USING NEURAL NETWORK FOR PREDICTION OF THE DYNAMIC PERIOD AND AMPLIFICATION FACTOR OF SOIL FOR MICROZONATION IN URBAN AREA

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ABSTRACT :

Millions of financial losses and thousands of people which die are due to earthquakes that happen every now and then in all corners of the world. Safety against the hazards of earthquake relates to two basic factors: safety of the structure and site. Site's conditions play an important role in damages of structures. This factor has a geotechnical cause and could be appeared as seismic wave amplification and change in frequency content. Major point in this article is to determine the dynamic period and amplification factor of soil, that in order of calculating them neural network and engineering software has been used. Software's inputs are dynamical and geotechnical soil data profiles and its outputs are amplification factor (A_f) and dynamic period (T_d) of soil. Afterwards these data will be used to train the neural network. Finally the advantages of using neural network and effective factors to its precision will be considered.

KEYWORDS: Microzoation, Neural Network, Dynamic Period, Amplification Factor

1. INTRODUCTION

In recent years the effects of soil conditions and geology on the intensity of ground motions and earthquake damages have been known. For the first time people like Mac Murdo (1894), Wood (1908) and Reid (1910) showed that intensity of ground motions in different earthquakes relates to site and geology conditions. Gutenberg (1927) presented the amplification factor from different site conditions base on the earthquakes that were recorded there. In primary Housner [1] and Newmark [2] spectrums, the effect of ground specifications was not considered.

Other researchers like Seed [3] brought up this idea that the frequency content of the accelerograph upon bedrock and alluvial makes a considerable difference. He studied 104 horizontal components out of 23 earthquakes with the peak ground acceleration more than 0.05g and divided these records into four groups: rock, dense soil with the depth of about 45m, sandy soil with the depth of about 75m and fine to average clay. He found out that the softening in ground substance, decreases acceleration amplification factor in high frequencies and increases it in lower frequencies. In addition of amplification factor, dynamic period of soil can show the domain of resonance in soil and it can also affect designing of a structure by determining structure's response, its appropriate height and etc.

The amplification factor and dynamic period of soil play an important role in structural designing and ground response analysis method is used for calculating them. It is considered in the following sections.

2. GROUND RESPONSE ANALYSIS

Ground response analyses are used in order to predict ground motions, provide of design response spectrum and calculation of earthquake force in structures. In the meantime, they can be used to determine the dynamical stresses and strains to evaluate the liquefaction hazards, ground instability and design of retaining structures and etc. In an ideal condition for a thorough ground response analysis, rupture is modeled in the focus, and the manner of stress propagation among the soil and the effect of soil on it, is determined. Considering the complexity of fault rapture, some estimated equations along with seismic risk analysis are used in order to predict movement characteristic in the bedrock of site. Therefore, ground response analysis in determining of amplification factor and different periods, transforms into the response of soil surface against the bedrock movements [4].

There are many methods for analysis of ground motion; however, researchers have used one-dimensional alluvium response more. In fact Two-dimensional and three-dimensional analysis methods are generalized forms of one-dimensional analysis which are used when there is special topographic, ground shapes or non-isotopic soil layers. Meanwhile, these analyses can be done as linear or non-linear or equivalent linear forms which in this research a one-dimensional equivalent linear analysis has been used.

2.1. One-dimensional Ground Response Analysis

This analysis is based on horizontal layer borderline and also the response of soil mostly appears because of SH waves, which are being distributed vertically from bedrock. For one-dimensional ground response analysis it is assumed that on the horizontal direction, ground surface and bedrock are infinite. Ground responses resulted from methods based on this theory, have a logical correspondence with the measured results on different conditions [4].

Whereas the non-linear behavior of soil is partly understood, for determining the logical ground response, an equivalent linear method is used by modifying the linear method. In this method after estimating the shear modulus (G_i) and damping ratio (ξ_i) in a strain level, these values are used for calculation of ground response including time-history of shear strain for every layer. After determining the effective shearing strain, new equivalent linear value G_{i+1} and ξ_{i+1} will be selected for the next iteration. By repeating this process, G and ξ compatible with strain, are calculated and controlled. According to the one-dimensional equivalent linear analysis software ONSA in FORTRAN programming language was produced. That is under the license of AZAD University of Kermanshah and its results in comparison with advanced softwares have been approved.

3. NEURAL NETWORK

Artificial Neural Networks (ANN) are systems that are able to perform operations like biological neural systems. Training of an ANN is the modification of network's parameters in order that it can show a desirable behavior against the external excitations. A multi-layer feedforward neural network has been used in this research. These kinds of networks consist of a number of processing units that can be divided into input, hidden and output units. In every unit, activation function has an effect on the weighted sum of inputs and specifies the output, and is defined as Sigmoid, Sine, hyperbolic tangent function and etc. The effect of every unit on the next units depends on its activation content. Manner and pattern of relations between the units play an important role in the response of the system. Network training could be defined as: creating new units, creating new connections, elimination of some connections or weight correction of the existing connections.

Network training is performed based on generalized δ rule [5]. In order of a better training procedure, coefficients as learning ratio and Momentum term [6] are defined to control the changes made in the weights on each step. A neural network with one input layer, a hidden layer, an output layer and sigmoid activation function is able to learn every non-linear behavior [7]. In the mean time in these kinds of networks the number of nodes in hidden layer is considered as system's degree of freedom [8] and is obtained by trial an error [7].

While training, it is possible that the neural network gets stuck in a local minimum and the level of error remains steady. Therefore getting an acceptable neural network even by using generalized δ rule, can be difficult. Precision of emulator, which is called to a trained neural network, depends on: number of nodes in the hidden layer, type of connections of network, learning rate, momentum term, activation function, number of input-output pairs and etc. The major point is that, with every level of precision, getting an appropriate neural network is obtainable, although it could be difficult.

The software of neural network was produced in FORTRAN programming language and its learning algorithm is based on generalized δ rule. In order to eliminate the local minimum effects in this software, the following techniques have been used [6]:

I- Randomized selection of the input-output pairs

At every training cycle for the input-output pairs, a randomized arrangement is selected and the error back propagation is performed. The reason of randomized arranged selecting is to avoid similarity of every cycle with its previous one, and also to reduce the probability of neural network halting in a local minimum.

II- Automatic node generating in the hidden layer and weight freezing

If the error level does not decrease and remains steady in several training cycles, the program automatically generates a node in hidden layer and chooses randomly weights for its connections. In the beginning, by freezing the rest of the connections, the new connections are being updated, after a few cycles the whole network is trained.

III- Using different activation function simultaneously

The program uses sigmoid, linear, sine, parabola and etc. as activation function to have a better output. However, activation function in a few number of nodes are selected as linear, sine and etc. and most of them are sigmoid.

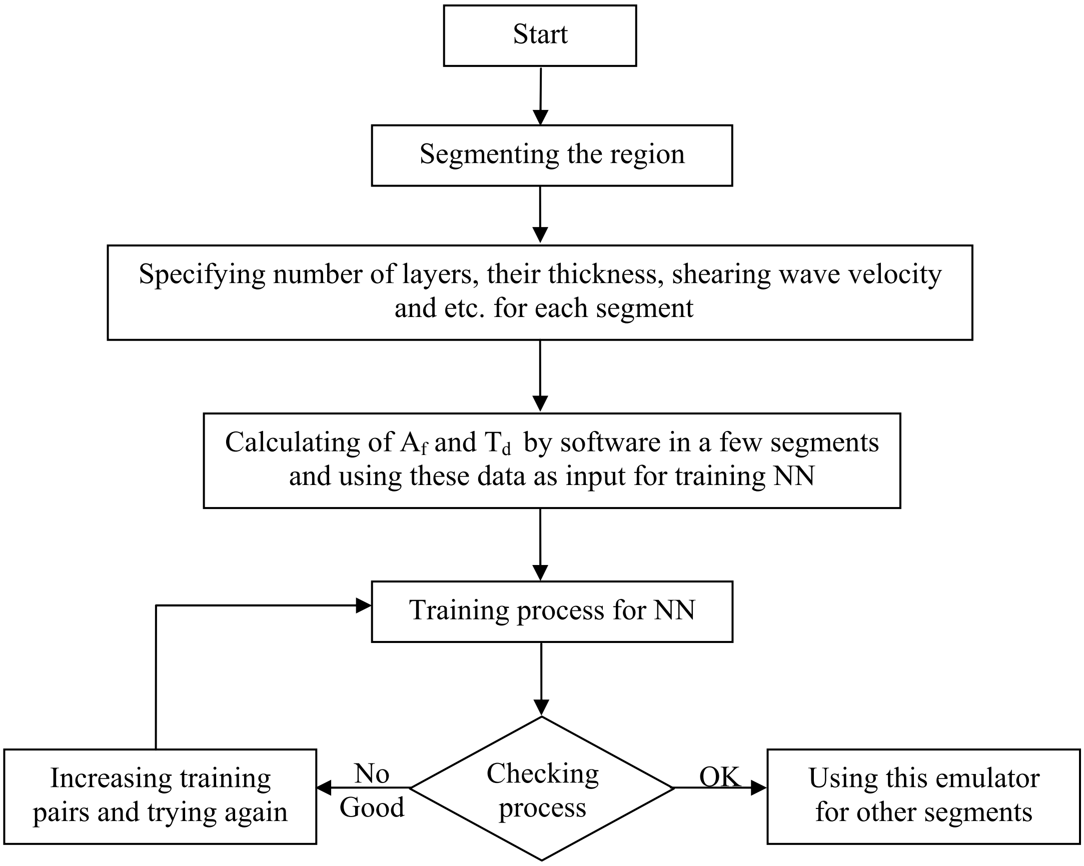
4. RECOMMENDED ALGORITHM FOR DETERMINATION OF A_f AND T_d OF SOIL BY USING NEURAL NETWORK

The aim of this section is to use neural network to determine the soil dynamic period and amplification factor of a region. For this, after segmenting the specified region, a representative profile that includes the summery of Geotechnical, geophysical and geological information is selected for each segment. After analyzing these representative profiles by using ONSA, the outputs including dynamic period and amplification factor are determined. A few numbers of these profiles which are to explain regional soil characteristics have been selected, and their inputs and outputs are introduced to the neural network. Based on these inputs-outputs the neural network is trained, and its results precision in a few other profiles is tested. After verification of the obtained neural network, this emulator could be used so as to calculate the dynamic period and amplification factor of other profiles. Flowchart 1 demonstrates a summary of this algorithm.

5. CASE STUDY

The case study has been performed for Kermanshah, Iran. In order to examine and study the behavior of the site against strong motions, among 20 suitable acceleration records in the region, 5 records were selected. The city has been divided into 110 segments (Fig.1) and in each segment the representative profile characteristics including: shearing wave velocity (V_{si}), layer thickness (h_i) and density (γ_i) have been determined. Characteristics for profile E14 have been presented in table 1. After determining the soil non-linear behavior model, according to 5 normalized records of the same peak ground acceleration, wave propagation analysis was performed for all segments of the city and after 550 analyses the results were obtained.

An example of these results for profile E14 has been presented on table 2. Finally, average of the 5 obtained values in each segment has been considered for (A_f) and (T_d). More results of other segments are available on Table 3.



Flowchart 1- Recommended method for determining A_f and T_d by using neural network

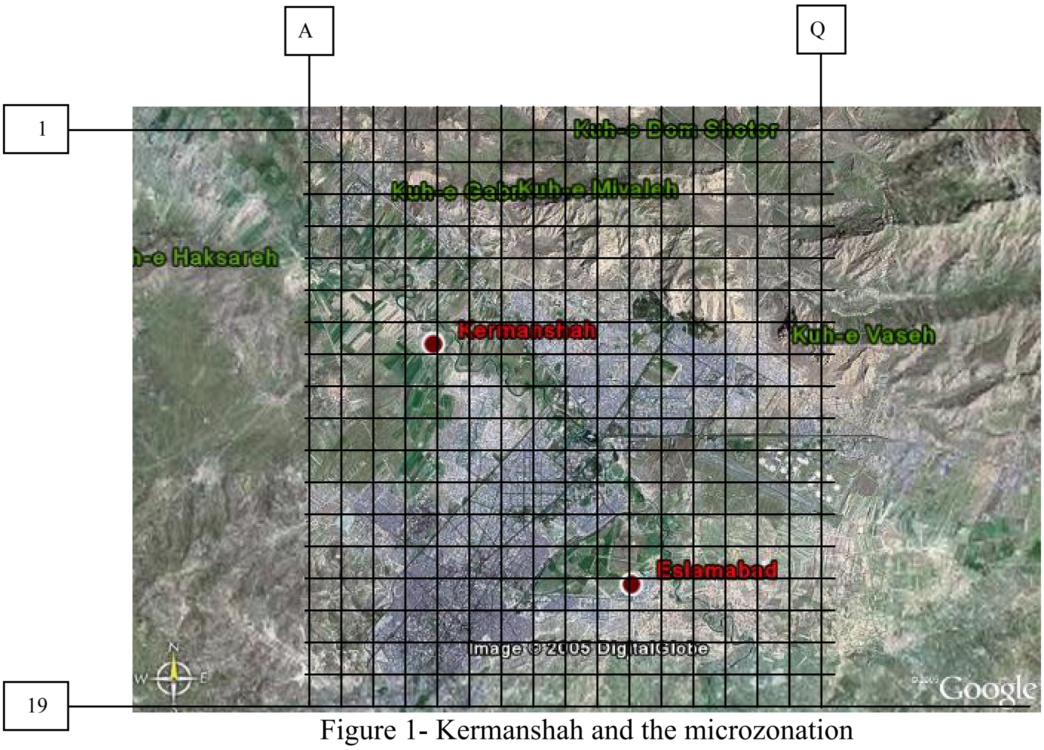


Figure 1- Kermanshah and the microzonation

Table 1- Characteristics of profile E14

Layer No.	Layer diameter (m)	Density (t/m^3)	Shearing wave velocity (m/s)
1	2	1.7	150
2	3	1.8	290
3	2	1.9	350
4	3	2	360
Bedrock	-	2.4	1000

Table 2- Amplification factor and dynamic period for profile E14

Earthquake	T_d	A_f
1	0.24	1.17
2	0.25	1.15
3	0.19	1.30
4	0.23	1.21
5	0.22	1.20
Average	0.23	1.21

Table 3- T_d and A_f for a number of profiles in Kermanshah

Profile	K8	I8	D15	F14	H11
T_d	0.94	0.83	0.15	0.69	0.96
A_f	0.89	1.29	2.30	1.80	1.41

Precision of the trained neural network is highly influenced by the number of input-output pairs and also an equation could be obtained which has not been considered here. 40 profiles among the 110 existing profiles in the city were selected and in each one of them V_s, h and γ were considered as inputs and the outputs were A_f and T_d. The neural network was trained for 1E-4 accuracy and was tested and verified according to some other profiles data. Table 4 demonstrates the amount of A_f and T_d for some profiles that had no interference with the training and testing procedure of the neural network.

Table 4- Comparison between neural network and real output for some profiles

Profile	L8	J6	G5	E14
Real T_d	0.91	0.74	0.92	0.22
NN T_d	0.86	0.71	0.95	0.22
Real A_f	2.34	1.92	1.13	1.23
NN A_f	2.25	1.86	1.18	1.21

After considering all the profiles, it was found that the neural network maximum error was 11.3% and the average error for T_d was 5.07% and for A_f was 4.21%.

6. CONCLUSIONS

By using neural network for calculating A_f and T_d the error level will be acceptable and in comparison with usual softwares, a shorter CPU time will be spent. In addition, since the real soil characteristics are probabilistic and not deterministic parameters, in determining the reliability of structures when the cumulative distribution function of soil parameters exists, while using numerical methods like Mont Carlo simulation, T_d and A_f must be calculated over and over again (approximately about 1E4 times or more). In these situations, using softwares like ONSA, SHAKE and etc. is impossible and a confident and acceptable way is to use neural network. In case of incomplete profile information, estimating the A_f and T_d becomes easier by using neural network. Finally, the obtained emulator could be used for other cities with rather similar soil.

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