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ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTION OF LIQUEFACTION POTENTIAL IN SOIL DEPOSITS

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ABSTRACT

With the increase in population, the evaluation of liquefaction is becoming more important for land use planning and development. In soil deposits under undrained condition, earthquakes induce cyclic shear stresses, may lead to soil liquefaction. Artificial neural network (ANN) is one of the, artificial intelligence (AI) approaches that can be classified as machine learning. Simplified methods have been practiced by researchers to assess nonlinear liquefaction potential of soil. In order to address the collective knowledge built up in conventional liquefaction engineering, an alternative general regression neural network model is proposed in this paper.

To meet this objective, a total of 30 boreholes are introduced into the model. The data includes the results of field test from (Babol, Mazandaran, Iran).

The results produced by the proposed Artificial Neural Network model compared well with the determined liquefaction decision obtained by simplified methods. It provides a viable liquefaction potential assessment tool that assist geotechnical engineers in making an accurate and realistic predictions. Furthermore, this study integrates knowledge learned from field test and seismic parameters to the ongoing development of liquefaction analysis.

The results show that there is liquefaction potential in western part of Babol, and in southern part of Babol no liquefaction potential were seen. In middle part and eastern part low liquefaction potential were predicted by ANNs. This study shows that neural networks are a powerful computational tool which can analyze the complex relationship between soil liquefaction potential and effective parameters in liquefaction.

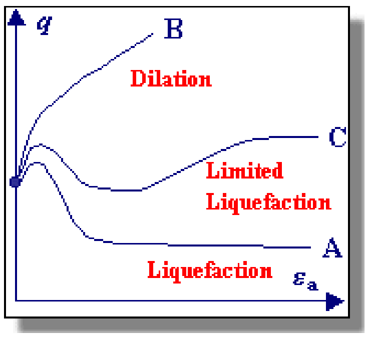
INTRODUCTION

When saturated sand deposits are subjected to earthquake-induced shaking, pore water pressures are built-up leading to liquefaction or loss of soil strength. Major earthquakes that have occurred during past years, such as the 1964 Alaska, 1964 Niigata, 1989 Loma-prieta and the 1995 Hyogoken-Nambu have demonstrated the damaging effects of soil liquefaction. Therefore, it is necessary to obtain a proper understanding of effective parameters such as soil properties and nature of earthquake on severity of soil liquefaction (Seed HB, Idriss IM, Makdisi F, Banerjee N).

Liquefaction is a phenomenon in which the strength and stiffness of a soil is reduced by earthquake shaking or other rapid loading. During the liquefaction, pore water presure exerts a pressure on the soil particles that influences how tightly the particles themselves are pressed together. Prior to an earthquake, the water pressure is relatively low (Ishihara K, Yasuda S). However, earthquake shaking can cause the water pressure to increase to the point where the soil particles can readily move with respect to each other.Earthquake shaking often triggers this increase in water pressure, but construction related activities such as blasting can also cause an increase in water pressure.

When liquefaction occurs, the strength of the soil decreases and, the ability of a soil deposit to support foundations for buildings and bridges is reduced (Seed HB, Idriss IM).

In the 1960, Gonzalo Castro, a student of Casagrande, performed an important series of undrained, stress-controlled triaxial tests. Castro observed three different types of stress-strain behavior depending upon the soil state. Dense specimens initially contracted but then dilated with increasing effective confining pressure and shear stress. Very loose samples collapsed at a small shear strain level and failed rapidly with large strains. Castro called this behavior liquefaction; it is also commonly referred to as flow liquefaction. Medium dense soils initially showed the same behavior as the loose samples but, after initially exhibiting contractive behavior, the soil transformed and began exhibiting dilative behavior. Castro referred to this type of behavior as limited liquefaction (Whitman RV).



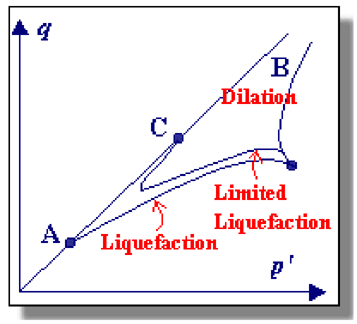


Fig. 1.Static triaxial test stress paths for two specimens of different densities.

Ground response analyses based on the finite element method provide a better assessment of liquefaction of a soil deposit by taking into account the nature of the earthquake and the pore pressure dissipation; they are often costly and time consuming. In addition, constitutive models used in those programs need large number of parameters to determine the pore pressure generation in soil due to earthquake loading. Therefore, simplified methods in assessing soil liquefaction are popular among practicing engineers. These procedures are very useful at the preliminary design stages to assess the liquefaction risk. If the liquefaction risk is high, then a detailed finite element analysis can be carried out to obtain the pore pressure distribution and ground displacement along the depth of the soil deposit, which is necessary in subsequent design of deep foundations. In more details improving the reliability of liquefaction risk, may lead to cost reduction and helps to operation planning (NCEER).

An artificial neural network is a mathematical model or computational model based on Biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

Artificial neural networks mimic human brains to learn the relationships between certain inputs and outputs from experience. They are considered as information processing systems that have the abilities to learn, recall and generalize from training data. An ANN consists of several layers of highly interconnected computational units called neurons. Figure 2 shows the general structure of a three layer feed-forward ANN. The neural network contains one input layer, one or two hidden layers, and one output layer The number of nodes in the input layer equals the number of parameters in the process. The output layer represents the quality responses of the product (Agrawal, G., Weeraratne, S., and Khilnani, K). The hidden layer represents the interactions between the input and output layers. Normally the number of nodes in the hidden layer is set to be half of the total number of input nodes and output nodes. If the relationships between the operation parameters and quality responses are difficult to identify, two hidden layers may be used. Such neural networks are capable of capturing complex nonlinear relationships inherent in a process (Hornik K).

The ANN uses a set of examples in a training database as input, a learning algorithm to adjust the weights and an activation function to derive an output. If the connection weight between the neurons is changed, the relationship of the network's output to its input will be altered. The process of adjusting the connection weights by repeatedly exposing the network to known input-output data is called training. The error back-propagation learning method is the most popular and successful training technique. A trained ANN can take inputs and produce outputs very quickly, which is an advantage in doing optimization in the proposed approach (Agrawal, G., Chameau, J. A., and Bourdeau, P. L).

ANNs have been proved to be an universal estimator, hence they are promising techniques in solving pattern recognition and classification, optimization and function approximation problems. Recently, ANNs are used to model complex manufacturing processes and to identify the optimal process setting. In this research, the ANN is used to establish the nonlinear multivariate relationships between liquefaction potential and parameters, which can be used to predict the liquefaction potential in soil.

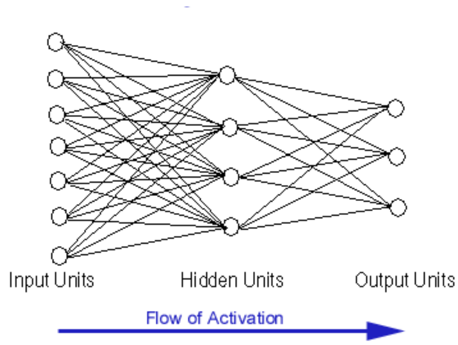


Fig. 2. A three-layer feed-forward neural network structure.

Recently, extensive studies have been done on application of ANN to Geotechnical engineering problems. Chan et al. (1995) developed a neural network as an alternative to pile driving formulae. The network was trained with the same input parameters listed in the simplified Hiley formula (Broms and Lim 1988), including the elastic compression of the pile and soil, the pile set and the driving energy delivered to the pile (Abu-Kiefa, M. A).

Lee (1996) utilized neural networks to predict the ultimate bearing capacity of piles. The problem was simulated using data obtained from model pile load tests using a calibration chamber and results of insitu pile load tests. Teh et al. (1997) proposed a neural network for estimating the static pile capacity determined from dynamic stress-wave data for precast reinforced concrete piles with a square section.

Sivakugan et al. (1998) explored the possibility of using neural networks to predict the settlement of shallow foundations on granular soils. A neural network was trained with five inputs representing the net applied pressure, average blow count from the standard penetration test, width of foundation, shape of foundation and depth of foundation. The output was the settlement of the foundation (Riedmiller, M. and Braun, H).

Most recently, Shahin et al. (2000) carried out similar work for predicting the settlement of shallow foundations on cohesionless soils. In this work, 272 data records were used for modelling. The input variables considered to have the most significant impact on settlement prediction were the footing width, the footing length, the applied pressure of the footing and the soil compressibility (). The results of the ANN were compared with three of the most commonly used traditional methods. These methods were Meyerhof (1965), Schultze and Sherif (1973) and Schmertmann et al. (1978). The results of the study confirmed those found by Sivakugan et al. (1998), in the sense that ANNs were able to predict the settlement well and outperform the traditional methods (Cal, Y).

Ellis et al. (1995) developed an ANN model for sands based on grain size distribution and stress history. Sidarta and Ghaboussi (1998) employed an ANN model within a finite element analysis to extract the geometerial constitutive behaviour from non-uniform material tests. Penumadu and Jean-Lou (1997) used neural networks for representing the behaviour of sand and clay soils. Ghaboussi and Sidarta (1998) used neural networks to model both the drained and undrained behaviour of sandy soil subjected to triaxial compression-type testing. Penumadu and Zhao (1999) also used ANNs to model the stress-strain and volume change behaviour of sand and gravel under drained triaxial compression test conditions. Zhu et al. (1998a; 1998b) used neural networks for modelling the shearing behaviour of a fine-grained residual soil, dune sand and Hawaiian volcanic soil (Malvić, T., Velić, J. And Cvetković).

It is known, that the engineering properties of soil varied from point to point and uncertain behaviour due to the complex and partially predictable physical processes associated with the forming of these deposits. This is in contrast to most other civil engineering materials, such as steel, concrete and timber, which exhibit far greater homogeneity and isotropy. In order to cope with the complexity of geotechnical behaviour, and the spatial variability of soil deposits, traditional forms of engineering design models are justifiably simplified. It is also known, that assessing liquefaction potential of soil plays an important role in geotechnical evaluation for construction of major structures (Cvetković).

Several methods for liquefaction assessment have been developed. One method of analyses (Seed and Idriss) proposes using the estimated shear stress level and cycle number likely to be developed in the field, due to a design earthquake. Comparison of these stresses with those causing liquefaction of soil samples obtained from laboratory tests helps identifying the liquefiable zones of a deposit. Another method (Seed et al.) considers field observations of performance of sites during previous earthquakes. By combining the data on earthquake characteristics and insitu properties of soil deposits, an empirical relationship is established.

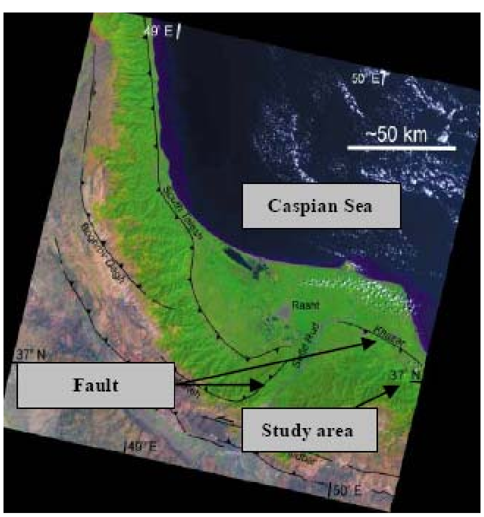
The purpose of this research is to investigate the effect of the soil and seismic parameters, with an artificial intelligence computational tool, and its success in assessing liquefaction potential (National Research Council).

Data collection in explored soils is important for assessing of liquefaction as well as estimation of strata thickness, soil type, groundwater table etc. It is also time consuming and often expensive process, which includes many field and laboratory experiments. Therefore reliable prediction of liquefaction asks for carefully planning of sampling, testing and exploration methods. Data had been collected from the boreholes (maximum depth: 30 m) over a 6 square kilometres area of Babol municipal region. Artificial neural networks are trained with 60% and validated with 10% of borehole data for prediction of liquefaction. The whole system is eventually tested for efficiency, using 30% of borehole data left for test of the network, distributed randomly over the study area. Based on the obtained results and considering that the test data were not presented to the network in the training and validation process, it can be stated that the trained neural networks are capable of predicting variations in the liquefaction potential of soil with an acceptable level of confidence (Malvić, T. And Prskalo, S).

Successful prediction of liquefaction in soil deposit using the existing data leads to improve the reliability of data which will be used for construction in future. Such approach is presented in the following text that generally comprises presentation of the study area, then description and selection of the neural model, its training, improving, and developing of final model used for prediction of liquefaction by specific ANN (Agrawal, G., Weeraratne, S., and Khilnani, K).

MATERIALS AND METHODS

Babol, a city of Mazandaran province in the northern part of Iran, is considered as the study area. As shown in Figure 3 the city is located approximately 20 kilometres south of Caspian sea on the west bank of the river Babolrood and receives abundant annual rainfall. Babolrood has 2 groups of river terraces, namely H1 and H2. H1 is referred to as river terraces with down surface level of height one to 2.5 (m) and width of 0 to150 m. It is as boundary of active (yearly) flood plain in parts of river and it is as alternative flood plain in many sections. It consists of fine-grained and unconsolidated alluvial sediments. H2 is referred to as river terraces; with high surface level of 4-6 (m). Vegetation on surface of terrace is compact. It consists of materials of Aeolian deposits (i.e. loess). Most major earthquakes occur around the boundaries of the tectonic plates such as those that exist in north of Iran.



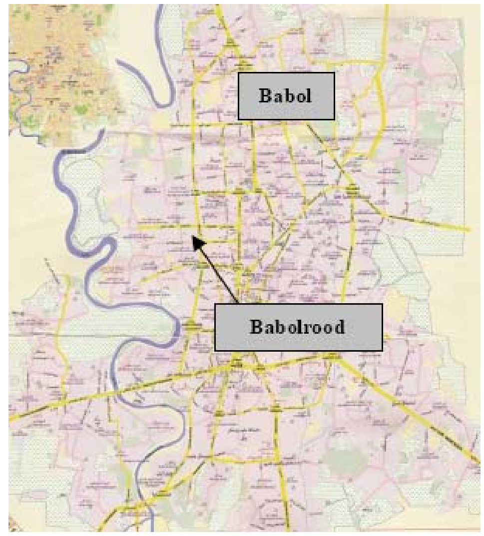
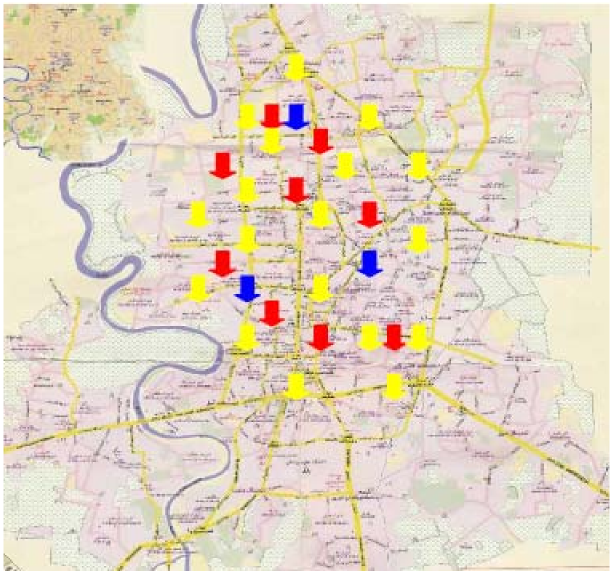


Fig. 3. Map of study area (top) and the zone of the Babolrood river (bottom).

Very often in geotechnical engineering, it is possible to encounter some types of problems that are very complex and can not be completely understood. Mathematical models that attempt to solve such problems can not included entire physics of process and necessarily need to simplify the model or incorporating some assumptions. Mathematical models also assumed the knowing of model structure in advance, which does not need to be optimal. Consequently, many mathematical models fail to simulate the complex behavior of most geotechnical engineering problems. In contrast, ANNs are based mostly on the input data structure, assuming that such structure and interaction among data can describe the prediction model. In this case, there is no need to neither simplify the problem nor incorporate any assumptions (expect user selection of data that are in some meaningful connection). Moreover, one obtained neural models can always be again trained with more extensive and newer dataset from the same area with goal to reach better results.

The data used in presented research, includes borehole logs (data collected from digging boreholes) bored in the study area (Figure 4) and is collected by different institutions for different research purposes. The database includes more than 40 borehole logs in an area of more than 6 square kilometres from Babol zone.



Training borehole ….

Validation borehole …

Testing borehole …….

Fig. 4. The 6 zones in Babol area.

From the total of 40 raw borehole data, only 30 logs with a depth range of 10 to 30 meters were acceptable for using in ANN. The regular tests were performed on the samples.

The available data set is divided into three sets, namely training, validation, and test sets, based on random selection. This way we can examine the validity of the model in a more comprehensive manner (Choobbasti AJ, Farrokhzad F, Barari A). In ANN forecasting models, 60% of the records are selected as training, 30% are taken for test for final evaluation, and the remaining 10% used for validation or monitoring the performance of the model during the training phase (Table 1).

Table 1. Performance of different sets of data used in ANN.

	Training set	**Validation set**	**Testing set**
Number of boreholes	18	3	9
Number of data (I/O data pairs)	1500	250	750

In problems dealing with different variables and with different ranges and dimensions, the application of several networks may be a good choice. Neural networks are efficient tools when used as pattern classifiers, it is important to properly select the input variables for training (learning) process of ANNs, as the way how to determine relationships between input and output variables. A set of known input and output values is named as input-output pair. All such pairs are usually divided into three sets. The first and second are described as training and validation sets which are used to determine the connection weights or weighting coefficients (like in interpolation methods), usually marked as w_{ij}[1], Also the training and validation sets are used during the training process and the test set is used for obtaining the estimates. All ANN models was trained using the automated regularization algorithm to improve generalization. The validation set served as a constraint on training, in order to minimize over fitting.

The usefulness of the neural network approach for populating the similarity model is presented In this case study. The inputs to the network were data on a set of soil formative environmental factors; the output from the network was a set of similarity values to a set of prescribed soil classes divided by grain size, thickness of each layer and groundwater table. A set of 2500 samplings are performed in study area from 30 boreholes. Data are collected using geotechnical investigation. Each sample is carefully checked, because to ensure the accurate prediction of an ANN model we need to build a reliable training, validating and testing sets.

In this analysis, regarding the available data and their quality, a neural network program written in back propagation algorithm, is used. Eight soil and seismic parameters are selected as input in different models, and these parameters are divided into data groups. Each data group is introduced to the network individually, and performance of the network on the assessment of liquefaction potential is investigated. The network predictions are compared with the conventional liquefaction determination method proposed by Seed *et al.*

Back propagation is selected as the training algorithm of neural network (Table 2). It is the best known training algorithm for multilayer perceptrons neural networks, and still one of the most useful and later improved in some advanced forms like RProp. Back propagation algorithm means that network training includes determination of the difference between true and wanted network response, i.e. means calculation of error that is backed in the neural network for obtaining optimal training. It has lower memory requirements than most algorithms, and usually reaches an acceptable estimation error quite quickly (in relative low number of iterations or epochs).

The ANN model for this study was developed, trained, validated and tested within STATISTICA computational environment utilizing the neural network toolbox. And the accuracy of the ANN model was evaluated using RMSE between measured and predicted values and pressed as:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(z_s - z_0)^2}{n}} \quad (1)$$

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[1] - $y_i^k = f(y_i' k) = f(\sum_{j=1}^{n_{k-1}} w_{ij}^k y_i^{k-1})$

Where z_s is observed value, z_0 is predicted value, n is number of samples. The RMSE of the different neurons in hidden layer is plotted in Figure 5. The ANN architecture for prediction of soil classification and layers thickness in the study area was a feed forward, supervised, multilayer perceptron (MLP) network with one hidden layer and an output layer. The best fitting training data set was obtained with six neurons in the hidden layer for prediction of liquefaction.

In the selection of learning / training algorithm number of neurons in different layers (input, hidden, output), number of epochs, learning rate and the momentum have been applied instant.

Table 2. Results of research in order to Learning / training algorithm selection.

Supervised Learning/ training algorithms	Back propagation	Conjugate Gradient Descent	Levenberg-Marquardt	Quick Propagation	Delta -bar-Delta
RMSE (%)	6.3	12.1	8.7	10	9.2
	✓(min.error)				

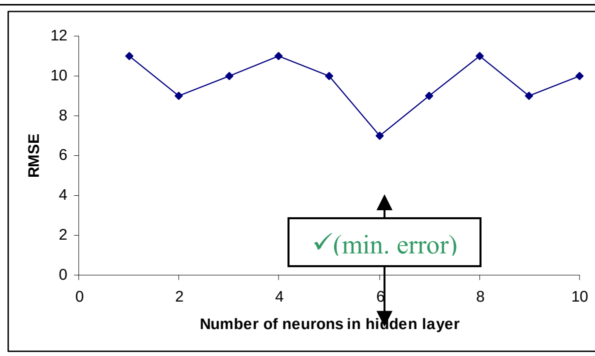

Fig. 5. The RMSE of the different neurons in hidden layer for prediction of soil liquefaction potential.

In each epoch, the entire training set is fed through the network, and used to adjust the network weights. Numbers of epochs are specified at the start, but also alternative stopping criterion may also be specified, and if over-trained network occurs the best network discovered during training can be retrieved. In this analysis, the number of epochs varied between 100 and 400.

A batch mode feed-forward multilayer perceptron (MLP) with back-propagation learning rules was used to create the desired ANN model using STATISTICA software. Also, an adaptive learning rate was employed to keep the learning step size as large as possible while the training is stable. According to a universal approximation theorem, demonstrated concurrently by several researchers for traditional MLP, a single hidden layer network is sufficient to uniformly approximate any continuous and nonlinear function. The model architecture was built with one hidden layer, a learning rate of 0.1 updated with a coefficient of 1.1 after each epoch and a momentum term of 0.9 updated with a coefficient of 0.95 after each epoch. The input vector is fully connected to the hidden neurons by a tan-sigmoid transfer function and the neurons of hidden layer are fully connected to the output layer via a linear function. Experimental studies were started with one hidden neurons to reach the optimum number of hidden neurons and desired precision. Input vector contains soil initial parameters and output (the target vector) is liquefaction potential. In order to obtain a more efficient training process, the input and target were standardized to have zero mean and unity standard deviation. Cross-validation or employing another set of data for more testing can be used to increase the generality of the models for future predictions. In this study, 10% of borehole data were used as validation set. In fact, several ANN models using element tests data were constituted for generating the models. Among them, the model with better performance (greater coefficient of determination and smaller RMSE) for validation data set was selected. In other words, the ANN models were developed with the best performance concurrently for training, testing and validation data sets. Three different ANN models were developed using different combinations of input parameters in Table 3.

It can be seen from Table 3 that, except for model #1, performances of the models are generally improved when input parameters are increased.

Table . 3. Different combinations of input parameters.

Model #	1	2	3
Input	M, $\frac{a}{g}$, $\sigma, \sigma', R_d, D_r$	M, $\frac{\tau}{\sigma'}$, V_s, R_d, σ	$V_s, \frac{\tau}{\sigma'}$, R_d, σ
RMSE	13%	17%	16%

RESULTS AND DISCUSSION

In the previous section, the learning or training dataset is used to determine the weights. Then a second validation set is used to monitor the performance of the model during the training phase and to minimize over fitting and finally the test sets to evaluate the trained neural network. It is evident from test data sets that the experimental ANN can be applied successfully to predict liquefaction potential.

The samples are divided in to 3 groups (training, validation and testing). In Figure 6 samples of testing group are correlated in terms of sample number and the accuracy (comparison between prediction and real data) of each sample is shown. In these figures, terms of the ratio of actual data per predicted value (in Y-axis) versus Case number (in X-axis) for different soil samples are presented. It is clear that if the predicted and the true values were the same, such point lie on line y=1. Scattering pattern indicates on differences. It is clear that the average correlation of the ANN model and true data in all case is over 90%. So it can be concluded, that the prediction of liquefaction potential agrees with calculated value collected from boreholes.

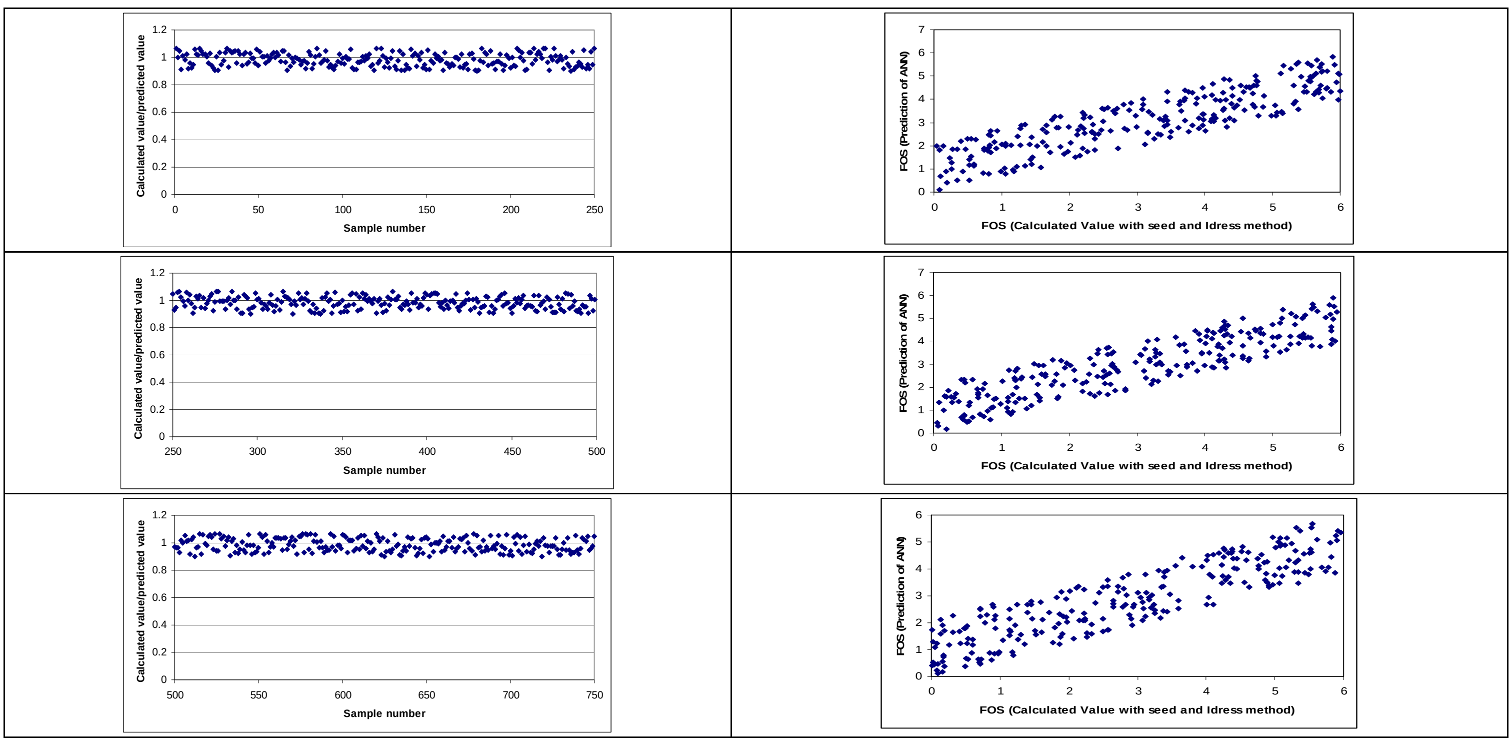

Fig. 6. Errors involved ANN for prediction of liquefaction potential.

CONCLUSION

In this research, the data used to train the model were taken from area of 6 km^2 of Babol region in the northern Iran. The dataset encompasses 2500 sampling points (samples) from 30 boreholes. The average accuracy between the ANN prediction and real data in all cases is over 90%. The liquefaction potential of a soil mass during an earthquake is dependent on both seismic and soil parameters. The impact of these soil and seismic variables on the liquefaction potential of soil is investigated through computational and knowledge based tools called neural networks. A back-propagation neural network model is utilized. The back propagation learning algorithm is a developing computational technique that assists in the evaluation of experimental and field data. The artificial neural network is trained using actual field soil records. The performance of the network models is investigated by changing the soil and seismic variables including earthquake magnitude, initial confining pressure, seismic coefficient, relative density, shear modulus, friction angle, shear wave velocity and electrical characteristics of the soil. The most efficient and global model for assessing liquefaction potential and the most significant input parameters affecting liquefaction are summarized. A forecast study is performed for the city of Babol, Iran.

Based on the obtained results, it can be stated that the trained neural networks are capable of predicting liquefaction potential with an acceptable level of confidence. It is believed that, the prediction of liquefaction potential is a complex area of research requiring detailed investigation also with other methods, fieldwork and laboratory experiments. Further work on presented topic would be very useful to modify the procedure for better adapting artificial neural network with concept of prediction of liquefaction potential.

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