A Sensitivity Analysis of Amplification Factor of Peak Ground Acceleration by means of Neural Network and Time History Analysis: a Case Study

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SUMMARY:
In this paper, the effect of soil characteristics of Neka site in south eastern coast of Caspian Sea (Iran), have been investigated on the amplification factor (AF) of bedrock maximum earthquake acceleration (Peak Ground Acceleration or PGA). To do so, several time history analyses have been carried out by CA2 program (an Iranian Finite Difference Code) and design acceleration time history of Neka site. The mentioned analysis results have been used for training and testing a back propagation neural network (NN). Then, equation obtained from NN has been utilized for a sensitivity analysis of AF of bedrock PGA. To do so, variation of mentioned equation related to each input parameters of NN have calculated and finally, related importance and effect of each NN's inputs (the characteristics of soil on bedrock) on amplification factor have been obtained by means of a statistic analysis on inputs domain.

Keywords: Sensitivity, time history, neural network, amplification, Neka

1. INTRODUCTION

Iran is one of the seismically active countries in the world. In this paper, the effect of soil characteristics of Neka site in south eastern coast of Caspian Sea (Iran), has been investigated to determine amplification factor (AF) of bedrock maximum earthquake acceleration (Peak Ground Acceleration or PGA), the most important parameter in structural seismic design. Safety against the hazards of earthquake relates to two basic factors: safety of the structure and subsurface ground conditions. Soil layer conditions play an important role in damages of structures. This factor has a geotechnical reason and could appear as seismic wave amplification and changes the PGA. 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. 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, etc [Tahamoli Roodsari, 2008].
In this research, the effect of shear wave velocity (Vs), soil unit weight (γ), soil cohesion (C), soil internal friction angle (φ), and thickness of soil layer upon bedrock (H) have been investigated on the amplification factor of PGA. To do so, several fully dynamic (time history) analyses were carried out by means of an Iranian 2-dimensional finite difference code named CA2 and the amplification factor of soil was obtained. Then, to predict the behavior of soil, a neural network (NN) was trained according to the input-output pairs which obtained from mentioned analyses, and this emulator (NN) was used as an alternative for the CA2 program. Just based on the trained NN, the sensitivity of output related to input parameters cannot be investigated [Lu et al 2001]. So, in the next step, the equation obtained from NN was used to calculate the partial differential equations of AF (sensitivity equations) for each input parameters. Then, a great number of input data were generated based on a random selection from input domain with uniform distribution and used to calculate the values of AF sensitivities. The mentioned procedure is presented in the following sections.

2. FULLY DYNAMIC (TIME HISTORY) ANALYSIS

In this research, fully dynamic analysis was used as a relatively exact method in prediction of ground response to earthquake in each moment of earthquake. Earthquake loading on soil should be applied as time history of acceleration, velocity, displacement or stress or force on bedrock to simulate dynamic loading on real subsurface ground layers [Mojtaba Heidari and Mahmoud Hassanlou Rad. (2008)]. In this research acceleration time history was used for project area (fig. 2.1) [SADRA Company. (2004).]. By means of an Iranian 2-dimensional finite difference code named CA2, dynamic analysis based on acceleration time history was carried out for Neka site. Then, time history of acceleration upon a point of ground surface during the analysis was recorded to study the dynamic behavior of soil. Also, upon ground surface and bedrock PGA were used to calculate the site amplification factor.

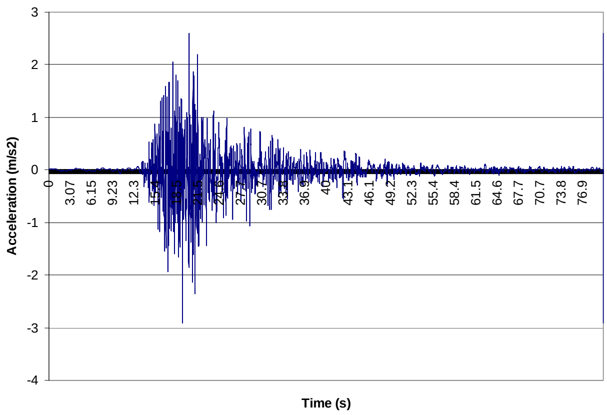

Figure 2.1. Acceleration time history in Neka site

2.1. CA2 Program and Assumptions

Iranian CA2 program is a code based on finite difference method in order to analyze two dimensional problems in soil mechanics [Heidari M. & Tahamoli Roodsari M., 2009]. In this software, after definition of problem geometry and mesh generation, initial stresses are produced after confidence of system's equilibrium by a stress-deformation analysis under system weight with linear or nonlinear behaviors. Soil shear strength parameters in Mohr-Coulomb failure criteria were utilised in dynamic analyses. Also, a sensitivity analysis of AF to size of mesh (square elements) and distance of boundaries was carried out and their optimum values 1m for elements and 160m for distance of boundaries were obtained.

2.2. Dynamic Boundary Conditions

To achieve a correct modelling of real situation and to obtain valid results, it is necessary to select correct dynamic boundary condition. Thus, dynamic boundary conditions were selected as energy absorbent and free boundary (like semi-infinite natural ground) to avoid reflection of earthquake waves into the model after reception to these boundaries. Also, selected earthquake acceleration time history was affected on the bedrock (lower horizontal boundary) to apply earthquake acceleration on the model.

3. ARTIFICIAL 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 feed forward (MLFF) 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 layers (Fig. 3.1). 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, 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.

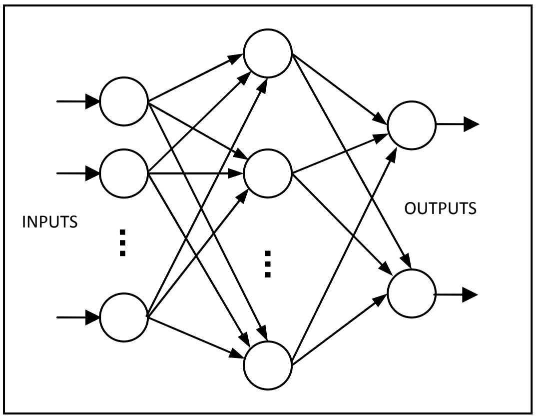

Figure 3.1. A multi-layer feed forward neural network with three layers

Network training is performed based on generalized δ rule (Rumelhart, D.E. and McClelland, J.L. 1980). In order of a better training procedure, coefficients as learning ratio and Momentum term (Jogataie, A.R. 1995) 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 (Chau, K.W. 2007). In the mean time, in these kinds of networks the number of nodes in hidden layer is considered as system's degree of freedom (Zhang, J. and Foschi, R.O. 2004) and is obtained by trial and error (Chau, K.W. 2007).

While training, it is possible that the neural network gets stuck in a local minimum and the level of error remain steady. Therefore getting an acceptable neural network can be difficult even using generalized δ rule. 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 (Tahamouli R. M. and Habibi M. R. 2008):

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 is selected as linear, sine and etc. and most of

them are sigmoid.
The small number of input-output pairs in training set decreases the operation of ANN in training phase, and a large number of pairs without a proper distribution on inputs' n-dimensional domain decreases the operation of network in addition to taking too much CPU time. Therefore, optimum number and distribution of training pairs should be selected to decrease the training time and increase the operation of ANN. Hence, Hypercube method has been utilized according to Eq. 3.1 (Yun, C. B. & Bahng, E. Y. 2000).

$$\text{The Number of Training Pairs} = 2^M + 2 \times M + 1 \tag{3.1}$$

Which; M is the dimension of inputs' domain.

4. AMPLIFICATION FACTOR BY MEANS OF NEURAL NETWORK

In this paper, the MLFF Neural Network has been used to predict the AF of soil upon bedrock based on Neka site acceleration time history. The input parameters of ANN have been selected as the effective factors on AF are shear wave velocity (Vs), soil unit weight (γ), soil cohesion (C), soil internal friction angle (φ), and thickness of soil layer upon bedrock (H). The range of variation for each mentioned parameters has been presented in Table 4.1.

Table 4.1. The range of variation for each input parameters of neural network

Input Parameters	Minimum	Maximum
H (m)	4	40
C (kg / cm^2)	0.05	2
φ (deg.)	5	45
γ (kN / m3)	14	22
V_S (m/s)	50	700

Several time history analyses (70 analyses) by means of CA2 program have been used for training of ANN to learn the AF values which, the training set includes 43 analyses (based on Eq. 3.1) and the testing set consists 27 analyses. The selection of different values of input parameters and their distribution are based on the hypercube method for training set, and random uniform distribution for testing set of ANN.
As mentioned before, the ANN with three layers and enough neuron in a hidden layer can estimate every complex nonlinear function. So, in this research, 14 neurons have been obtained as optimum number of neurons in the hidden layer for the ANN with 5 input neurons and the AF as one output.
Figure 4.1 shows the ability of ANN in FS prediction with a high correlation factor between ANN outputs and target values. As mentioned before, just based on the trained NN, the sensitivity of output related to input parameters cannot be investigated. Thus, to study the effect of each input parameters on AF, a statistic sensitivity analysis is required.

5. SENSITIVITY ANALYSIS

The input parameters don't have the same effect on the variations of AF. It is important to know which parameters have more effect on AF, especially during an optimization process. Therefore, a sensitivity analysis of AF related to input parameters has been carried out. To do so, the equation of trained NN including inputs, output, weights and biases, was used to obtain partial differential equations of AF (sensitivity equations) for each input parameters. Then, a great number of input data (1000 sets) were generated based on a random selection from input domain with uniform distribution and were used to calculate the values of AF sensitivities.

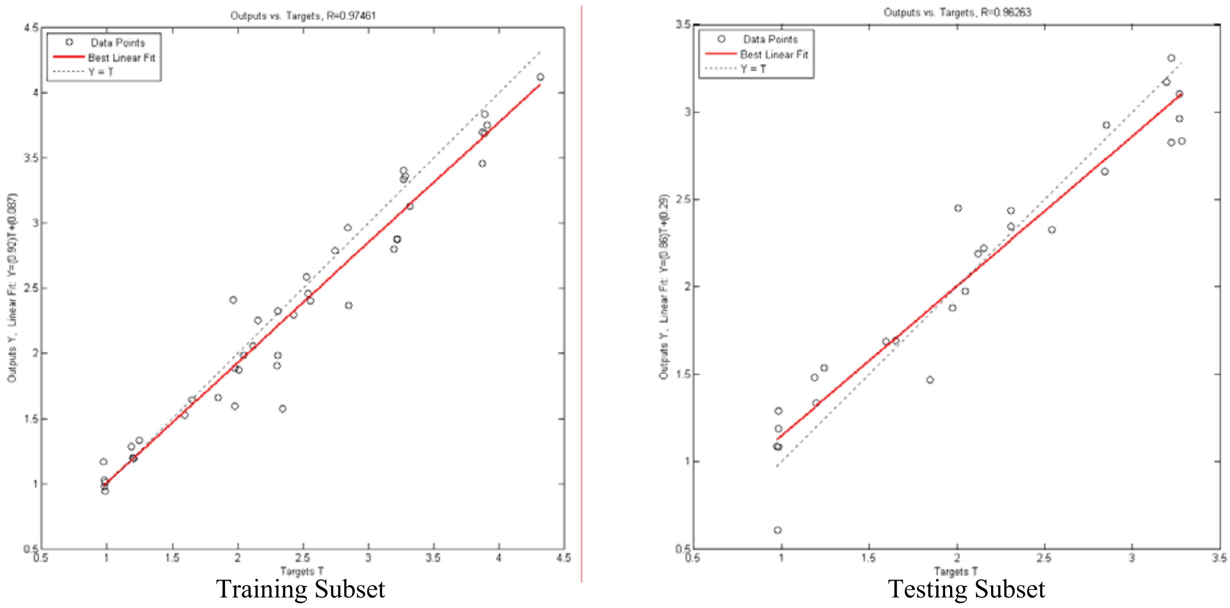

Figure 4.1. The well trained ANN in prediction of AF

Then, five statistic percent (D10, D25, D50, D75, D90) of sensitivity values related to each input parameters were calculated [Lu et al 2001] in which D10 indicates a value of sensitivity with 10 percent less than it but 90 percent greater. Positive value of D10 reveals the probability of increasing in AF more than 90 percent which is connected to increase in target input. By means of this method, the effect of increase or decrease of each input on AF and total dominant procedure can be determined. The results of sensitivity analysis of AF related to each input parameters have been presented in Fig. 5.1.

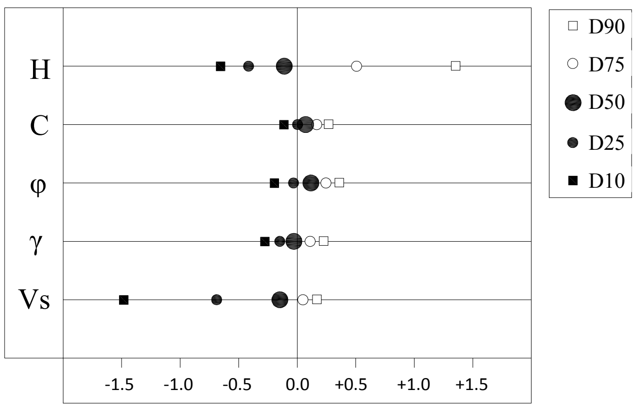

Figure 5.1. Sensitivity analysis of AF related to input domain

5. CONCLUSION

As shown in Fig. 5.1, thickness of soil upon bedrock (H) and shear wave velocity (Vs) have higher effect on amplification factor of Neka bedrock PGA than the other three parameters C, φ and γ. For Vs, more than 50 percent of sensitivity values are negative and it means that by increasing in Vs, AF decreases with probability over 50 percent. But, for H, more than 50 percent of sensitivity values are negative and more than 25 percent of sensitivity values are positive, which means the effect of soil thickness upon bedrock (H) depends on different levels of its own values or other parameters. Over 50 percent of sensitivity values for cohesion and internal friction angle are positive. It shows that an increase in C and φ, increases AF with over 50 percent probability. That is why increasing in C and φ leads to an increase in shear strength of soil, and plastic zones are not formed and earthquake energy is not absorbed and transfered to ground surface. Also, the unit weight of soil (γ) doesn't have prominent effect on AF.

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