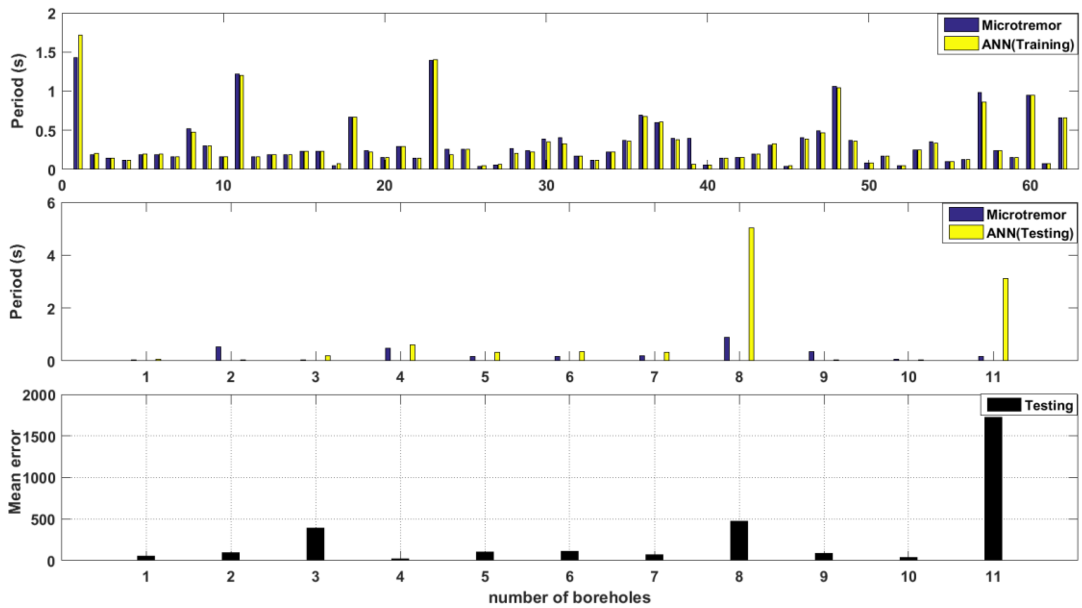

Figure 9. Evaluation of dominant period by using microtremor and estimation of ANFIS neural networks along with mean error

8. The Performance of Neural Networks

The most common parameters for evaluating the performance of ANNs are Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation Coefficient(R).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|M_i - P_i|\left|\frac{M_i - P_i}{M_i}\right| \times 100 \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(M_i - P_i)^2}{n}} \tag{4}$$

$$R = \frac{n\sum_{i=1}^{n}(M_i P_i) - \sum_{i=1}^{n}(M_i)\sum_{i=1}^{n}(P_i)}{\sqrt{n\sum_{i=1}^{n}(P_i)^2 - (\sum_{i=1}^{n}(P_i))^2}\sqrt{n\sum_{i=1}^{n}(M_i)^2 - (\sum_{i=1}^{n}(M_i))^2}} \times 100\% \tag{5}$$

M_i, P_i and n are the measured and estimated value of the dominant period, and total number of individual sets, respectively. Among the models, the one with least error value is the best model for estimation. Table 1 shows that RBF ANNs presents the best performance in estimation of resonance period. In addition, table 2 shows the performance of neural networks for different sets of input variables (i.e. first and second series of analysis). Regarding the results, it is seen that in practical engineering problems where geotechnical parameters are measured through field measurements in a global scale, the proper selection of parameters plays an important role in the training of neural network models. It is worth noting that calculations without the presence of Atterberg limits (liquid limit and plastic index) led to an increase in the error values and reduction of the power of estimation in all models, which indicates its importance.

Table 1: Error values for different neural network models

Category	ANN (artificial neural networks)				ANFIS (adaptive neuro-fuzzy inference system)	
	BP		RBF			
	TRAINING DATA	TESTING DATA	TRAINING DATA	TESTING DATA	TRAINING DATA	TESTING DATA
Correlation, R	0.9665	0.8429 1	1	0.9773	0.9836	0.6214
RMSE	0.0876	0.1389	1.2119e-11	3.5034	0.0611	1.5474
MAE	0.0341	0.2051	7.7055e-12	2.2001	0.0219	0.8790
MEAN ERROR, %	-	34.7	-	<10	-	<289

Table 2: the performance of neural networks for different sets of input variables

Input parameters	Output parameter	Site condition	Function	ANNs estimation
First Series: layer thickness, average shear wave velocity	Dominant period obtained from microtremor data	Damping soil layers on the bedrock	$T_s = \frac{4H}{V_s}$	Inappropriate
Second Series: layer thickness, soil type, specific gravity, effective stress, shear wave velocity, modified standard penetration number, liquid limit and plastic index			... ...	Appropriate

In addition to dominant period of the site, one of the important steps in seismic hazard mitigation is to prepare the seismic microzonation maps. Microzonation is well known to be a strong tool for risk analysis. Microzonation is usually performed by understanding earthquake source failure mechanism, evaluation of waves' propagation from the source to the layers above the bedrock, determining the effects of local soil profile, and finally developing a hazard map that shows the vulnerability of the area to the probable seismic risks.

The Technical Committee for Earthquake Geotechnical Engineering, TC4, of the International Society of Soil Mechanics and Foundation Engineering, provided a table for different levels of zonation for ground motions (Table 3).

Table 3: Use of data for three levels of zonation [35]

	Grade-1	Grade-2	Grade-3
Ground motions	-Historical earthquakes and existing information -Geological maps -Interviews with local residents	-Microtremor -Simplified geotechnical study	-Geotechnical investigation -Ground response analysis

Based on table 3, the level of zonation for this study falls in the level of Grade-2. Seismic microzonation can be used extensively as a guide for the city plan, design and development of future structures and buried vital arteries including tunnels, and water, wastewater, gas, and oil lines, and power and communication lines. Fig. 10 illustrates the distribution of dominant periods at Urmia city. In order to present the spectral distribution of dominant period for Urmia city, Interpolation has been performed between microtremor stations by using the GIS software.

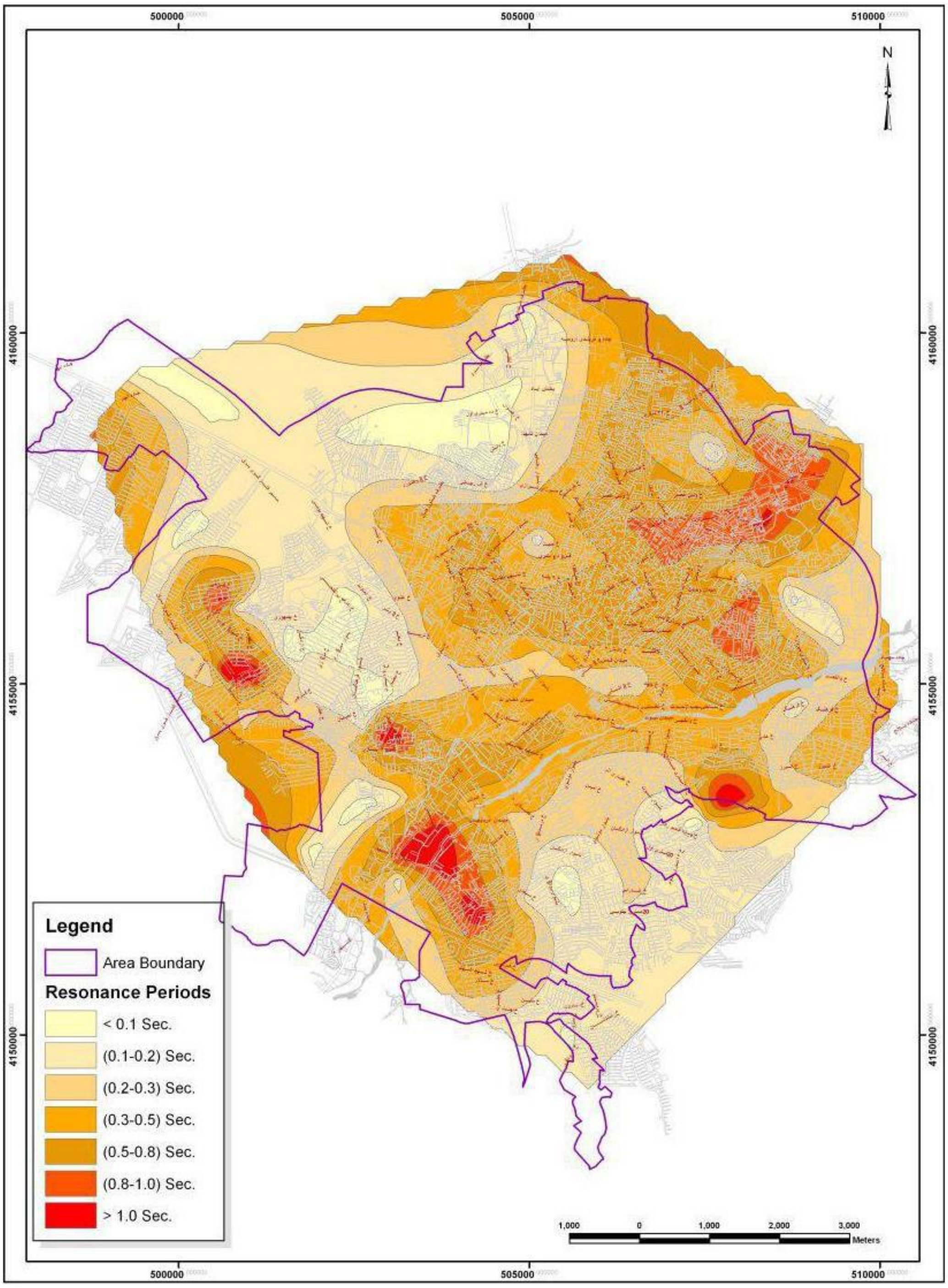

Figure 10. Equipotential curves of resonance period for Urmia city

9. CONCLUSIONS

The presented study has been carried out in Urmia city to establish a relationship between the geotechnical parameters of the soil layers and the dominant period obtained from microtremor measurements. The analysis was performed by using three different neural network models (BP, RBF and ANFIS) to determine the best neural network model for this specific problem. Artificial intelligence models are data-based models that only rely on data to obtain the accurate functional relationships between available data, while physical models use the basic principles (physical rules) to obtain basic relationships for a system. In addition, physical models are usually obtained by making justifiable simplifications and assumptions which limit their application and validity. Consequently, artificial neural networks offer significant benefits for complex systems. The results of this study showed that neural networks are powerful and practical tools that have a high performance in solving geotechnical problems and estimating geotechnical parameters such as the dominant period of a site using available datasets. It was shown that neural networks are useful techniques that can be used to significantly reduce seismic hazards, and play an important role in cost reduction and proper locating for sensitive structures such as powerplants and dams. Among the three models of the neural network used in this study, the emulator generated by the RBF model had the highest accuracy in estimating the dominant period of the site.

Acknowledgement: In this paper, the microtremor data measured during the microzonation project at Urmia city are used. The Authors would like to show their sincere gratitude to the employers of Organization for Management and Planning, and Organization for Urban Development of Urmia city.

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