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SYNOPSIS Neural networks have emerged as a powerful computational technique for modeling nonlinear multivariate relationships. The neural network is a product of artificial intelligence research. This paper examines the feasibility of using neural networks for assessing liquefaction potential, from actual field records. The paper starts with a brief overview of the basic architecture and concepts of neural networks. The application of the neural network methodology to evaluate seismic liquefaction potential is then presented.

INTRODUCTION

Neural networks have emerged as a powerful computational technique for modeling nonlinear multivariate relationships. The neural network is a product of artificial intelligence research. A neural network is a "computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping" (Garrett 1994). This paper examines the feasibility of using neural networks for assessing liquefaction potential, from actual field records. The paper starts with a brief overview of the basic architecture and concepts of neural networks. The application of the neural network methodology to evaluate seismic liquefaction potential is then presented.

ARCHITECTURE OF NEURAL NETWORKS

The basic architecture of neural networks has been covered widely (Rumelhart and McClelland 1986; Lippmann 1987; Flood and Kartam 1994). A neural network consists of a number of interconnected processing elements, commonly referred to as neurons. Each neuron receives an input signal from neurons to which it is connected. Each of these connections has numerical weights associated with them. The neurons are logically arranged into two or more layers as shown in Fig. 1, and interact with each other via these weighted connections. These scalar weights determine the nature and strength of the influence between the interconnected neurons. Each neuron is connected to all the neurons in the next layer. There is an input layer where data are presented to the neural network, one or more intermediate layers also known as hidden layers, and an output layer that holds the response of the network to the input. Each hidden and output neuron processes its inputs by multiplying each input by its weight, summing the product and then passing the sum through a nonlinear transfer function to produce a result. A sigmoid curve is commonly used as the transfer function. The sigmoid function modulates the weighted sum of the inputs so that the output approaches unity when the input gets larger and approaches zero when the input gets smaller.

Neural networks essentially "learn" from a set of example patterns, through the adaptation of their connection weights. A number of these learning strategies are described in detail in Rumelhart and McClelland (1986) and Lippmann (1987). The most popular learning strategy is the back-propagation algorithm (Rumelhart et al. 1986).

BACK-PROPAGATION ALGORITHM

The neural network paradigm adopted in most civil engineering applications is the back-propagation learning algorithm (Rumelhart et al. 1986). The basic mathematical concepts of the back-propagation algorithm are found in the literature (Caudill and Butler 1990; Eberhart and Dobbins 1990). Training of the neural network is carried out through the presentation of a series of example patterns of associated input and target (expected) output. The neural network "learns" by modifying the weights of the neurons in the hidden and output layers in response to the errors between the actual (predicted) output and the target (expected) output. This is carried out through the gradient descent on the sum of squares of the errors for all the training patterns (Rumelhart et al. 1986). The changes in weights are in proportion to the negative of the derivative of the error term. One pass through

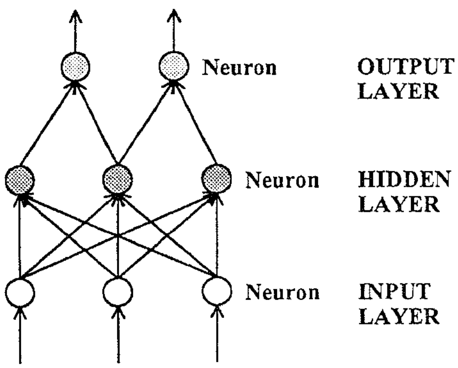

Fig. 1. Typical Neural Network Architecture

the set of training patterns along with the updating of the weights is called a cycle or epoch. Training is carried out by repeatedly presenting the entire set of training patterns (with the weights updated at the end of each cycle) until the average sum squared error over all the training patterns are minimized and within the tolerance specified for the problem.

At the end of the training phase, the neural network predictions should correctly approximate the target output for the training data 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 fed a separate set of data. In this testing phase, the neural network predictions (using the trained weights) are compared to the target output values. This assesses the ability of the neural network to detect the distinct features of the training patterns and to generalize correct responses for the testing patterns that only broadly resemble the data in the training set. No additional learning or weight adjustments occur during this phase. Once the training and testing phases are found to be successful, the neural network can then be put to use in practical applications. The neural network will produce almost instantaneous results of the output for the practical input provided. As with any empirical or statistical regression technique, the neural network predictions are safe to apply only in the context for which they were formulated i.e. the input values fall within the bounds of the training set.

APPLICATION TO SOIL LIQUEFACTION

The prediction of soil liquefaction is difficult because there are many critical factors influencing liquefaction, including the magnitude and intensity of the earthquake, the properties of the soil, the depth of the soil deposit, the distance from the source of the earthquake, and the seismic attenuation properties. One common method of evaluating liquefaction potential uses the Standard Penetration Test (SPT) value as an index of soil liquefaction resistance. The method of Seed et al. (1985) was developed by analyzing field records, and establishing empirical correlations between the SPT and seismic properties, and the occurrence or nonoccurrence of liquefaction at the site.

Neural Network Modeling

The back-propagation neural network algorithm was adopted in this study (Goh 1994). The neural network training and testing patterns were obtained from the case records of Tokimatsu and Yoshimi (1983). A total of 85 case records was considered. This represented 42 sites that liquefied and 43 sites that did not liquefy. 59 of these case records were used for the training phase and 26 for the testing phase. The testing records are shown in Table 1.

F is the % fines content and D_{50} is the mean grain size of the soil. The following expression from Tokimatsu and Yoshimi (1983) was used to determine the equivalent dynamic shear stress (τ_{av}/σ_o') at depth z.

$$\frac{\tau_{av}}{\sigma_o'} = 0.1\frac{a}{g}(M-1)\frac{\sigma_o}{\sigma_o'}(1-0.015z) \qquad (1)$$

σ_o is the total vertical stress, σ_o' is the effective vertical stress, M is the earthquake magnitude, and a/g is the peak horizontal acceleration at ground surface. The standardized SPT $(N_1)_{60}$ values were used for all the cases (Seed et al. 1985). N_1 is the SPT N value normalized for effective overburden pressure (Seed et al. 1979). $(N_1)_{60}$ is N_1 standardized for the driving energy in the drill rods of 60% of the theoretical free-fall energy of the SPT hammer.

The output consisted of a single neuron, representing the liquefaction potential. The desired output was given a binary value of 1 for a liquefied site and a value of 0 for a nonliquefied site. The number of input variables in the neural network models was varied, to determine the most reliable model. The optimal solution was deduced as the model giving the least number of errors. A single hidden layer was found to be sufficient for this study. The optimal number of neurons in the hidden layer were determined through trial and error. Training was carried out until the average sum squared error over all the training patterns were minimized. This occurred after about 30,000 cycles of training. Training time on a 80486-33 MHz personal computer was less than 10 minutes.

RESULTS

The neural network's accuracy improved as more input variables are provided. For brevity, only the most successful model M8, is described. The model consisted of 8 input variables. The variables were: σ_o, σ_o', M, $(N_1)_{60}$, a/g, τ_{av}/σ_o', F, and D_{50}. The convergence of the neural network during the training phase is shown in Fig. 2. The results of the predictions for the testing phase, using this model have been tabulated in Table 1 alongside the actual field performance. The results from the testing phase suggests that although the neural network models was not explicitly trained for these data, it was capable of generalization and gave reasonable predictions. Altogether there were 2 errors in the training data and 2 errors in testing data, for M8. Overall, 95% of the predictions were correct. In comparison, the Seed et al. (1985) procedure gave 14 errors or a 84% success rate.

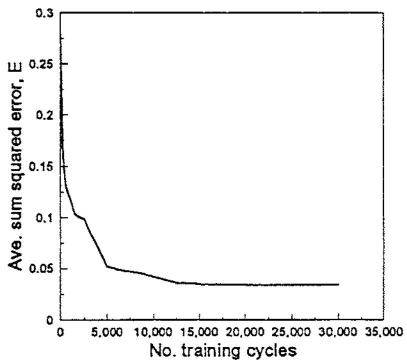

Fig. 2. Convergence of Model M8

PARAMETRIC STUDIES

Parametric studies can be carried out using the generalization capabilities of the neural network, on the successful completion of the testing phase. Fig. 3 shows the results of a typical parametric study using model M8. The parameters a/g and $(N_1)_{60}$ were varied to extract indicators for determining the boundary curves separating liquefaction and nonliquefaction. The soil was assumed to be at a depth z = 7 m, with unit weight γ = 18 kN/m^3 and the water table at the ground surface. τ_{av}/σ_o' was calculated using eqn. (1). The neural network predictions for D_{50} = 0.35 mm and 0.5 mm, with M = 7.5 and F = 5%, indicate that the critical SPT values for liquefaction increase with an increase in D_{50}. The results exhibit the same trends as the solution proposed by Seed et al. (1985).

DISCUSSION

The neural network modeling approach is simpler to apply than the method by Seed et al. (1985). Only minimal processing of the data is required, essentially to obtain values of $(N_1)_{60}$ and τ_{av}/σ_o', for a given peak horizontal acceleration and earthquake magnitude M. In comparison, as the method of Seed et al. (1985) is essentially applicable only for M = 7.5, further calibration of τ_{av}/σ_o' is required for earthquakes of

Table 1. Summary of Testing Data

Earthquake	M	σ_o (kPa)	σ_o' (kPa)	SPT N	a/g	τ_{av}/σ_o'	F (%)	D_{50} (mm)	Field record Liquefaction?	Neural network.
Miyagiken-oki	7.4	118.7	66.7	10.0	0.20	0.21	0.0	0.60	Yes	Yes
(1978)	7.4	61.8	38.3	19.0	0.32	0.31	4.0	0.28	No	No
	7.4	61.8	34.3	5.0	0.32	0.35	5.0	0.70	Yes	Yes
	7.4	61.8	41.2	7.0	0.32	0.29	4.0	0.28	Yes	Yes
	7.4	80.4	47.1	11.0	0.24	0.25	0.0	0.40	Yes	Yes
	7.4	97.1	66.7	20.0	0.24	0.21	0.0	0.60	No	No
	7.4	80.4	54.9	4.0	0.24	0.21	10.0	0.40	Yes	Yes
	7.4	61.8	41.2	13.0	0.24	0.22	7.0	1.60	Yes	Yes
	7.4	80.4	41.2	8.0	0.24	0.28	12.0	1.20	Yes	Yes
	7.4	136.4	77.5	17.0	0.24	0.24	17.0	0.35	No	No
	7.4	103.0	83.4	9.0	0.24	0.17	5.0	0.34	Yes	Yes
	7.4	108.9	70.6	8.0	0.24	0.21	4.0	0.36	Yes	Yes
	7.4	59.8	56.9	11.0	0.28	0.18	5.0	0.53	Yes	Yes
	7.4	109.9	80.4	23.0	0.28	0.22	0.0	0.41	No	No
	7.4	111.8	77.5	10.0	0.24	0.20	10.0	0.30	No	Yes
	7.4	74.6	59.8	6.0	0.24	0.18	10.0	0.25	Yes	Yes
	7.4	130.5	86.3	21.0	0.24	0.21	5.0	0.35	No	No
	7.4	93.2	68.7	9.0	0.24	0.19	20.0	0.15	Yes	No
	7.4	83.4	63.8	10.0	0.24	0.19	26.0	0.12	No	No
	7.4	111.8	77.5	12.0	0.24	0.20	3.0	0.35	Yes	Yes
	7.4	106.9	71.6	15.0	0.24	0.21	11.0	0.30	No	No
	7.4	124.6	91.2	17.0	0.24	0.19	12.0	0.30	No	No
	7.4	74.6	49.1	4.0	0.20	0.18	10.0	0.15	Yes	Yes
	7.4	111.8	66.7	15.0	0.20	0.20	10.0	0.18	No	No
Chibakenchubu	6.1	105.9	56.9	5.0	0.10	0.09	13.0	0.18	No	No
(1980)	6.1	247.2	105.9	4.0	0.10	0.09	27.0	0.17	No	No

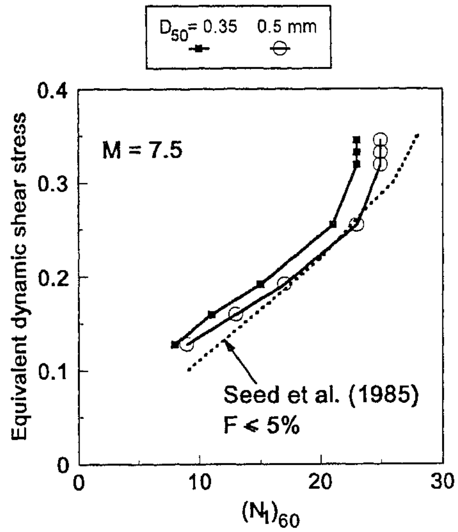

Fig. 3. Results of Parametric Study

different magnitudes. In addition, the boundary curve separating the liquefaction and nonliquefaction zones needs to be calibrated for different fines content of the soil.

When the back-propagation neural networks are trained on actual field data, they are trained to deal with inherent noisy or imprecise data. As more field data become available, the back-propagation neural network can be readily retrained and refined with patterns that include these additional data. The main criticism of the neural network methodology is its inability at present to trace and explain the step-by-step logic it uses to arrive at the outputs from the inputs provided. This is expected to be a temporary drawback that will be overcome with further research.

SUMMARY AND CONCLUSIONS

Neural networks have been successfully used to model the complex relationship between the seismic and soil parameters, and the liquefaction potential. Actual field records were used in the analysis. Comparisons indicate that the neural network model is more reliable than the method by Seed et al. (1985). As with any empirical or statistical regression technique, the neural network predictions are safe to apply only in the context for which they were formulated.

REFERENCES

Caudill, M. and C. Butler (1990), "Naturally Intelligent Systems", MIT Press, Cambridge, Mass.

Eberhart, R. C. and R. W. Dobbins, (1990), "Neural Network PC Tools: A Practical Guide", Academic Press, San Diego, CA.

Flood, I. and N. Kartam, (1994), "Neural Networks in Civil Engineering. I: Principles and Understanding", J. Computing in Civil Engrg., ASCE, 8(2), 131-148.

Garrett, Jr, J. H. (1994), "Where and Why Artificial Neural Networks are Applicable in Civil Engineering", Editorial, J. Computing in Civil Engrg., ASCE, 8(2), 129-130.

Goh, A. T. C. (1994), "Seismic Liquefaction Potential Assessed by Neural Networks", J. Geotech. Engrg., ASCE. (in press).

Lippmann, R. P. (1987), "An Introduction to Computing with Neural Nets", IEEE Acoustics Speech and Signal Processing, 4(2), 4-22.

Rumelhart, D. E., G. E. Hinton, and R. J. Williams (1986), "Learning Internal Representation by Error Propagation", in Parallel Distributed Processing, vol. 1: Foundations, ed. D. E. Rumelhart and J. L. McClelland, MIT Press, Cambridge, MA.

Rumelhart, D. E. and J. L. Mcclelland (1986), "Parallel Distributed Processing - Explorations in the Microstructure of Cognition", Vols. 1 and 2, MIT Press, Cambridge, MA.

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), 1425-1445.

Tokimatsu, K. and Y. Yoshimi (1983), "Empirical Correlation of Soil Liquefaction Based on SPT N-value and Fines Content", Soils Found., 23(4), 56-74.