29 Mar 2001, 7:30 pm - 9:30 pm

CPT Evaluation of Liquefaction Potential Using Neural Networks

Pradeep U. Kurup
University of Massachusetts, Lowell, MA

Nitin K. Dudani
University of Massachusetts, Lowell, MA

CPT EVALUATION OF LIQUEFACTION POTENTIAL USING NEURAL NETWORKS

Pradeep U. Kurup
University of Massachusetts Lowell
Lowell, MA-USA-01854

Nitin K. Dudani
University of Massachusetts Lowell
Lowell, MA-USA-01854

ABSTRACT

The increasing popularity of the cone penetration test (CPT) for site investigations has led to several methods for predicting liquefaction potential from CPT data. This paper describes a feed-forward neural network model trained by back-propagation for predicting liquefaction potential. The model requires the following seven input variables: cone resistance, total vertical stress, effective vertical stress, earthquake magnitude, maximum horizontal acceleration at ground surface, the mean grain size D_{50}, and the seismic shear-stress ratio. A total of ninety-six data sets from different sites around the world were used for training, and eighty-two data sets were used for testing and validating the neural network model. The model gave an overall success rate of 96% for correctly predicting the liquefaction potential.

INTRODUCTION

One of the major causes of destruction during an earthquake is the loss of strength and stiffness of cohesionless soils. This phenomenon, called liquefaction, occurs mainly in loose and saturated sands. Liquefaction of sandy soils during earthquakes can cause enormous damage to buildings, bridges, highway embankments and other civil engineering structures. Determination of liquefaction potential due to an earthquake is a complex geotechnical engineering problem. Many factors, including soil parameters and seismic characteristics influence this problem.

Methods have been developed in the past for assessing the liquefaction potential of sand using the standard penetration test data (Tokimatsu and Yoshimi 1983, Seed et al. 1985, Goh 1994). The cone penetration test (CPT) gives continuous, detailed soil profiles with depth and is capable of locating even thin liquefiable seams of sand or silts. This is important in sand and silts because of the non-uniformity of these deposits. Several methods have been developed for predicting liquefaction potential from CPT data (Robertson and Campanella 1985, Seed and De Alba 1986, Shibata and Teparaksa 1988, Goh 1996). This paper examines the prospect of using neural networks for assessing liquefaction potential from actual CPT data.

Artificial neural networks (ANN) are data processing paradigms that work similar to the brain in processing information (Khanna 1989, Dowla and Rogers 1995, Hagan et al. 1999). Neural networks have been found to be very useful in learning complex relationships between multidimensional data. A particular strength of ANN is its relative tolerance to noisy and fuzzy data that makes it more robust and flexible than mathematical models. Many types of neural network exist. These neural networks differ in the topography or architecture and the rules of learning and self-organization. In this paper a feed-forward neural network with back-propagation algorithm is used to predict liquefaction potential from CPT data.

ANN MODEL ARCHITECTURE

A typical neural network consists of processing units (neurons) organized in layers. The architecture of the ANN model used in this study is illustrated in Fig. 1. The seven parameters that were used as input for the neural network model are the earthquake magnitude, M; effective vertical stress, σ'_0; total vertical stress, σ_0; cone tip resistance, q_c; the peak acceleration at the ground surface of the site, a_{max}; seismic shear-stress ratio, SSR; and the median grain diameter of the soil, D_{50}. Hence the input layer has seven neurons. The only output is the liquefaction potential, and therefore there is only one output neuron (in the output layer). The hidden layer enables non-linear modeling of the sensor data. The number of neurons in the hidden layer is determined by a trial and error method, i.e. by training the network with different number of hidden neurons and comparing the results with the desired output. A hidden layer with seven neurons gave good results for predicting the liquefaction potential of the sites. Thus a 7x7x1 network architecture was trained and tested for predicting the liquefaction potential of sites using CPT data from actual field records.

The connection between the neurons in the different layers are as shown in Fig. 1, where the output from one neuron is one of the inputs to all the neurons in the next layer and the inputs are the outputs from all the neurons in the previous layer. With each connection is associated a modifiable weight (models the synapse in the brain). Each neuron transforms the weighted sum of the inputs into a single outgoing activity that it transmits to all other neurons in the next layer. A tangent sigmoid function was used as the activation function to transform the input values to the hidden layer neurons, where as a log sigmoid function was used for transformations by the output layer neuron.

ANNs, like people, learn by examples. Training of a neural network is conducted by presenting a series of example pattern of associated input and output values. Initially when a network is created the connection weights are set to random values (random numbers). As the training sets of inputs and outputs are presented, the weights are automatically modified by the adopted learning rule (back-propagation) until the ANN gives the desired output. A feed-forward network, trained by back-propagation, was used in this research because of its simplicity and robustness. Once the ANN is trained for evaluating liquefaction potential, the prediction mode simply consists of propagating the data through the network, giving immediate predictions.

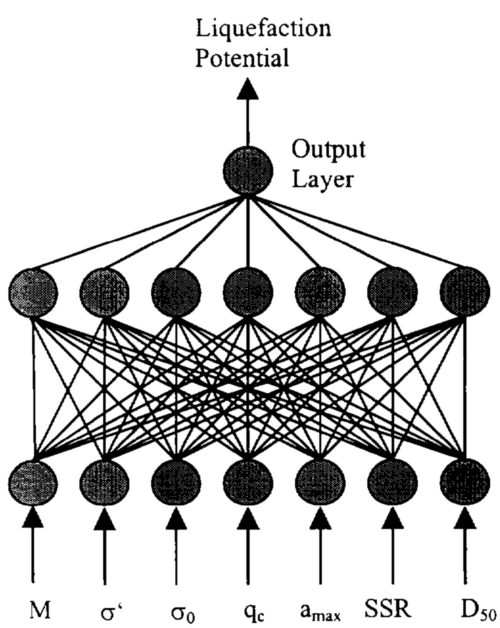

Fig. 1 Architecture of the Neural Network Model

TRAINING, TESTING AND VALIDATING THE MODEL

Many databases are available for CPT assessment of liquefaction and non-liquefaction of a site. The database used in this paper consists of total of 178 CPT soundings (108 records of sites that liquefied, and 70 records of sites that did not liquefy), from nine sites, from all over the world (Stark & Olson 1995, Goh 1996). Out of 178 soundings, 96 soundings were selected in random and used for training the neural network and the remaining 82 sounding data were used for testing the model.

In the training phase, the output neuron was given a value of one for sites that liquefied, and zero for sites that did not liquefy. The training was performed on a PC having 128 MB RAM and 400 MHz CPU speed. Training was performed until the average sum squared errors over the entire training pattern reached 0.004. This occurred after approximately 1000 cycles of training and took less than 5 minutes. The weight matrix obtained after the training phase are given below. After training, the neural network was once again presented with the data that was used for training. This step consisted of simply propagating the data through the network. There were only two errors when tested using the data records used for training (ninety-six records). The model was further evaluated using eighty-two new sounding records, not previously used for training the model (Table 1). The model gave accurate predictions for seventy-seven soundings (i.e. only five errors). The neural network model developed in this study was found to have an overall success rate of 96% for correctly predicting the liquefaction potential of a site.

Weight and Bias Matrices for the Neural Network Model

Connection weights between input layer and hidden layer (H x I - Hidden layer neurons x Input layer neurons):

$$\begin{bmatrix} -3130 & -10 & -110 & -10 & 92040 & -75100 & 104740 \\ -4580 & 40 & 200 & -70 & -12850 & -104580 & -84420 \\ -16230 & -380 & -240 & 10 & -48020 & -13180 & 66050 \\ -25320 & 110 & 110 & 10 & 36820 & 77750 & 139600 \\ 13900 & 150 & 220 & -10 & -28970 & 98900 & 53430 \\ 16030 & 290 & -150 & 10 & -23320 & -54580 & 122070 \\ 17310 & -270 & -60 & -1 & 18930 & -74480 & -152860 \end{bmatrix}$$

Bias for the hidden layer neurons in the form H x 1:

$$\begin{bmatrix} 14.02 \\ 31.73 \\ 6.09 \\ 3.38 \\ -12.89 \\ -17.33 \\ -1.38 \end{bmatrix}$$

Connection weights between hidden layer and output layer (O x H - Output layer neurons x Hidden layer neurons):

$$\begin{bmatrix} 4.50 & 61.49 & 201.67 & -519.16 & -7.81 & -1.31 & -341.20 \end{bmatrix}$$

Bias for the output neuron in the form O x 1:

$$\left[3.32 \right]$$

Many of the existing methods to evaluate liquefaction potential use the normalized, corrected tip resistance q_{c1} where as the neural network model does not require any transformation of data. The conventional approach requires subjective determination of an empirical boundary curve. This is not necessary in neural network, as it is able to "learn" the relationship between input and output variables. The trained neural network model provides instantaneous results unlike some of the existing methods. Also the neural network model can be retrained to improve its performance, as additional CPT field case records become available.

CONCLUSIONS

A feed-forward back-propagation neural network model was developed to evaluate liquefaction potential using actual CPT records. The model was found to be very reliable and gave an overall success rate of 96% for predicting the liquefaction potential. The advantage of the neural network model is that it can be retrained as more data becomes available, and the prediction accuracy improved.

ACKNOWLEDGEMENTS

The authors acknowledge the support of the National Science Foundation, Career Award CMS-9875037 under the direction of Dr. Richard J. Fragaszy, Program Director for Geomechanics and Geotechnical Systems, and Dr. Priscilla P. Nelson, Director of Civil and Mechanical Systems.

REFERENCES

Dowla, F.U. and L.L. Rogers. [1995]. "*Solving problems in environmental engineering and geoscience with artificial neural networks.*" The MIT Press.

Goh, A.T.C. [1994]. "Seismic liquefaction potential assessed by neural networks.", J. Geotech. Engrg., ASCE, 120 (9), pp. 1467-1480.

Goh, A.T.C. [1996]. "Neural network modeling of CPT seismic liquefaction data.", J. Geotech. Engrg.,, ASCE, 122 (1), pp. 70-73.

Hagan, M.T., H.B. Demuth and M. Beale. [1999]. "*Neural network design.*" PWS Publishing Company.
Khanna, T. [1989]. "*Foundations of neural networks.*" Addison-Wesley Publishing Company.

Robertson, P.K. and R.G. Campanella. [1985]. "Liquefaction potential of sands using the CPT.", J. Geotech. Engrg., ASCE, 111 (3), pp. 384-403.

Seed, H.B., H. Tokimatsu, L.F. Harder and R.M. Chung. [1985]. "Influence of SPT procedure in seismic liquefaction resistance evaluations.", J. Geotech. Engrg., ASCE, 111(12), pp. 1425-1445.

Seed, H. B. and De Alba. [1986]. "Use of SPT and CPT tests for evaluating the liquefaction resistance of sands." Proc. INSITU '86, ASCE special conf. on use of in situ testing in geotechnical engineering, special pub. No. 6, ASCE, New York, N.Y., pp. 281-302.

Shibata, T. and W. Teparaksa. [1988]. "Evaluation of liquefaction potentials of soils using cone penetration tests.", Soils and Found., 28(2), pp. 49-60.

Stark, T.D. and S.M. Olson. [1995]. "Liquefaction resistance using CPT and field case histories.", J. Geotech. Engrg.,, ASCE, 121 (12), 856-869.

Tokimatsu, K. and Y. Yoshimi. [1983]. "Empirical correlation of soil liquefaction based on SPT N-value and fines content.", Soils and Found., 23(4), pp. 56-74.

Table 1. Testing Data for the Neural Network Model

Site	Sounding	M	σ'_o (kPa)	σ_o (kPa)	q_c (kPa)	a_{max} (g)	SSR (M = 7.5)	D_{50} (mm)	Liquefaction Field	Liquefaction ANN Prediction
1976 Tangshan Earthquake										
Tangshan Area	T-12	7.8	33.3	37.3	2450	0.4	0.29	0.14	Yes	Yes
	T-12	7.8	42.2	55.9	2550	0.4	0.34	0.14	Yes	Yes
	T-12	7.8	51.0	74.5	3140	0.4	0.37	0.16	Yes	Yes
	T-12	7.8	56.9	87.3	5690	0.4	0.39	0.16	Yes	Yes
	T-12	7.8	72.6	119.6	3430	0.4	0.41	0.16	Yes	Yes
	T-12	7.8	100	177.5	8240	0.4	0.42	0.16	Yes	Yes
	T-13	7.8	28.4	37.3	1670	0.4	0.34	0.12	Yes	Yes
	T-13	7.8	28.4	39.2	3430	0.4	0.36	0.12	Yes	Yes
	T-13	7.8	34.3	50	4020	0.4	0.38	0.12	Yes	Yes
	T-16	7.8	69.6	74.5	11250	0.4	0.27	0.16	No	No
	T-16	7.8	108.9	156.9	15460	0.4	0.34	0.2	No	No
	T-17	7.8	54.9	57.9	11170	0.2	0.14	0.21	No	No
	T-17	7.8	63.7	76.5	11890	0.2	0.15	0.21	No	No
	T-17	7.8	73.5	97.1	17420	0.2	0.17	0.14	No	No
	T-18	7.8	76.5	87.3	1620	0.2	0.14	0.17	Yes	Yes
	T-18	7.8	81.4	97.1	3580	0.2	0.15	0.17	Yes	Yes
	T-19	7.8	24.5	28.4	1010	0.2	0.15	0.19	Yes	Yes
	T-19	7.8	36.3	53.9	4900	0.2	0.19	0.31	Yes	Yes
	T-19	7.8	46.1	74.5	2850	0.2	0.21	0.18	Yes	Yes
	T-19	7.8	59.8	103	5940	0.2	0.22	0.18	Yes	Yes
	T-20	7.8	21.6	22.6	12980	0.2	0.14	0.17	No	No
	T-20	7.8	25.5	31.4	12810	0.2	0.16	0.17	No	No
	T-20	7.8	29.4	39.2	16270	0.2	0.17	0.17	No	No
	T-21	7.8	57.9	57.9	10390	0.2	0.13	0.26	No	No
	T-21	7.8	59.8	61.8	8940	0.2	0.13	0.26	No	No
	T-21	7.8	65.7	74.5	11070	0.2	0.15	0.26	No	No
	T-22	7.8	40.2	68.6	1900	0.2	0.22	0.16	Yes	Yes
	T-22	7.8	43.1	74.5	4900	0.2	0.22	0.16	Yes	Yes
	T-23	7.8	46.1	68.6	2200	0.2	0.19	0.14	Yes	Yes
	T-23	7.8	48.1	72.6	2600	0.2	0.19	0.14	Yes	Yes
	T-24	7.8	34.3	52	4310	0.2	0.2	0.16	Yes	Yes

	T-24	7.8	38.2	59.8	2940	0.2	0.2	0.16	Yes	Yes
	T-25	7.8	79.4	153	8830	0.2	0.23	0.08	Yes	No
	T-26	7.8	53.9	97	1960	0.1	0.11	0.14	Yes	Yes
	T-27	7.8	51	93.2	1080	0.2	0.23	0.07	Yes	Yes
	T-28	7.8	103.9	205	15200	0.1	0.12	0.08	No	No
	T-28	7.8	107.9	212.8	6370	0.1	0.11	0.08	No	No
	T-31	7.8	43.1	43.1	3450	0.2	0.13	0.16	Yes	Yes
	T-31	7.8	50	57.9	2680	0.2	0.15	0.16	Yes	Yes
	T-32	7.8	49	55.9	3230	0.2	0.15	0.21	Yes	Yes
	T-32	7.8	51	59.8	4040	0.2	0.15	0.21	Yes	Yes
	T-32	7.8	55.9	70.6	2880	0.2	0.16	0.21	Yes	Yes
	T-33	7.8	51	59.8	2940	0.2	0.15	0.15	Yes	Yes
	T-33	7.8	66.7	93.2	5740	0.2	0.18	0.32	Yes	Yes
	T-33	7.8	77.6	103.9	8830	0.2	0.18	0.32	Yes	Yes
	T-34	7.8	47.1	48.1	1840	0.2	0.13	0.13	Yes	Yes
	T-35	7.8	62.8	72.6	2500	0.2	0.15	0.17	Yes	Yes
	T-35	7.8	63.7	74.5	4410	0.2	0.15	0.17	Yes	Yes
	T-35	7.8	77.5	103.9	4160	0.2	0.17	0.17	Yes	Yes
	T-36	7.8	75.5	111.8	7850	0.2	0.18	0.22	No	Yes
					1977 Vrancea Earthquake					
Dimbovitza site (1)		7.2	47.1	78.5	5120	0.22	0.22	0.2	Yes	Yes
		7.2	53.9	93.2	3660	0.22	0.22	0.2	Yes	Yes
		7.2	62.8	111.8	3050	0.22	0.23	0.2	Yes	Yes
		7.2	71.6	130.4	1290	0.22	0.23	0.2	Yes	Yes
		7.2	80.4	149.1	5120	0.22	0.23	0.2	Yes	Yes
					1983 Nihonkaichubu Earthquake					
Noshirocho		7.7	47.1	56.9	9810	0.23	0.18	0.32	No	No
		7.7	53	71.6	15690	0.23	0.2	0.32	No	No
		7.7	63.7	94.1	15080	0.23	0.21	0.32	No	No
		7.7	45.1	53	1760	0.23	0.17	0.32	Yes	Yes
		7.7	51	62.8	4020	0.23	0.18	0.32	Yes	Yes
		7.7	65.7	94.1	7800	0.23	0.21	0.32	Yes	Yes
		7.7	73.5	111.8	8800	0.23	0.22	0.32	Yes	Yes
					1988 Sanguenary Earthquake					
Ferland, Quebec, Canada		5.9	63	90	2760	0.25	0.16	0.1	Yes	No
		5.9	72.8	109.6	5710	0.25	0.17	0.1	No	No

		5.9	82.6	129.3	6510	0.25	0.18	0.1	No	No
		5.9	92.4	148.9	7770	0.25	0.18	0.1	No	No
		5.9	102.2	168.5	7770	0.25	0.18	0.1	No	No
1989 Loma Prieta Earthquake										
San Francisco Marina District	3-Mar	7.1	67.2	77.6	13940	0.24	0.16	0.275	No	No
	3-Mar	7.1	78.9	100	18000	0.24	0.18	0.361	No	No
	3-Mar	7.1	100.1	140.9	13000	0.24	0.19	0.35	No	No
	4-Mar	7.1	59.1	64.1	3350	0.24	0.15	0.178	Yes	Yes
	4-Mar	7.1	83.6	115	750	0.24	0.19	0.16	Yes	Yes
	5-Mar	7.1	81.8	120	1200	0.24	0.2	0.197	Yes	Yes
	6-Mar	7.1	117.1	131.9	5500	0.24	0.15	0.244	No	Yes
Leonardini Farm	39	7.1	36.4	45.6	1300	0.14	0.1	0.1	Yes	Yes
	38	7.1	39.5	44.1	1500	0.14	0.09	0.1	Yes	Yes
	37	7.1	51.8	60.4	2500	0.14	0.1	0.12	No	Yes
Port of Richmond	POR2	7.1	66.2	108.9	1700	0.16	0.14	0.07	Yes	Yes
	POR3	7.1	66.2	108.9	1900	0.16	0.14	0.07	Yes	Yes
	POR4	7.1	66.2	108.9	1500	0.16	0.14	0.07	Yes	Yes
San Francisco Oakland Bay Bridge	SOFBB4	7.1	100.6	154.5	5000	0.29	0.25	0.25	Yes	Yes
	SOFBB5	7.1	100.6	154.5	9400	0.29	0.25	0.25	Yes	Yes