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An approach for probability analysis of nonlinear site response using an optimized developed artificial neural network based model - A case study

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ABSTRACT

In the current paper and approach to convert an optimized developed artificial neural network (ANN) based model is presented to estimate the probability analysis of nonlinear seismic response spectra for earthquake acceleration records. The specified area in this study is located in Tehran, the capital city of Iran which is considered as a high seismic risk zone. More than 560 ANN topologies have been tested using a developed Matlab computer code with capability of using from several different training algorithm as well as various activation transfer functions. A total of 113 data sets from the executed in-situ and laboratory tests as well as earthquake records and geophysical investigations were used as input values of the ANN with applying the back propagation algorithm. The performance of proposed model with ability in solving the related problem to various types of data and mathematical simplifications, has been controlled and analyzed using statistical, mathematical and graph analyses criteria as well as sensitivity analysis. The ANN results present acceptable concordance with the actual seismic response spectra preserving a minimum error between the actual and the estimated spectra using ANN.

Keywords: *probability analysis, Tehran, seismic response spectrum, optimized ANN model.*

INTRODUCTION

The concept of response spectrum as one of the most useful tools in earthquake engineering for estimation the seismic demand on structures as well as investigating the general character of ground motions has introduced by Benioff (1934), Housner (1941) and Biot (1941).

The identified strategies using mathematical technologies can be categorized into time-domain and frequency-domain approaches (e.g. Agbabian et al., 1991; Koh et al., 1991; Mcverry, 1980; Yun and Lee, 1997; Wu et al., 1996). However, most of these techniques inherentlyinvolve complicated search processes and are thus computationally inefficient as well as numerical unstability for large-scale infrastructures that have a significant number of degrees of freedom.

Estimating of site response due to soil nonlinearity, unavoidable uncertainties, inherent limitation of available approaches and adopted simplifications is a hard task. In the recent years, ANNs as an alternate solution have recently drawn considerable attention in civil engineering and in particular earthquake geotechnical engineering due mainly to their ability to approximate an arbitrary continuous function and mapping (e.g. Masri et al., 1993 and 2000; Shahin et al., 2008; Hanna et al., 2007; Agrawal et al., 1997; Goh, 1994; Basheer, 2002; Habibagahi and Bamdad; 2003; Kerh and Ting, 2005, Rajasekaran and David, 2007). The interest in neural networks comes from the networks' ability to mimic human brain aswell as its ability to learn and respond. The ANNs paradigms employ different learning rules, but all in some way determine pattern statistics from a set of training samples and then classify new patterns on the basis of these statistics. Therefore, it is important to be able to provide performance guarantees.

Motivated by all the successful applications of ANN to solve earthquake engineering applications (e.g. Alves, 2006; Lee and Han, 2002; Kerh and Ting, 2005; Barrile et al., 2006; Garc´ıa et al., 2007; Arjun and Kumar, 2009; Cheng and Li, 2002; Chandler et al., 2002) this study aims to propose an optimized developed ANNs model to predict the 1D nonlinear seismic site response for a specified area in Tehran , Iran subjected to Baladeh Earthquake (2004, Ms6.5, Iran) as input motion to site. In the presented model, the importance of the soil behaviour using the in-situ and laboratory geotechnical tests as well as geophysical surveying are considered to simulateand generate the earthquake site response. Application of simultaneous different ANNs training algorithms, as well as using the results of in-situ tests to predict the nonlinear seismic site response is the main advantage of this paper which converted to probability analysis. The comparison of the obtained results from presented model and conventional dynamic site response as well as evaluating using various statistical and analytical criteria, indicate an attractive alternative method with the ability to cover some limitations of the conventional and it is shown that these can be solved by using the ANNs based models.

ANNs concept

An ANN as a mathematical or computational model of biological neural networks is a dense and highly interconnected adaptive simple processing elements (neurons) which are interconnected via a set of weights to allow signals to travel through the network in parallel. The learning rule of ANNs is one major difference compared with traditional statistical or rule-based systems. At the very beginning of a training process an ANN contains no explicit information. Then a large number of cases with a known outcome are presented to the system and the weights of the inter-neuronal connections are changed by a training algorithm designed to minimise the total error of the system. A trained network has extracted rules that are represented by the matrix of the weights between the neurons. This feature is called generalisation and allows the ANN to predict cases that have never been presented to the system before. These abilities make ANNs to be useful predicting various events and inparticular complex, non-linear, and time depending relationships (Schalkoff, 1997; Fausett, 1994; Boussabaine, 1996).

As presented in Figure1, the input signals come from either the environment or outputs of other processing elements (PEs) and form an input vector (Eq.1).

$$P = (p_1, \dots p_i, \dots p_n) \qquad (1)$$

where, p_i is the i^{th} PE input. There are weights (w_1, w_2, . . . ,w_n) bound to the input connections as well as bias b for each neuron. The sum of the weighted inputs and the bias form the net input signal, n, can be calculated by Eqs.2 and 3.

$$n = \sum_{i=1}^{n} w_{ij} p_i + b_j \qquad (2)$$

$$\mathrm{w} = \begin{bmatrix} \mathrm{w}_{11} & \mathrm{w}_{12} & \cdots & \mathrm{w}_{1j} \\ \mathrm{w}_{21} & . & & \vdots \\ \vdots & \vdots & & \vdots \\ \mathrm{w}_{i1} & \dots & & \mathrm{w}_{ij} \end{bmatrix} \qquad (3)$$

The input signal is then sent to a transfer function, which serves as a non-linear threshold. The transfer function calculates output signal of the PE (j) as Eqs.4 and 5.

$$a_j = f(n) \qquad (4)$$

$$f = \left(\begin{bmatrix} \mathrm{w}_{11} & \mathrm{w}_{12} & \cdots & \mathrm{w}_{1j} \\ \mathrm{w}_{21} & . & & \vdots \\ \vdots & \vdots & & \vdots \\ \mathrm{w}_{i1} & \dots & & \mathrm{w}_{ij} \end{bmatrix} \times \begin{Bmatrix} \mathrm{P}_1 \\ \mathrm{P}_2 \\ \vdots \\ \mathrm{P}_i \end{Bmatrix} + \begin{Bmatrix} \mathrm{b}_1 \\ \mathrm{b}_2 \\ \vdots \\ \mathrm{b}_i \end{Bmatrix} \right) = \begin{Bmatrix} \mathrm{a}_1 \\ \mathrm{a}_2 \\ \vdots \\ \mathrm{a}_i \end{Bmatrix} \qquad (5)$$

where, a_j is the output signal from PE(j); f is a transfer function; and n is the net input signal to PE(j).

Except for the input layer, all neurons in the back-propagation network are associated with a bias neuron and a transfer function (Figure1). Transfer functions are used to transform the weighted sum of all input signals to a neuron and determine the neuron output strength. The bias is much like a weight, except that it has a constant input of 1, while the transfer function sifts the summed signals received from this neuron (Majidi and Rezaei, 2013; Basheer and Hajmeer, 2000).

Convergence is the eventual minimization of error between the desired and computed PE outputs. One common convergence methodis convergence in the means-squaresense (Eq.6).

$$\lim_{n \to \infty} E\{|x_n - x|^2\} = 0 \qquad (6)$$

where, E{x}represents the estimated value of x.

The typical performance function that is used for training multilayer feedforward network is the mean sum of squares of the network errors (MSE) as given in Eq. 7.

$$MSE = \frac{1}{2} \sum_k (t_k - a_k)^2 \qquad (7)$$

Where; t_k is the target output at layer k and a_k is the final output at the output layer.

The achieve the minimum error during the learning process iterations, the derivative of MSE with respect to weight is computed and back-propagated to the layers to compute the new weight value. Asin Figure2, this operation is known as the delta rule (Eq. 8). Then the new weight value at $(t+1)^{th}$ iteration between output layer to hidden layer j can be calculated by Eq.9.

$$\Delta w_{kj}(t) = -\eta \frac{\partial MSE}{\partial w_{kj}} + \beta \Delta w_{kj}(t-1) \qquad (8)$$

$$w_{kj}(t+1) = \Delta w_{kj}(t) + w_{kj}(t) \qquad (9)$$

Where; η and β are the learning and momentum parameters and t is the number of iteration respectively.

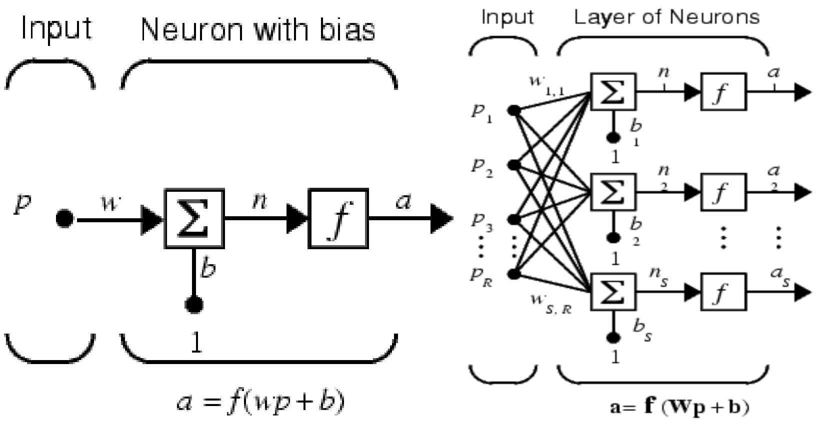

Figure 1. Concept of a neroun (left) and multineurons (right) processing system with associated bias (Asadniya, 2015)

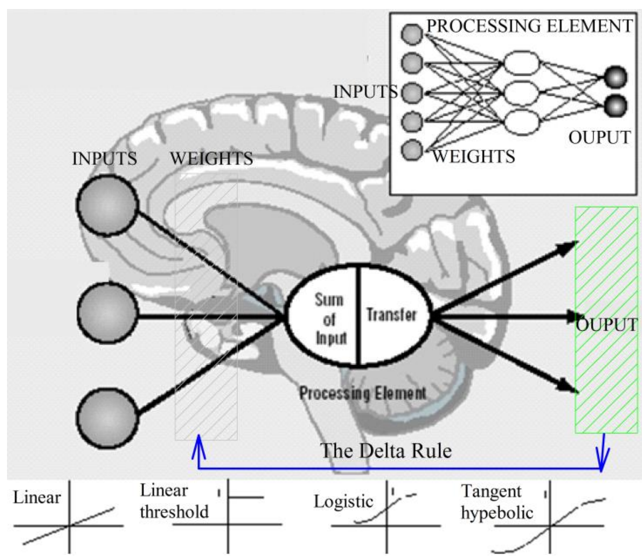

Figure 2. Data processing procdure in artificial neurons and common used activation functions (the activation function of a neuron implies the threshold value)

Selected area and available datasets

Alborz mountains in north of Iran as boundary of southern Caspian depression and central Iran is a high seismic active belt. The Central Alborz is the site of historical and recent large earthquakes. Considering the quick expansion of the cities such as Tehran which are located in this zone and due to their socio-economical activities, great attempts are need to characterize seismicity studies. Based on the existing data, Tehran has so far been hit by over 1000 small and big earthquakes within the 100 kilometers of its around (Figure3). Existance of several active faults that with mostly compressional component indicate possible longer recurrence interval and hence stronger earthquakes (Table 1).

Tehran province in approximately in north of Iran with an area of 19196Km^2 as well as 1190m height from the sea level is situated between 50° 10' to 53° 10' east longitude and 34°52' to 36°21' north latitudes.

Tehran as the capital and largest city of both Tehran province and Iran is located in this high risk seismic area. It should arouse more concern to the seismic safety of this city given that the last damaging earthquake occurred nearly 200 years ago, and the geotechnical condition in the study area possibly could cause site amplification. The sesected area in this study (Figure4), is situated in north of Tehran at the flank of Alborz mountains belt as afored mentioned.

The target area in this paper contains a huge 15 stories steel structure for the purpose of providing a trade center as well as private and governmental offices (Adadniya, 2015).

Considering to importance of data collection as well as their quality in ANNs (Wang and Strong, 1996), a greatbattempt has been made to use those data which can be obtained directly from mechanical, geotechnical and geophysical tests. This task has been performed using the retrieved core samples from 14 drilled boreholes with maximum depth of 40m related to selected site. The histogram variation and frequency content of some data based on the samplinfg depth are given in Figure5.

The collected data are categorized in borelog data (e.g. soil layer, types and thickness, depth to bedrock level) and in-situ and laboratory test data (e.g. SPT, sieve analysis, unit weight, shear wave velocity (V_S), Atturberg limits, ground water table). The provided ANNs model in this study is based on 1D nonlinear seismic site response analysis under baladeh earthquake provokes (2004, Ms 6.5, Iran) as input motion to idealized soil profile of selected site (Figure6) (Asadniya, 2015).

The obtained data from standard penetration test (SPT), soil type, V_S, thickness, depth to bedrock, density and Atturberg limits (Liquid limit, LL; Plasticity limit, PL) were the used as ANN inputs and the pseudo spectral acceleration (PSA) as output respectively. The SPT provides an indication of the relative density of the subsurface soil and is used in empirical geotechnical correlation to estimate the approximate shear strength properties of the soils. The observed soil types in the studied site are classified based on Unified Soil Classification System (USCS) and were coded to be applicable in ANN. The V_S were obtained from borehole logging test. The complexity of soil deposit structures cause a highly nonlinear behavior in site response analysis which is contributed to quantitative physical parameters such as V_S and damping factors (De Martin, 2010; Johnson et al., 2009). Therefore, it is necessary to know the soil related properties and the variability in V_S with change in soil properties.

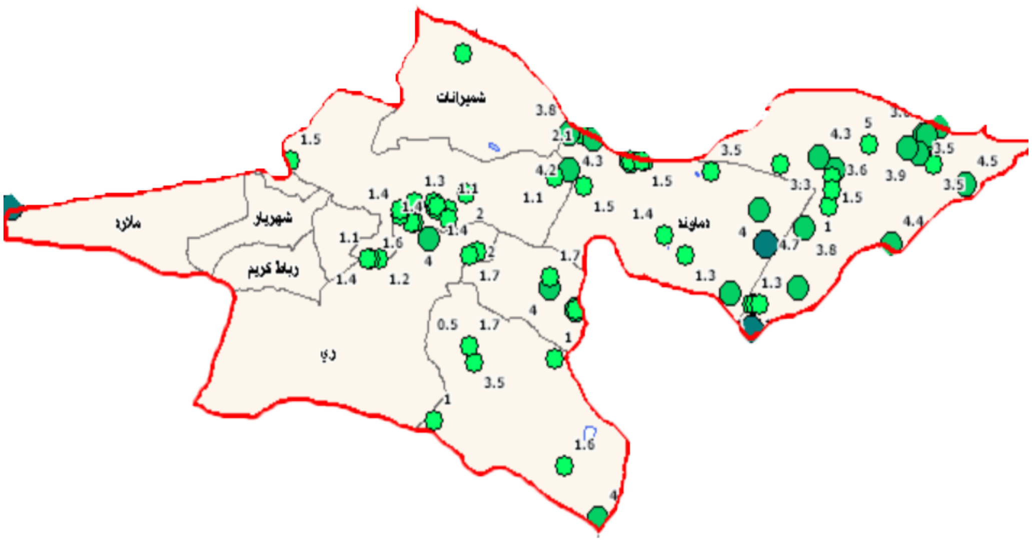

Figure 3. Recent recorded earthquakes in Tehran Province with magnitude between 1 to 5 in Ritcher scale (Adaniya, 2015)

Table 1. Poperties and distance of several potential seismic fault respect to selected site (Asadniya, 2015)

Minimum distance to selected site (Km)	Length (Km)	Potential seismic source
1.40	75	North Tehran thrust
0.50	18	Niyavaran thrust
0.80	11	Mahmoudiyeh fault
4.10	18	Shiyan Kosar fault

Converting the optimized ANN model to probability analysis

The ANN model to predict the nonlinear seismic site response was found throught the trial and error method. A Matlab code is developed to test several training algorithms as well as various activation transfer functions. The Limited memory quasi Newton, conjugate gradient descent and Levenberg-Marquardt were the implemented algorithms. The logistic, hyperbolic tangent and linear functions were used for activation of hidden and output layers and the sum-of squares were impelented as output error function respectively. By application of the developed code, more than 700 structures using different training algorithms with various activation function in hidden layers were controlled. The optimized model were selected via the network correlations and minimum root mean square error (RMSE) criteria. The results showed that, the 8-6-3-5-1structure (Figure7) under limited memory quasi Newton training algorithm and hyperbolic tanget activation function satisfied the used criteria. The characteristics of used database and tested models are given in Tables (2) and (3). The percentage of data for training, testing and validation with randomized selection were considered as 55%, 25% and 20% respectively.

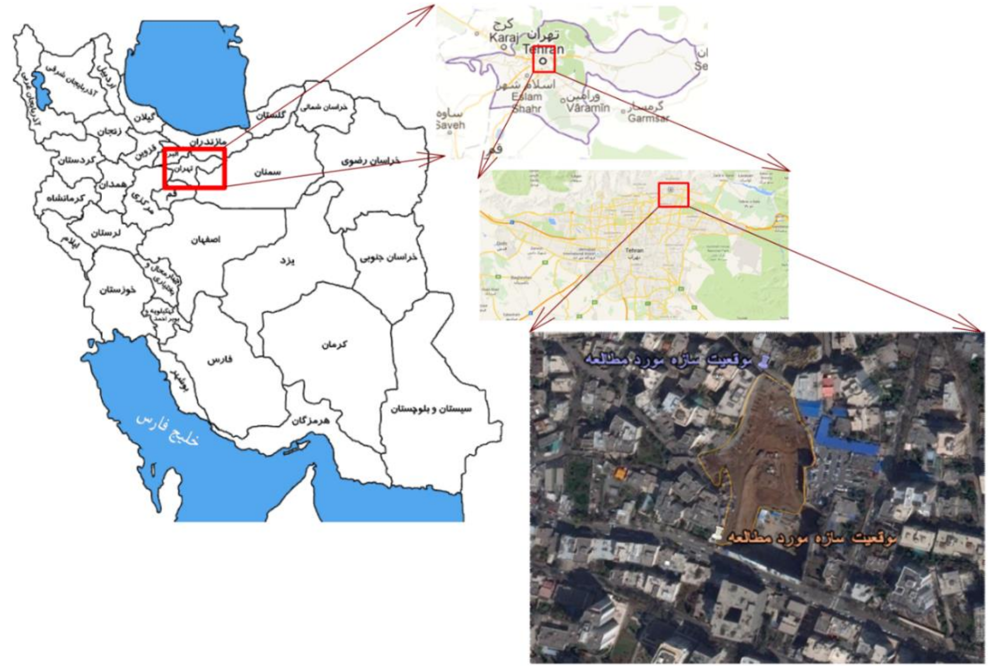

Figure 4. Location of Tehran province and and selected target in this study (Asadniya, 2015)

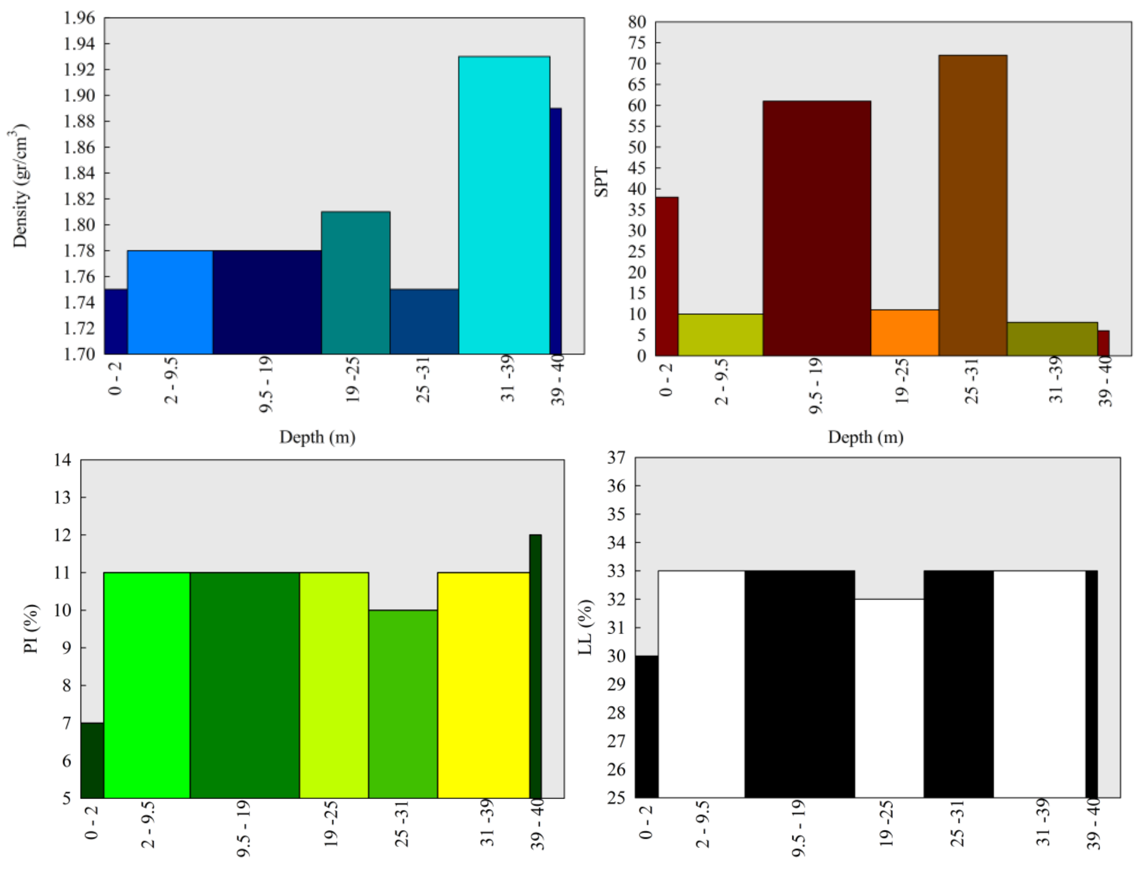

Figure 5. Some of the idealized soil profile parameter in the selected area (Asadniya, 2015)

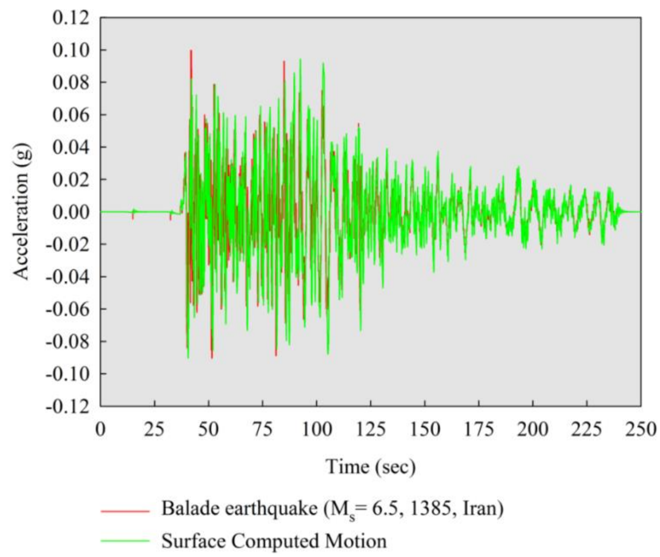

Figure 6. Recorded of baladeh earthquake in Tehran station as the selected input motion to site and correspond computed surface motion (Asadniya, 2015)

Table 2. Results of tested algorithms using 8-6-3-5-1ANN structure model

ANN training algorithm	Network error	Network correlation	Number of iteration	Activation function	
				Hidden layer	Output layer
Limited memory quasi-Newton	0.0258	0.895	501	hyperbolic tangent	hyperbolic tangent
conjugate gradient descent	0.0342	0.843	501	logistic	logistic
Levenberg-Marquardt	0.0351	0.824	501	logistic	hyperbolic tangent

Table 3. Characteristics of employed ANN architecture

Number of input neurons	8		
Number of output neurons	1		
Number of hidden layers	3 layers (layer 1: 6; layer 2: 3; layer 3: 5)		
Number of total dataset	113		
Activation function	Hidden and output layer: Hyperbolic tangent		
Range of input data for ANN	Soil type	1 (SM)	4 (CL)
	SPT-N value	6 (Min)	72 (Max)
	Shear wave velocity (m/s)	169.04 (Min)	394.04 (Max)
	Depth (m)	0 (Min)	40 (Max)
	PI (%)	7 (Min)	12 (Max)
	Thickness (m)	1 (Min)	9.5 (Max)
	Density (gr/cm^3)	1.75 (Min)	1.93 (Max)
	LL (%)	30 (Min)	33 (Max)

After training the ANN model (Figure6), the associated weights to all individual inputs (outside inputs or intra-NN inputs) are fixed and then can be used for classifying purposes. Therefore, The main algorithm is to compute an activation value for each neuron, as the sum of the input, x, weight for that neuron. This value is then fed to an activation function which purpose's is to normalize it and then convert it to a Boolean. The activation function can be more complex than linear as this study considered (logistic and hyperbolic tangent). The basic algorithm then processes all neurons at a given layer before proceeding to the next. Therefore, using the perceptron's ability to qualify its guess with a percentage value, finds an easy answer. The model output (s) will be real-valued (if anything in need of normalizing) before convert to a discrete value (a boolean or a category ID in the case of several categories), using the activation functions and the threshold. The receiving the percentage depends on the NN implementation, and more importantly, the implementation dictates the type of normalization functions that can be used to bring activation values in the 0-1 range and in a fashion that the sum of all percentages add up to 1. In its simplest form, the activation function can be used to normalize the value and the weights of the input to the output layer to ensure the add up to 1. The results of this operation process are presented in Figure8 and Table (4).

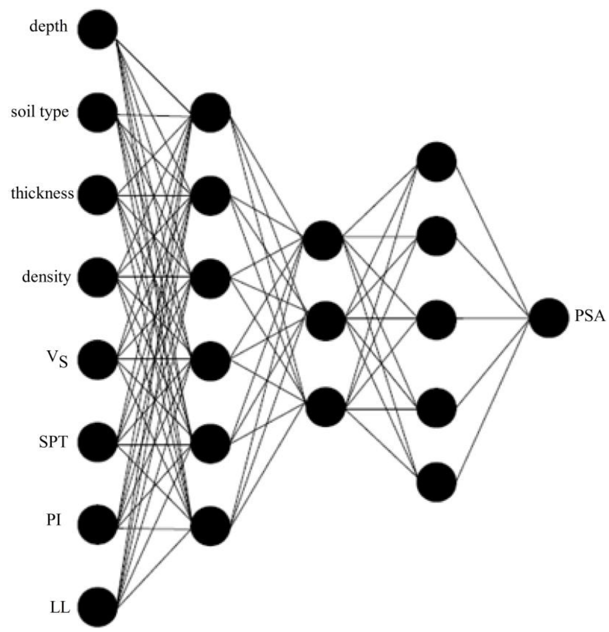

Figure 7. Structure of optimized ANN model to predict the nonlinear site response in this study (Asadniya, 2015)

RESULTS AND DISCUSSION

The performance of introduced optimized model can be investigated using different statistical criteria as given in Eq. 8 to 12 (mean absolute percentage error, MAPE; variance account for, VAF; variance absolute relative error, VARE) as well as absolute error (AE) and absolute relative error (ARE). The better model performance can be found in higher correlation coefficient and VAF as well as lower RMSE, MAPE, VARE, MEDAE, AE and ARE (Table5).

$$MAPE = \frac{1}{n} \times \left[\sum_{1=1}^{n} \left|\frac{t_i - x_i}{t_i}\right| \times 100\right] \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n} \times \left[\sum_{i=1}^{n} [(t_i - x_i)^2]\right]} \quad (11)$$

$$VARE = \frac{1}{n} \times \left[\sum_{i=1}^{n} \left(\left|\frac{t_i - x_i}{t_i}\right| - mean\left|\frac{t_i - x_i}{t_i}\right|\right)^2\right] \times 100 \quad (12)$$

$$VAF = \left[1 - \frac{var(t_i - x_i)}{var(t_i)}\right] \times 100 \quad (13)$$

The AE and ARE values define the deviation of the predicted output from the desired values. The AE (in percentage term) is the difference between the actual and predicted values whereas the ARE index is calculated by dividing the difference between actual and desired output values by the module of the desired output value. Both of AE and ARE are correspond to model quality and hence smaller error indicates better performance in training (Figure9). Furthermore, the data scattering using the employed training algorithms regarding a 1:1 slope line is presented in Figure10. The located data on this 1:1 slope line can be interpreted as exact prediction.

Using the sensitivity analysis, the effectiveness of input parameters on output can be calculated. In the current paper the Cosine Amplitude (Jong and Lee, 2004) (Eq. 14) was used and presented in Figure11. As it can be seen, in the present study V_S and soil type are introduced as the most effective factor on site response spectrum whereas the density is the least one.

$$R_{ij} = \frac{\sum_{k=1}^{m}(x_{ik} \times x_{jk})}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}}, x_i \text{ and } x_j\text{: elements of data pairs} \quad (14)$$

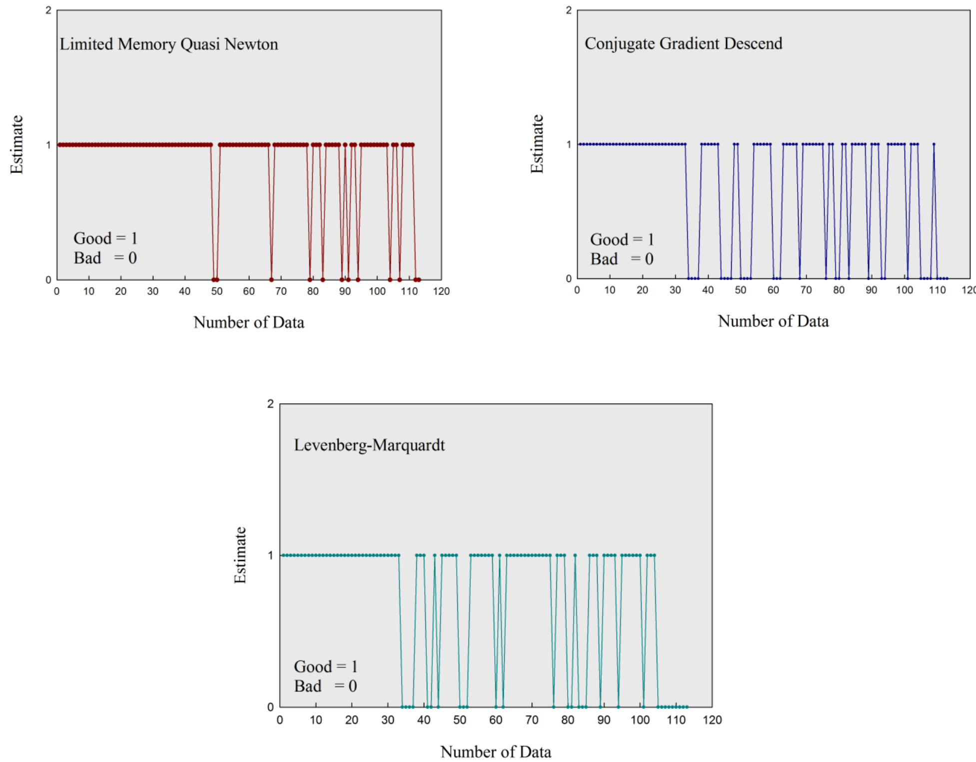

Figure 8. Probablity analysis of training algorithms in this paper using the optimized model (Asadniya, 2015)

Table 4. Converted results of optimized ANN model to probability analysis (Asadniya, 2015)

Training Algorithm	Accuracy in probability analysis	Probability (%)
Limited memory quasi Newton	0.8938	89.38
Conjugate gradient descent	0.7168	71.68
Levenberg-Marquardt	0.7345	73.45

Table 5. Results of statistical criteria for tested ANN algorithms

	Limited mmory quasi Newton	conjugate gradient descent	Levenberg-Marquardt
MAPE	4.08	7.20	8.21
RMSE	0.0258	0.0342	0.0351
VARE	0.164	0.436	0.706
VAF	98.7	97.9	97.3
R^2	0.981	0.968	0.952

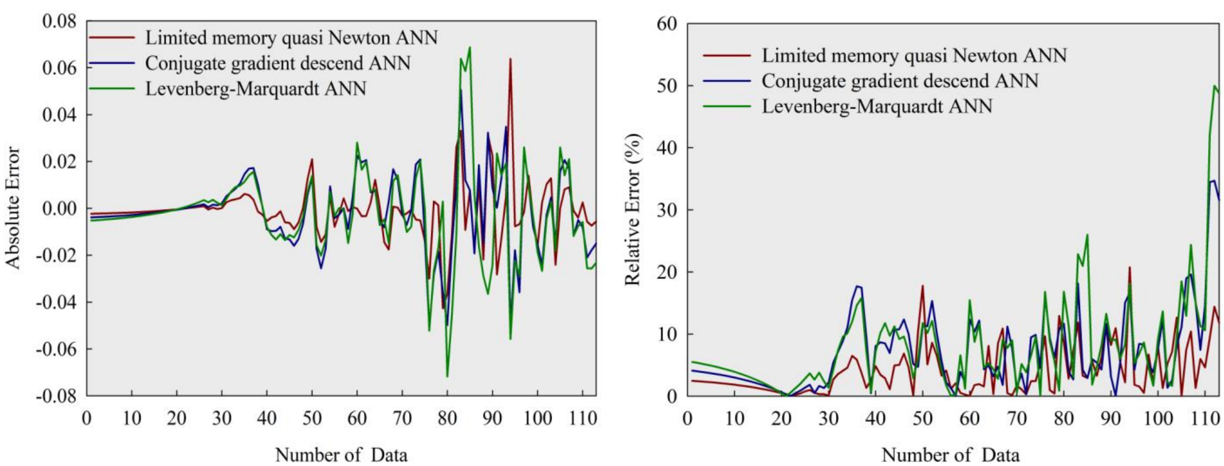

Figure 9. Comparison of AE and ARE(%) using different algorithms for optimized ANN model (Asadniya, 2015)

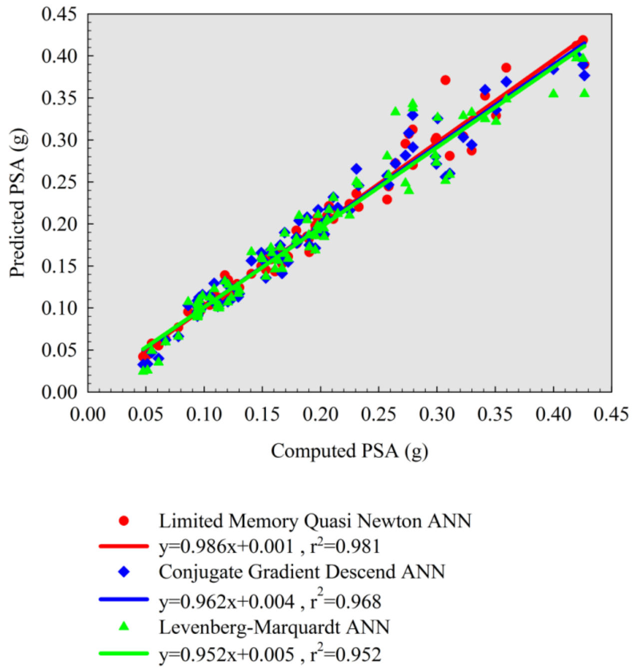

Figure 10. Data scattering of implemented ANN training algorithms regading a 1:1 slope line (Asadniya, 2015)

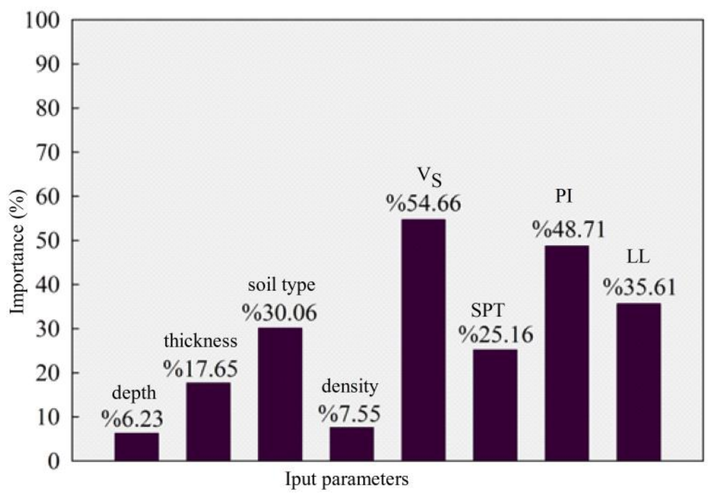

Figure 11. Influence of input parameters on output of optimized ANN model in this study (Asadniya, 2015)

Considering that the required data for 1D site response analysis, the introduced optimized ANN model uses less types of input data which can be obtained from routine in-situ or laboratory tests. The conducted comparison between ANN's outputs and conventional dyanamic time domain nonlinear analysis show propoer compatibility (Figure12). The generated PSA response spectrum can provide a convenient and practical way to summarize the frequency content of a given acceleration, velocity or displacement time history as well as knowledge of structural dynamics to design of structures and development of lateral force requirements in building codes. The PSA also provides a physically meaningful quantity which is useful in understanding the nature of an earthquake and its influence on the design.

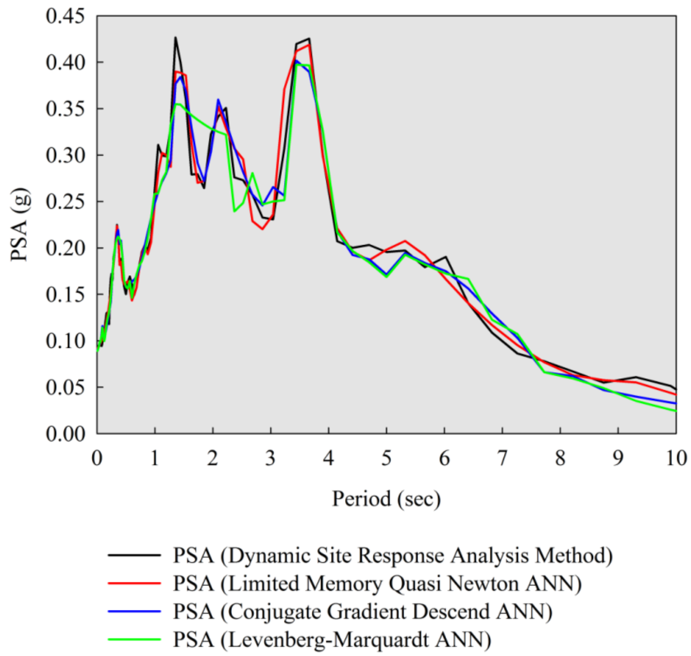

Figure 12. Comparison of obtained results of tested ANN algorithms and dynamic analysis in the study area (Asdniya, 2015)

CONCLUSIONS

In this paper using a simple approach, the results of an optimized developed ANN model converted to probability analysis. The appropriate condition of predicted site response spectrum using the optimized ANN model indicate an economical applicable alternative method to replace for the conventional 1D nonlinear seismic analysis. Using simple accessible data as well as different training algorithms and various activation functions gives the opportunity for better quality performance respect to numerical analyses methods and proved by applying several statistical criteria and the sensitivity analysis. The tested model for a specified area in Tehran showed good results. However the introduced model can be considered as the intial guess to developed for another area because, the ANN models are varied from case to case.

The results proved that the optimized ANN model is simpler, more effective and economical rather than the complicated dynamic procedures which may be required special softwares and data.

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