Liquefaction Analysis in 3D based on Neural Network Algorithm

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SUMMARY:
Simplified techniques based on in situ testing methods are commonly used to assess seismic liquefaction potential. Many of these simplified methods are based on finding the liquefaction boundary. As the liquefaction classification problem is highly nonlinear in nature, it is difficult to develop a comprehensive model taking into account all the independent variables, such as the seismic and soil properties, using conventional modeling techniques. These various simplified procedure have been developed, using case studies that liquefied or not during earthquake, to estimate liquefaction potential of soils. In order to address liquefaction engineering, this paper proposed to use an artificial neural network. ANN has the capability to train itself with available data sets and extrapolate outcome for unknown scenario based on the training. It is particularly helpful for large data sets when human brain is inefficient. Various ANN models have already been in used for liquefaction assessment. However, this paper is more objective in applying ANN in liquefaction prediction in 3D dataset. In this study, a neural network approach is used to evaluate seismic liquefaction potential based on actual 3D field records have done. First, the data with 3D parameters used for training and testing. Second, the inputs for the model are selected on their physical meaning with respect to liquefaction. Finally, the contribution strengths of the parameters calculated to see which parameter more affects the liquefaction potential of the area. Also, with this saved model, it can be used as a forecasting tool for analysis 3D liquefaction potentials in a short way.

Keywords: Liquefaction, neural network algorithm, earthquake hazard, geotechnical earthquake engineering.

1. INTRODUCTION

Soil liquefaction is often one of the major causes of damage to buildings, highways, bridges and other infrastructure components in an earthquake. Any improvement to the existing methods for assessing liquefaction potential is a contribution to the field of civil engineering. In recent years, performance based design concepts in earthquake engineering have been receiving wider acceptance than previously. Today, artificial intelligence method approaches are new valid methods for evaluating liquefaction potential.

Liquefaction is a phenomenon in which the strength and stiffness of a soil is reduced by strong ground motion or earthquake shaking or other rapid cyclic loading. Liquefaction has historically been responsible for tremendous amounts of damage including landslides, differential settlements, lateral spreading, structural and earth system failures throughout the world.

Because of this, liquefaction problems have received a great deal of attention. Since the effect of this phenomenon on human life and the economy is significant, geotechnical engineers have given their interest to investigate this problem.

2. METHOD

This study is mainly based on numerical models. The method given in this paper is based on artificial neural network methods and these are systems and computational devices that are constructed to make use of some organizational principles resembling those of the human brain. Normally there are a large number of highly connected computational nodes (neurons) that are operated and configured in parallel regular architectures. Like human brain an artificial neural network has the ability to learn; recall and generalize from the data which are used to train the system.

Neurons are also grouped into layers by their connection to the outside world. For example, if a neuron receives data from outside of the network, it is considered to be in the input layer. If a neuron contains the network's predictions or classifications, it is in the output layer. Neurons in between the input and output layers are in the hidden layer(s). A layer may contain one or more slabs of neurons. There are different types of neural network architectures. These architectures differences are their algorithm and function formulas. In detail, a typical structure of ANNs consists of a number of interconnected processing elements (PEs), commonly referred to as neurons. The neurons are logically arranged in layers: an input layer, an output layer, and one or more hidden layers.

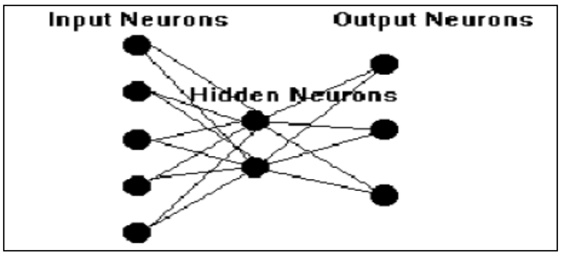

Figure 1. Neural Networks Structure [1].

The back-propagation learning algorithm is the most commonly used neural network algorithm. The back-propagation neural network has been applied with great success to model many phenomena in the field of geotechnical and geo-environmental engineering. Each neuron in a layer receives and processes weighted inputs from neurons in the previous layer and transmits its output to neurons in the following layer through links. Each link is assigned a weight that is a numerical estimate of the connection strength.

General Regression Neural Networks (GRNN) are known for their ability to train quickly on sparse data sets. GRNN is a type of supervised network. Rather than categorizing data like PNN, however, GRNN applications are able to produce continuous valued outputs. It is especially useful for continuous function approximation. GRNN can have multidimensional input, and it will fit multidimensional surfaces through data. GRNN is a three-layer network where there must be one hidden neuron for each training pattern. There are no training parameters such as learning rate and momentum as in Back propagation, but there is a smoothing factor, that is applied after the network is trained. General Regression Neural Networks (GRNN) work by measuring how far a given sample pattern is from patterns in the training set in N dimensional space, where N is the number of inputs in the problem. [2]

When a new pattern is presented to the network that input pattern is compared in N dimensional space to all of the patterns in the training set to determine how far in distance it is from those patterns. The output that is predicted by the network is a proportional amount of all of the outputs in the training set. The proportion is based upon how far the new pattern is from the given patterns in the training set. For example, if a new pattern is in a cluster with other patterns in the training set, the outputs for the new pattern are going to be very close to the other patterns in the cluster around it.

Probabilistic Neural Networks (PNN) is known for their ability to train quickly on sparse data sets. PNN separates data into a specified number of output categories. PNN networks are three layer networks wherein the training patterns are presented to the input layer and the output layer has one neuron for each possible category. There must be as many neurons in the hidden layer as there are training patterns. The network produces activations in the output layer corresponding to the probability density function estimate for that category. The highest output represents the most probable category. PNN networks work by comparing patterns based upon their distance from each other. [2]

The weighted summation of inputs to a neuron is converted to an output according to a nonlinear transfer function. The common transfer function widely used in the literature is the sigmoid function. At the end of the training phase, the neural network should correctly reproduce the target output values for the training data and provided the errors are minimal. The associated trained weights of the neurons are then stored in the neural network memory. In the next phase, the trained neural network is feed by a separate set of data. In this testing phase, the neural network predictions using the trained weights are compared with the target output values. The performance of the overall ANN model can be assessed by several criteria. These criteria include the coefficient of determination (R^2), mean-squared error, mean absolute error, minimum absolute error, and maximum absolute error. A well-trained model should result in an R^2 value close to 1 and small values of the error terms.

3. MODELS AND PARAMETERS

The architectures of BPNN, GRNN and PNN's are introduced for neural network approaches to evaluate 3D liquefaction analysis. Factor of safety for liquefaction in 3D can be examined by NN approaces. Values are obtained from your case study data. These values will be used in NN approaches. Neural Network parameters for liquefaction analysis are given below.

The proposed soil liquefaction potential models consist of separate experimental datasets. One of the dataset can be composed mostly of SPT parameters and the other can be composed mostly of CPT parameters. According to the case histories taken from liquefied and non-liquefied sites datasets are arranged. These datasets have to be divided randomly into testing, training, and validation datasets and these numbers must be appropriate for process. For a case study example, suitable numbers are given in Table 1.

Table 1. Distribution of the data among phases

Database	SPT Database (%)	CPT Database (%)
Training	30	30
Testing	40	40
Forecast	30	30
Total	100	100

Soil and seismic parameters characterizing soil type and material properties, seismic attenuation characteristics, magnitude and nature of loads, and other site conditions including stress, strain, strength, saturation and seismological aspects have to be selected and incorporated into the databases. The soil elements given in Table 2 and Table 3 have to use in modeling and you can include other parameters which you want to focuses on.

Table 2. Soil parameters from SPT

SPT Database Parameters	Abbreviations	Unit
Depth of soil specimen	z	m
Corrected SPT blowcount	(N1)60	---

Table 3. Soil parameters from CPT

CPT Database Parameters	Abbreviations	Unit
Depth of soil specimen	z	m
Total overburden stress	σ_{vo}	kPa

The earthquake motions parameters have to use in modeling when you are working with three dimensional calculations are given in Table 4.

Table 4. Earthquake motion parameters

Database Parameters	Abbreviations
Magnitude	M
Acceleration in x direction	ax
Acceleration in y direction	ay
Acceleration in z direction	az

4. ANALYSIS

In SPT database, maximum horizontal acceleration at ground surface values, earthquake magnitude in 3D parameters, depth of the soil samples, SPT – N values, fines contents, shear wave velocities and ground water table elevations, etc. are the actual measured values.

In CPT database, CPT tip resistance, CPT sleeve friction resistance, CPT friction ratio, maximum horizontal acceleration at ground surface values, earthquake magnitude in 3D, depth of the soil samples, shear wave velocities and ground water table elevations, etc. are the actual measured values.

In this phase, the distance of the sample pattern from the given training set can measured. The training data will be represented in N dimensional space, where N is the number of inputs introduced into the network.

In learning phase, training data are presented into the network and network's outcome is applied to the testing data and best smoothing factor for the network is explored. The value of the smoothing factor giving the smallest error is used in the final network.

The objective is minimizing the mean squared error of the test set: therefore, amid presented test data, random testing datasets are generated in order to observe the network's performance.

While applying the network's outcome to the test patterns, statistical values, are utilized to understand network's performance as learning progresses.

In validation phase, model accuracy and efficiency were examined by making prediction against case records, which were not used during model training and testing. In this phase, the proposed algorithm does not require human development of the proposed model: it rather confirms the architecture's prediction capabilities of the model.

5. RESULTS

Due to the models, the results can be taken according to 1 or 0; one (1) describes the liquefaction occurrence and zero (0) for liquefaction non-occurrence. Because of the area described by three dimensional parameters, the results will represent the area. The detailed results of the models will be presented with examples but as a general look, to reach the best results, different configurations and architectures have been trained.

Error – epochs elapsed, success rate r^2 and relative contribution factors from models have been checked. For the models, the main challenge can be the over learning of data sets during the training phase. Because of this situation, the error – epochs elapsed graph plotted for models and in these graphs, the minimum error is expected. Figure 2 shows a successful example for an error – epoch's elapsed relationship.

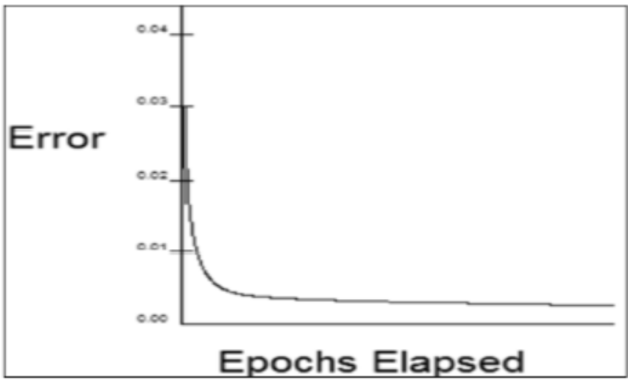

Figure 2. Example for an error and epochs elapsed graph.

Also, the model relative contribution factors graph will depict which parameter in the liquefaction analysis is affecting potential for the selected area (Figure 3).

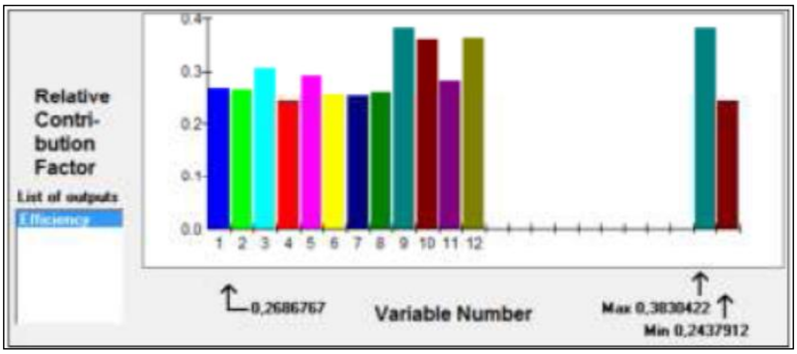

Figure 3. An example Model relative contribution factors graph.

With these tested models, it is seen that the back-propagation and general regression neural network are suitable architectures for this geotechnical problem. Also, it is seen that for the 3D liquefaction analysis the most important parameters for this case is the magnitude. Acceleration is the second important parameter however the wave arrival directions are not deterministic.

6. LIMITATIONS AND FUTURE WORKS

In order to perform reliable artificial intelligence analysis, numerous data sets are needed for training and testing. Due to this problem, there is a need to make a database for all previous projects including those from municipalities and private companies. For a future work, records of the geotechnical data from projects including 3-dimensional parameters, such as coordinates, magnitudes and accelerations will be analyzed.

7. CONCLUSION

In conclusion, this research shows that for three dimensional liquefaction analyses, the use of AI tools, enables the determination of the areas of potentially liquefiable soils. For evaluation of liquefaction in 3D, the results will show which architecture (BPNN, PNN, GRNN) is suitable, and which model has the best success rate.

Therefore AI tools, namely NN's used for solving and forecasting engineering problems are appropriate for three dimensional liquefaction evaluation processes, investigation and analysis. For future work, in order to decide if the area has a potential of liquefaction or not, it is recommended that using an AI tool, will lead to a reliable and easily attainable result.

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