ANN BASED STUDIES FOR LIQUEFACTION POTENTIAL AND SETTLEMENT PREDICTION

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ABSTRACT: In this study, totally 18 parameters were used for the analysis, seven models were developed out of which four were used for predicting liquefaction potential and three for settlement prediction. Further to the study, sensitive analyses were made to identify the parameter which influences the most on liquefaction potential and settlement due to liquefaction. It was found that SPT-N value, mean grain size, earthquake magnitude, fine content, relative density and Peak horizontal acceleration at ground surface were the main parameters that affected predictions. Using these influencing parameters two independent networks were developed; one for the liquefaction potential and the other for settlement prediction. Finally the results are compared with the conventional methods to evaluate the performance of models developed.

INTRODUCTION
The engineering properties of soil and rock exhibit varied and uncertain behaviour due to the complex and imprecise physical processes associated with the formation of these materials (Jaksa 1995,[1]). This is in contrast to most other civil engineering materials, such as steel and concrete which exhibit far greater homogeneity and isotropy. In order to cope with the complexity of geotechnical behaviour traditional forms of engineering design models are justifiably simplified. An alternative approach, which has been shown to have some degree of success and the technique is known as artificial neural networks (ANNs) and is well suited to model problems where the relationship between the model variables is complex.

Artificial neural networks (ANNs) are a form of artificial intelligence, which, by means of their architecture, attempt to simulate the biological structure of the human brain and nervous system. ANNs learn “by example,” in which an actual measured data set of input variables and the corresponding outputs are presented to determine the rules that govern the relationship between the variables. In this research it is proposed to apply the technique of ANN for evaluating liquefaction susceptibility of an area at which deposit is dominantly sand due to seismic activity and also to develop a model for predicting liquefaction induced settlement of the area. In order to develop the models for predicting liquefaction susceptibility and settlement; data were collected from the available literature and are used for developing the models in MATLAB platform.

OVERVIEW OF ARTIFICIAL NEURAL NETWORK
ANNs are a form of artificial intelligence which attempt to mimic, in a very simplistic fashion, the behaviour of the human brain and nervous system (Hubick 1992,[2]). Typically, the architecture of ANNs consists of a series of processing elements (PEs), or nodes, that are usually arranged in layers: an input layer, an output layer and one or more hidden layers, as shown in Fig 1. Its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error. This process is called ‘learning’ or ‘training.’ Once the training phase of the model has been successfully accomplished, the performance of the trained model needs to be validated using an independent data set.

As described above, ANNs learn from data presented to them and use these data to adjust their weights in an attempt to capture the relationship between the model input variables and the corresponding outputs. Consequently, ANNs need no prior knowledge regarding the nature of the relationship between the input and output variables. This is one of the main benefits of ANNs when compared with most empirical
and statistical methods. In this study ANN models are developed under MATLAB environment, which contains Neural Network Toolbox.

**OVERVIEW OF MATLAB**

There are four ways of using the Neural Network Toolbox software. First is by using GUI (graphical user interfaces) and the second is by using Command line operation. These provide a quick and easy way to access the power of the toolbox for the following tasks: i) Function fitting, ii) Pattern recognition, iii) Data clustering and iv) Time series analysis.

The third way to use the toolbox is through customization. The fourth way to use the toolbox is through the ability to modify any of the functions contained in the toolbox.

The graphical user interface guides you through the process of designing neural networks to solve problems in four important application areas, without requiring any background in neural networks or sophistication in using MATLAB. In addition, the GUIs can automatically generate both simple and advanced MATLAB scripts that can reproduce the steps performed by the GUI, but with the option to override default settings. These scripts can provide you with a template for creating customized code, and they can aid you in becoming familiar with the command-line functionality of the toolbox. The design steps involved in the neural network are well described elsewhere (Harris C and Brown, 1994, [4]).

**DATA USED FOR THE ARTIFICIAL NEURAL NETWORK DEVELOPMENT**

The data used for training and testing the ANN’s were collected from USGS website and literature (Saka and Ural (2002), [8] and Chern et al (2002),[9]). The data used in the analysis are from following four regions: Sichuan, Qinghai, Taiwan and Turkey. The data thus collected comprises a total of 427 data sets. Of the 427 data sets 86 are from Sichuan region, 149 are from Qinghai region, 42 are from Taiwan and 150 are from Turkey. The variables available in these data are earthquake magnitude, total and effective overburden pressure, SPT-N value, peak horizontal acceleration at ground surface, cyclic stress ratio, fine content, mean grain size, critical depth, height of water, earthquake induced shear stress, stress reduction factor, SPT-N modification coefficient factor, relative density, shear modulus, shear wave velocity and porosity.

**ANN MODEL**

Totally nine models were developed out of which five networks for predicting liquefaction potential and four for settlement prediction. Models were developed independently for different region, in order to identify the parameters that influence the most in the prediction of liquefaction potential and settlement. Each model differs from one another in number of neurons and variables used.

Out of the five networks developed for predicting liquefaction potential four of them were used for analyzing the sensitivity of the parameters and accuracy of the ANN over the conventional methods; fifth and final network was developed with the parameters that influenced the most in the prediction of liquefaction potential in the networks L1, L2, L3 and L4. Similarly for the settlement prediction three networks were used for analyzing the sensitivity of the parameters and accuracy of the ANN over the conventional methods; fourth and final network was developed with the parameters that influenced the most in the prediction of settlement S1, S2 and S3.

**RESULTS**

Final network LF for predicting liquefaction potential was developed using the variables which influenced the most in the networks L1, L2, L3 and L4. (i) corrected SPT-N value, (ii) mean grain size, (iii) relative density and (iv) peak horizontal acceleration at ground surface. Network LF is based on Feedforward back propagation method consisting of one hidden layer and ten numbers of neurons. Levenberg-Marquardt training method was adopted with logsig transfer function. The 150 database was divided into two one for training phase with 100 data sets and another for testing phase with 50 data sets.

Result obtained from the network LF was compared with the field data and Seed and Idriss (1971), [5]. The developed network LF predicted liquefaction potential with an accuracy of 96% and Seed and Idriss (1971), [5] method predicted liquefaction potential with an accuracy of 92%. Regression plot for the network LF is shown in Fig 2.

Finalized network LF’s structure with the weights is presented here,
clear all
cclc
wlf=[ 8.18 -4.57 31.93 37.38 -4.79 2.63 -4.12 -2.59 -12.07
25.79 99.95 -106.19 1.69 82.59 -10.14 -2.48 -7.71 -11.08 -
57.93 11.17 -104.97 15.42 4.79 35.19 -118.24 -1.65 -45.75
38.03 -89.61 10.54 -32.85 80.51 -15.84 -22.41 38.61 11.69
10.72 19.14 51.93 -35.93 -40.37 14.13 24.30 -1.25 21.41 -
7.98 6.57 -27.42 -1.32 4.70 -80.41 -66.46 101.70 60.34 8.24
117.57 -115.47 -126.37 125.76 -113.83 -69.66]
n=10
net1=newff([0 1;0 1;0 1;0 1], [n 1], {'logsig', 'logsig'},
'trainlm');
net1=setx(net1,wf)

For further analysis with a new set of data above shown LF
network can be used.

Network SF was developed using the variables which
influenced the most in the networks S1, S2 and S3. The most
influencing parameters are: (i) earthquake magnitude, (ii)
mean grain size, (iii) fine content and (iv) Corrected SPT-N
value. Network SF was developed using Feedforward back
propagation method consisting of one hidden layer and six
numbers of neurons. Training method adopted for the
network SF was Bayesian Regularization training with logsig
transfer function. It was trained with 60 data sets and tested
with 30 data sets.

Accuracy of the network SF was tested by comparing the
testing phase result of network SF and the Seed and
predicted settlement with near perfection. Regression plot for
the network SF is shown in Fig 3.

Finalized network SF’s structure with the weights is
presented here,

clear all
clc
wsf=[ -22.62 -7.21 -4.90 -10.08 -30.35 18.70 16.14 4.27 -
31.98 1.43 -13.73 -2.90 -33.31 40.42 -23.09 -16.15 143.98 -
455.63 437.34 -100.30 -6.08 -16.22 6.90 -1.91 32.91 0.86
10.31 33.47 139.31 -2.45 -7.57 2.66 7.08 14.07 3.64 18.05 -
19.93]
n=6
net1=newff([0 1;0 1;0 1;0 1], [n 1], {'logsig', 'logsig'},
'trainbr');
net1=setx(net1,wsf)

The SF network with weights given above can be used for
predicting settlement for predicting settlement if new data
were made available.

CONCLUSION

Single layered network performed well when compared to
more number of layers. The number of neurons in the
network also affected the prediction of liquefaction potential
and settlement. Levenberg-Marquardt and Bayesian
Regularization training methods performed better than the
other training methods for the problems that were carried out
in this research work. Feed forward back propagation
network gave better results than other networks.

In assessing liquefaction potential through ANN, exercising
on the combination of various parameters which have
influence on liquefaction is very much essential.
Out of 18 parameters considered for predicting liquefaction potential only Corrected SPT-N value, relative density, mean grain size and peak horizontal acceleration at ground surface were the most influencing parameters in predicting liquefaction potential. In overall Corrected SPT-N value is the dominating parameter in predicting liquefaction potential for the data sets of four locations. In all the cases considered in this study ANN’s predicted liquefaction potential with an accuracy over 90% where as this is not the case in the conventional methods and their accuracy level was below 90% in many cases.

Settlement prediction is also greatly influenced by Corrected SPT-N value for the data sets used (Sichuan, Qinghai, Turkey and Taiwan regions) as in the case of liquefaction potential.

Settlement prediction by ANN is excellent for the cases where earthquake induced settlement is less than 100mm irrespective of dry or saturated condition where as prediction is not that accurate if the settlement is more than 100mm. however the variation is less than 2.5%.

ANN is a new modeling technique in the field of geotechnical engineering. This technique is proved to be a reliable tool and capable of providing good predictions of liquefaction potential and settlement of liquefied soil. Hence, it is recommended to develop similar models for several other geotechnical problems where potentials of ANN approaches are yet to be established.

ANNs developed in this study can be improved by training the models by adding more quality data in the database as and where new data are obtained.

REFERENCES