17 SEAGC
The 17th Southeast Asian Geotechnical Conference
Taipei, Taiwan, May 10~13, 2010

Artificial Neural Network in CPT Base Liquefaction Prediction

M.M. Rahman[1], Sik-Cheung Robert Lo[2] and Sayed Abdul Mofiz[3]
[1]*Department of Civil and Natural Resources Engineering, University of Canterbury, Christchurch, New Zealand*
[2]*School of Engineering and Information Technology, UNSW@ADFA, Canberra, Australia*
[3]*Department of Civil Engineering, Rajshahi University of Engineering & Technology, Rajshahi, Bangladesh*
E-mail: md.rahman@canterbury.ac.nz

ABSTRACT: Various simplified procedue have been developed, using case studies that liquefied or not during earthquake, to estimate liquefaction potential of soils. In order to address the collective knowledge built up in conventional liquefaction engineering, this paper proposed to use a artificial neural network, ANN as an alternative tools. ANN has the capability to train itself with available data sets and extrapolate outcome for unknown senerio 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 liquefcation prediction. First, the data bases used for training and testing are well verified and well accepted in literature. Second, the inputs for the model are selected on their physical meaning with respect to liquefaction. Third, the source of data sets for training and testing are diffrent. The ANN model achieved a comparable accuracy with other publications where large number of inputs has been used.

1. INTRODUCTION

The conventional method of evaluating liquefaction potential of soil during earthquake was pioneered by Seed and Idriss (1971). Although a number of improvements and variations have been proposed, the conventional procedure consists of two inter-related components. The development of empirical expressions for cyclic stress ratio and cyclic resistance, the latter being indexed based on field testing; and ii) using these two measures to analyse historical experience on whether a site liquefied or not. There are several methods for establishing liquefaction potential based on field testing. The common methods are based on standard penetration test (SPT), cone penetration test (CPT), Self-boring pressure meter tests, measurement of shear wave velocity etc. Among them, the CPT based method is getting popular due to its simplicity, repeatability, accuracy and continuous record. This capability makes CPT advantageous for developing liquefied resistance profile.

The CPT based method was also developed based on the same principle outlined by Seed and Idriss (1971); however various modifications were suggested in literature for correcting and normalizing cone penetration resistance, q_c which is an important parameter for developing liquefaction assessment chart (Shibata and Wanchai 1988; Youd et al. 2001). Thus, the liquefaction assessment of a site often requires lengthy procedure and engineering judgement. On the other hand a common computer tools, artificial neural network (ANN), can be used in database based decision making like other liquefaction assessment chart. ANN has the capability to train itself with available data sets and extrapolate outcome for unknown scenario based on the training. Surprisingly, only few approaches have been found in literature for CPT based liquefaction assessment (Goh 1996; Juang et al. 2006) though it has greater potential application. These approaches often suffer from either using large number of input parameters or using very complex neural network. These networks also based on calibrated or corrected data as inputs (Goh 1996) and may not be directly applicable for different data sets. The objective of this paper is to identify the primary inputs parameters from conventional CPT based liquefaction assessment method and developed a smallest possible ANN network that can be used for liquefaction assessment with those primary input parameters.

2. CONVENTIONAL METHODS

Perhaps, the most commonly known CPT based liquefaction potential assessment procedure is outlined in Youd et al. (2001). This method is comprehensive and required engineering judgement to identify value of some parameters used in correcting and normalizing q_c. Another simplified method was outlined by Shibata and Wanchai (1988). However, these methods were based on the same principle outlined by Seed and Idriss (1971) and require same primary input parameters. For simplicity, the method outlined by Shibata and Wanchai (1988) is explained next sub-sections.

2.1 Normalization of cone penetration resistance, q_c

The q_c value is influenced by mean effective confining pressure, σ'_o (Seed et al. 1983). Thus, Shibata and Wanchai (1988) proposed to normalize the q_c values by the following method:

$$q_{c1} = \left(\frac{0.17}{\sigma'_0 + 0.07}\right) q_c \quad \text{(in MPa)} \tag{1}$$

The grain characteristic also play significant role in liquefaction potential of sand (Robertson and Campanella 1985; Seed et al. 1983; Youd et al. 2001). Thus, Shibata and Wanchai (1988) suggested following correction

$$\left(q_{c1}\right)_{cr} = \frac{q_{c1}}{C_2} \tag{2}$$

where C_2 = 1.0 for $D_{50} \geq$ 0.25mm and $C_2 = D_{50}/0.25$ for $D_{50} <$ 0.25mm, D_{50} = sand particle diameter at 50% finer.

2.2 Cyclic stress ratio from an earthquake

The cyclic stress ratio was determined from the following equation by Tokimatsu and Yoshimi (1983):

$$\frac{\tau}{\sigma'_o} = 0.1(M-1)\frac{a}{g}\frac{\sigma_o}{\sigma'_o}(1-0.015z) \tag{3}$$

where a = peak ground acceleration, g = acceleration of gravity, σ_o = total stress, z = depth of the soil (m). When M = 7.5 and r_d = (1-0.015z), this equation is comparable to Seed and Idriss's equation (1971).

2.3 Liquefaction characterization index

Following the above procedure, the historical liquefaction data outlined in Shibata and Wanchai (1988) are plotted in τ/σ'_o-q_{c1}/C_2 space and a clear boundary line between liquefied and non-liquefied zones are visible as shown in Fig. 1. Shibata and Wanchai (1988) presented the following equation, used for MPa units, as the boundary separating liquefied and non-liquefied zones.

$$\frac{q_{c1}}{C_2} = \left[5 + 20\left(\frac{(\tau/\sigma'_0) - 0.1}{(\tau/\sigma'_0) + 0.1}\right)\right] \tag{4}$$

Similar boundary lines for CPT based methods have been found in many literatures (Juang et al. 2006; Moss 2003; Youd et al. 2001).

However, it is noted that the expression for calculating cyclic stress ratio and cyclic resistance (or its index based on field testing) has to be compatible as discussed in Juang et al (2006). Indeed if a friction cone with an independent sleeve design was used, one may rightly argue for the use of q_T rather than q_c to correct for the water pressure acting on recess behind the cone (Lunne, Robertson, and Powell 1997). These factors, among others, indicate certain extent of compensating errors in these empirical expressions. An alternative approach is to identify the parameters governing liquefaction and use them in an artificial neural network (ANN) for predicting liquefaction.

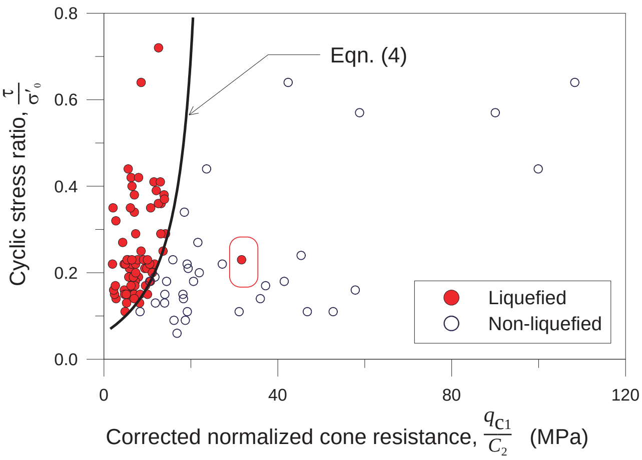

Figure 1: Correlation between cyclic stress ratio and normalized cone resistance for liquefied and non-liquefied site

2.4 Primary parameters

The primary input parameters can be identified from the theories/ equations of conventional liquefaction assessment methods. For example, three parameters are used in normalizing the CPT data to obtain a CPT-based index for cyclic resistance; q_c, σ'_o, D_{50} and five parameters are used for cyclic stress ratio calculation; M, a/g, z, unit weight of soil, ground water table. Thus eight parameters are used in conventional method out lined by Shibata and Wanchai (1988). However, the last three parameters can be reduced to σ_o, σ'_o. Thus, a total of six parameters can be considered as primary input parameters: q_c, σ'_o, σ_o, D_{50}, M, a/g for the ANN.

Further, the relation of these parameters with the observed behaviour can be identified with a statistical means such as correlation coefficient. The coefficient of correlation of these input parameters with observation (liquefied/non-liquefied) can be presented as

$$Correlation\ coeff. = \frac{\Sigma(x-\bar{x})(o-\bar{o})}{\sqrt{(x-\bar{x})^2(o-\bar{o})^2}} \tag{5}$$

where x is input parameter and o is the observed behaviour. The observed behaviours, liquefied or not-liquefied, can be presented as 1 or 0 respectively. It is a common practice for pattern recognition in neural network. The correlation coefficient of the data set collected from Shibata and Wanchai (1988) was calculated with these numbers and presented in Fig. 2. It shows that M, q_c and D_{50} are the most influential parameters for the observed behaviours. The positive number indicates, the parameter contributed to liquefaction and negative number indicates, the parameter contributed to liquefaction resistance.

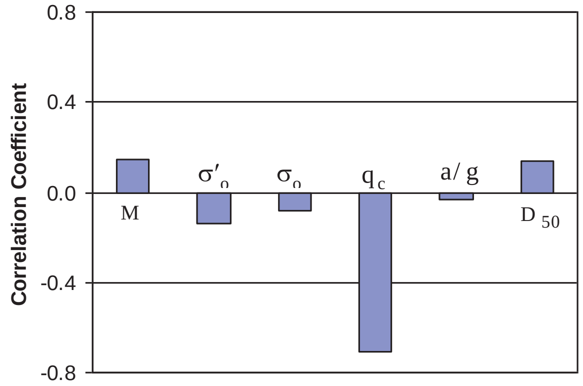

Figure 2: The correlation coefficient of input parameter with the observed behaviour.

3. THE NEURAL NETWORK

The method of neural network essentially involve the mapping of a complex input pattern with another complex output pattern using data processing paradigms made up of extensively interconnected neurons. The architecture of a typical artificial neural network is presented in Fig. 3.

3.1 Connection between neurons

Within the neural network system three layers of units (neurons) are used: input layer (indicated by index i) which receive data from outside the neural network, output layers (indicated by index o) which send data out of the neural network, and hidden layers (indicated by index h) whose input and output signal remain within the neural network. The units of input layer are interconnected to units of hidden layer and the units of the hidden units inter connected to units of output layer. Thus, the network is information processing system which follows a forward flow rule from input to output layer.

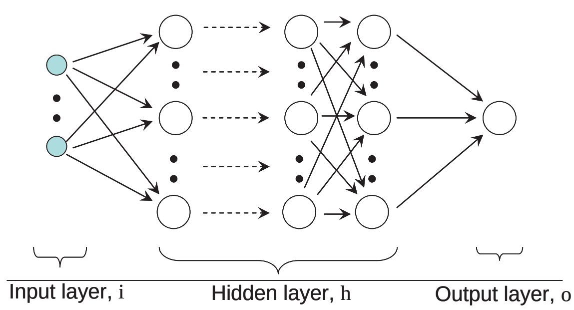

Figure 3: The architecture of a multilayer neural network

The units in the input layer send signals to the interconnected unit in next layer. In the connection between units, the signals are processed with numerical weights. These weights determine the properties and strength of the influence between interconnected units. The total input in the hidden h-th unit is simply the weighted sum of the separate outputs from each connected units plus an offset threshold:

$$s_h = \sum_i^n w_{ih} x_i + \theta_h \quad (6)$$

where, w_{ih} is the weight on the connection for the i-th unit in input layer and h-th unit in hidden layer, θ_h is the offset. The output of the h-th unit in the hidden layer is defined through an activation function as

$$y_h = f(s_h) \quad (7)$$

Generally, a some sort of threshold function, a hard limit threshold function (a sng function) or a linear or semi-linear function or a smoothly limiting threshold, is used as activation function. The activation function used in this study is a sigmoid function defined as

$$y_h = f(s_h) = \frac{1}{1+e^{-s_h}} \quad (8)$$

2.5 Training of the network:

In first step, for a set of inputs random numbers are assumed as weight for each connection to obtain an output in the output layer. All most all cases the computed output is not the same as desired output. The difference of these two can be defined by an error function. Thus, in second step the weights are updated in such a way that the computed output move toward to the desired output. In back propagation technique, the change in weights of the network is based on it localized portion of the input signal, x_i and its localized portion of the error, δ_o. The change is a proportional (scaled) of the product of these two quantities i.e. $\gamma\delta_o x_i$. To increase the convergence some time a momentum term, α which specify how much a previous weight change $\alpha\Delta w_{ih}$, should influence to the current weight change. Thus, the weight in a current step can be defined as

$$w_{ih(t+1)} = w_{ih(t)} + \gamma\, \delta_o\, x_i + \alpha\, \Delta w_{ih(t-1)} \quad (9)$$

where, $w_{ih(t+1)}$ and $w_{ih(t)}$ are the weight for i-th input unit and h-th hidden unit at (t+1)-th and t-th time steps respectively, $\Delta w_{ih(t-1)}$ is the change in weight in (t-1) time step, δ_o is the difference between the computed output and desired output, x_i is the i-th input, γ is learning rate, α is the moment parameter.

The learning rate, momentum parameter and error function control the update of the weights, i.e. the rate of merging in an optimum weights system. Usually in a neural network the learning rate and the momentum defined by the users. Normally little variation of these parameter resulted in the variation of training time.

3.2 Neural networks

Three different neural networks were used in this study. The first network was M-I which contained all six primary parameters as inputs. The second network is M-II was built by neglecting a/g from the inputs as it has very small correlation coefficient compared to others. This was done to study the effect of a/g on the network prediction. The third network was M-III which contained all parameters except D_{50} though it maybe an important parameter as outline by coefficient correlation. This was done partly because we also tested the performance of the network against a different data base extracted from Juang et al. (2006) and this data source does not contain D_{50}.

The number of hidden layers plays a significant role in prediction performance and its inherent complexity. The simplest possible network is a single layer (hidden) network but its application is limited to linear classifier. For liquefaction prediction a multilayer network is recommended. A simplest possible multilayer networks with two hidden layers were used in this study.

4. DATA BASES

Two different data bases have been used in this study. The first data base was extracted from Shibata and Wanchai (1988). This database was collected from sites from four different countries which suffer from five major earthquake earthquakes. The data sets contained 107 well varied cases. 72 cases were used in networks training and 35 cases were used for verification.

The second data base was extracted from Juang et al. (2006). This data base was use to verify M-III trained using Shibata and Wang's data base. Each case in this database was re-verified with their case history. The data are classified as A, B, C according to their quality as specified in Moss (2003). Only high quality data A and B are used in the network and this gives a total of 96 independent data points for verification.

5. RESULTS AND DISCUSSION

Table 1 summarizes the performance of the three different neural networks. For M-I, the network was able to predict 33 real observations out of 35 cases i.e. 2 false alarm. This outcome is comparable with Shibata and Wanchai (1988) conventional method and with Goh's (1996) neural networks where 3 to 5 hidden layers and calibrated data were used. M-II achieved similar performance with 5 input parameters i.e. without a/g. This is interesting because a/g is an important parameter in Eqn. (3) to obtain cyclic stress ratio, τ/σ'_o for a given earthquake. However, this is consistent with correlation coefficient of input parameters with observed behaviours. It should be noted that M-I and M-II network can not be evaluate with second data sets as the data sets do not contain D_{50} information.

Table 1 Different ANN model and their performance

Model	Input variables	Hidden layers	Error in ANN prediction	
			Test data 1	Test data 2
M-I	M, σ'_o, σ_o, q_c, a/g, D_{50}	2	2/35	----
M-II	M, σ'_o, σ_o, q_c, D_{50}	2	2/35	---
M-III	M, σ'_o, σ_o, q_c, a/g	2	4/35	14/96

Notes: Test data 1 = 35 cases from Shibata and Wanchai (1988)
Test data 2 = 96 cases from Juang et al (2006)

M-III was built without using D_{50} as input, and therefore both data bases were tested. For the first set of test data (35 cases from Shibata and Wanchai 1988), this network failed to predict 4 out of 35 cases. The higher unsuccessful predictions compared to M-II indicates that D_{50} is more influential than a/g, noting the effect of a/g is already embodied, indirectly, in M For the second set of test data which consist of all 96 cases from Juang et al (2006), the number of unsuccessful prediction was 14, (ie 15% unsuccessful rate). If the overall performance of M-III was considered, then the unsuccessful rate became 18/131, which is 14%. This significantly higher unsuccessful rate cannot be fully explained by the missing of an important parameter D_{50}. One important factor is that the network was trained with data from a different data base. Usually in a neural network, majority of data are used to train the network and rest of the data is used to validate the network. Furthercome, the number of cases used for training was 72 but 96 independent cases were tested.

6. CONCLUSION

Neural networks have been used to successfully capture the complex relationship between soil parameter and liquefaction potential due to earthquake. The input of the neural network was selected based on the theoretical basis from conventional methods. This gives smallest possible network with two hidden layers. The major outcomes of this study are given below.

- The correlation coefficients of input parameters with observe behaviours may be a good indication of relative importance of the parameters for an ANN network and can be used in selecting input parameters.
- The networks M-I and M-II were as good as conventional method as out lined by Shibata and Wanchai (1988).

Although the fundamental linkage between inputs and outputs of a neural network is not clear from a mechanistic point of view, the results indicates that the ANN have a strong potential to use as quick tool to interpolate/extrapolate liquefaction potential of a site from simple input parameters.

7. REFERENCES

[1] Seed, H. B., and Idriss, I. M. "Simplefied Prodecure For Evaluating Soil Liquefaction Potential." Journal of the Soil Mechanics and Foundation Division, ASCE, 97, Issue 9, 1971, pp1249-1273

[2] Shibata, T., and Wanchai, T. "Evaluation of liquefaction potential of soils using cone penetration tests." Soils and Foundations, 28, Issue 2, 1988, pp49-60

[3] Youd, T. L., Idriss, I. M., Andrus, R. D., Arango, I., Castro, G., Christian, J. T., Dobry, R., Finn, W. D. L., Harder, L. F., Hynes, M. E., Ishihara, K., Koester, J. P., Liao, S. S. C., Marcuson, W. F., Martin, G. R., Mitchell, J. K., Moriwaki, Y., Power, M. S., Robertson, P. K., Seed, R. B., and Stokoe, K. H. "Liquefaction resistance of soils: Summary report from the 1996 NCEER and 1998 NCEER/NSF Workshops on Evaluation of Liquefaction Resistance of Soils." Journal of Geotechnical and Geoenvironmental Engineering, 127, Issue 10, 2001, pp817-833

[4] Goh, A. T. C. "Neural-Network Modeling of CPT Seismic Liquefaction Data." Journal of Geotechnical Engineering, 122, Issue 1, 1996, pp70-73

[5] Juang, C. H., Sunny Ye, F., and Eng Hui, K. "First-Order Reliability Method for Probabilistic Liquefaction Triggering Analysis Using CPT." Journal of Geotechnical and Geoenvironmental Engineering, 132, Issue 3, 2006, pp337-350.

[6] Seed, H. B., Idriss, I. M., and Arango, I. "Evaluation of liquefaction potential using field performance data." Journal of the Soil Mechanics and Foundation Division, ASCE, 109, Issue 3, 1983, pp 458-482.

[7] Robertson, P., and Campanella, R. G. "Liquefaction potential of sand using CPT." Journal of the Soil Mechanics and Foundation Division, ASCE, 109, Issue 3, 1985, pp458-482.

[8] Tokimatsu, K., and Yoshimi, Y. "Emperical correlation of soils liquefaction based on SPT N-value and fines contents." *Soils and Foundations*, 23. Issue 4, 1983, pp56-74.

[9] Moss, R. E. S. "CPT-Based Probabilistic Assessment of Seismic Soil Liquefaction Initiation," PhD Thesis, University of California, Berkeley, 2003.

[10] Lunne, T., Robertson, P. k., and Powell, J. J. M. “Cone penetration testing in geotechnical practice”, Taylor & Francis Routledge, 1997.