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Review Article

Neural Network Applications in Geotechnical Engineering

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Geotechnical engineers often encounter complicated multivariate problems that involve a number of interacting factors. Commonly, the relationship between these factors is not precisely known. In addition, the data associated with these parameters are usually incomplete or erroneous (noisy). The extraction of knowledge from the data in order to develop a relationship between these factors is a formidable task requiring sophisticated modeling techniques as well as human intuition and experience. This paper demonstrates the use of neural networks to alleviate this problem. Neural networks have emerged as a powerful computational technique for modeling nonlinear multivariate relationships. This paper provides a brief overview of the basic architecture and concepts of neural networks, followed by a review of current applications of neural networks in geotechnical engineering and a discussion of some potential applications.

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. Since a neural network is essentially 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" [1], it can be readily applied to the field of geotechnical engineering. Geotechnical engineers often have to solve complex problems that involve a number of interacting factors. Commonly, the relationship between these factors are not precisely known. In addition, the data associated with these parameters are usually incomplete or erroneous (noisy). The extraction of knowledge from the data to develop the relationship between these factors is a formidable task requiring sophisticated modeling techniques as well as human intuition and experience. This paper demonstrates the use of neural networks to alleviate this problem. The growing interest in neural networks among researchers is due to its excellent performance in pattern recognition and the modeling of nonlinear relationships involving a multitude of variables, in place of conventional techniques.

This paper provides a brief overview of the basic architecture and concepts of neural networks, followed by a review of current applications of neural networks in geotechnical engineering and a discussion of some potential applications.

CHARACTERISTICS OF NEURAL NETWORKS

A thorough treatment of the neural network methodology is beyond the scope of this paper. The basic architecture of neural networks has been covered widely in [2-5]. 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 it. The neurons are logically arranged into two or more layers. The neurons 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 such as a sigmoid function to produce a result. Neural networks

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essentially "learn" from a set of example patterns, through the adaptation of their connection weights.

The neural network paradigm adopted in most civil engineering applications is the back-propagation (BP) learning algorithm [6]. The basic mathematical concepts of the back-propagation algorithm are found in the literature [4,7]. Back-propagation neural networks with a single hidden layer have been shown to be capable of providing accurate approximation to any continuous function provided there are sufficient hidden neurons [8].

One major drawback of the back-propagation algorithm is the time consuming iterative (trial and error) procedure required during training to obtain the optimal neural network learning coefficients (learning rate and momemtum factor), the number of hidden layers in the neural network and the number of neurons in each hidden layer. The training of weight coefficients in order to minimize the error can also be rather computationally expensive as the neural network has to be repeatedly presented (multiple passes) with the training patterns. Various modifications have been proposed to accelerate convergence. A number of heuristics and algorithms have been presented to improve back-propagation performance and to achieve the optimal network. Details of these techniques have been reviewed in [9,10].

To overcome the above limitations, Specht [11] proposed a memory-based neural network algorithm called the Generalized Regression Neural Network (GRNN) with emphasis on fast learning. Based on the Parzen window estimator strategy [12], the training process for the GRNN is fast as the training data needs to be presented to the neural network only once (one-pass) in contrast to the multipass back-propagation learning. Hence, learning time is generally an order of magnitude faster [11]. Only one parameter requires adjustment or optimization. Even in problems where the long training time involved in finding the optimal BP model is justifiable, the GRNN can be used to check that the BP training gives comparable accuracy. The main limitation of the GRNN is the long computational time when dealing with a large training data set, which also requires more memory. In such cases, a clustering technique [11] can be used to reduce the size of the training patterns, thereby reducing computational time as well as memory requirements. Another disadvantage is the substantial amount of computation required after training when a new output is to be calculated. Some recent applications in geotechnical engineering are mentioned in [13,14].

Comparison with Traditional Methods

Statistical methods are commonly used to model relationships involving a number of variables. This is often complex and circuitous, particularly for nonlinear relationships. Also, to formulate the statistical model, the important parameters must be known. By comparison, the modeling process in neural networks is more direct, as there is no need to specify an a-priori mathematical relationship between the input and output variables. The neural network is capable of capturing nonlinear interactions between input and output variables in a system. In addition, it can generalize correct responses that only broadly resemble the data in the training set. When the neural networks are trained on actual field data, they are trained to deal with inherent noisy or imprecise data. As more field data becomes available, the 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.

POTENTIAL APPLICATIONS

In this section, an attempt is made to identify the potential role back-propagation neural networks can play in assisting geotechnical engineers. The neural network approach would be particularly useful for problems lacking a precise analytical solution because of an inadequate understanding of the phenomena involved and the factors affecting them. Problem domains in which the behavior of the system is governed by nonlinear multivariate relationships and where reliable case records are available, offer the greatest promise. Some of the major applications in geotechnical engineering are envisaged in the following sections.

Engineering Property Estimation

In the field of geotechnical engineering, many researchers have employed neural networks to estimate correlations between various soil parameters. For example, the neural network approach can be used for developing engineering correlations between various soil parameters. As an example, consider the empirical relationship between the Cone Penetration Test (CPT) measurements and the engineering properties of soils. For sand, these correlations are commonly derived from large scale laboratory calibration chamber tests. The sand sample of known density is prepared in the chamber and then consolidated to the desired stresses. The cone is then pushed into the sample and the cone tip resistance q_c and the sleeve friction f_s are measured. The engineering properties of the sample are determined from laboratory testing. The cone measurements are then correlated directly to the engineering properties.

In this paper, the correlation between the tangent constrained modulus M_o during compression and q_c for normally consolidated sand is considered. The training and testing patterns for the neural network model were based on the comprehensive experimental results of Baldi et al. [15]. The correlation determined by Baldi et al. [15] from statistical analysis is shown below:

$$M_o/q_c = 1420(\sigma'_m/98.1)^{-0.116}e^{(-1.123D_R)}. \tag{1}$$

The mean effective stress σ'_m, M_o and q_c are in units of kPa and the sand relative density D_R is in decimals. This statistical correlation is used for comparison with the neural network predictions.

The back-propagation neural network program adopted in this study essentially follows the formulations of Eberhart and Dobbins [7]. The neural network model consisted of 3 input neurons representing D_R, σ'_m and q_c as well as a single output neuron representing M_o. The values for these parameters ranged from 16% to 96% for D_R, 26 to 458 kPa for σ'_m, 2 to 47 MPa for q_c and 16 to 150 MPa for M_o. A total of 73 training patterns and 29 testing patterns were employed. Some sample training and testing patterns are provided in Table 1.

The average sum squared error plotted as a function of the training cycles is shown in Figure 1 for the neural network model with 4 hidden neurons.

Table 1. Sample training and testing data.

D_R (%)	σ'_m (kPa)	q_c (MPa)	M_o (MPa)
Training			
92.4	366.4	46.5	147.6
92.9	221.2	39.1	119.6
92.9	80.5	23.9	80.3
74.6	221.3	26.1	106.1
74.6	369.1	34.4	131.4
74.9	516.3	40.7	144.3
61.8	370.2	20.1	111.4
63.4	515.3	25	120.5
91.8	46.7	18.4	71.1
75.8	46.4	10.9	66.3
Testing			
73.1	80.6	15.6	74.3
92.9	219.8	36.2	118.1
57.7	223.1	13.4	87.5
61.8	81.6	9.1	62.6
63.4	45.4	5.6	52.1
55.8	370.1	15.5	112.2
76.7	224.8	22.1	108.4
56.4	522.1	19.9	128.4
77.2	518.8	32.1	137.7
51.2	85	7.3	60.8

Experiments indicate that there is no significant improvement in convergence as the number of hidden neurons increases beyond 4. The neural network predictions for the training and testing sets are shown in Figure 2. The scatter of the predicted versus the measured M_o values was assessed using regression analysis. High coefficients of correlations for the training and testing data were obtained as shown in Table 2. The results demonstrate that the neural network was successful in modeling the nonlinear relationship between M_o and the other parameters. A comparison of the correlation coefficients in Table 2 indicates that the neural network model is more reliable than the statistical model. This is also evident from the plots in Figure 2.

Since the neural network is capable of generalization, parametric studies can be carried out to evaluate the effects of various input parameters on the output. This was conducted at the end of the testing phase, whereby some additional hypothetical data was fed into the trained neural network model. This is demonstrated in Figure 3 which shows the results of typical correlations between D_R, σ'_m, q_c and M_o using the trained neural network.

Other successful applications of neural networks include the estimation of the hydraulic conductivity of clay liners [16] based on soil data from 67 landfill sites in North America and the evaluation of the frictional

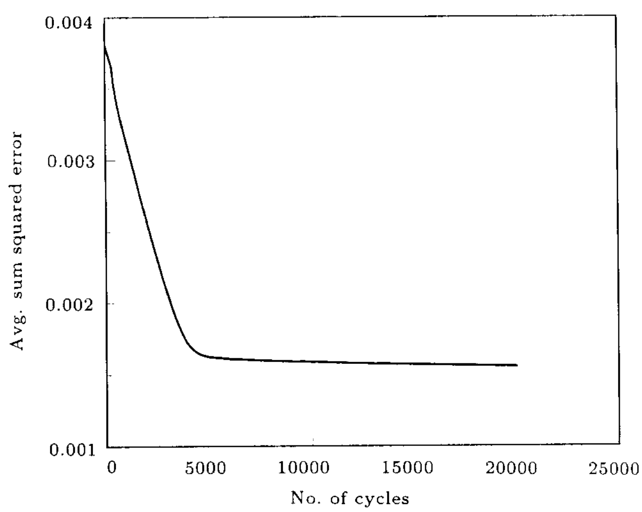

Figure 1. Neural network convergence characteristics during training.

Table 2. Summary of regression analysis results.

Coefficient of Correlation		
Method	**Training Data**	**Testing Data**
Neural Network	0.98	0.94
Equation 1	0.91	0.87

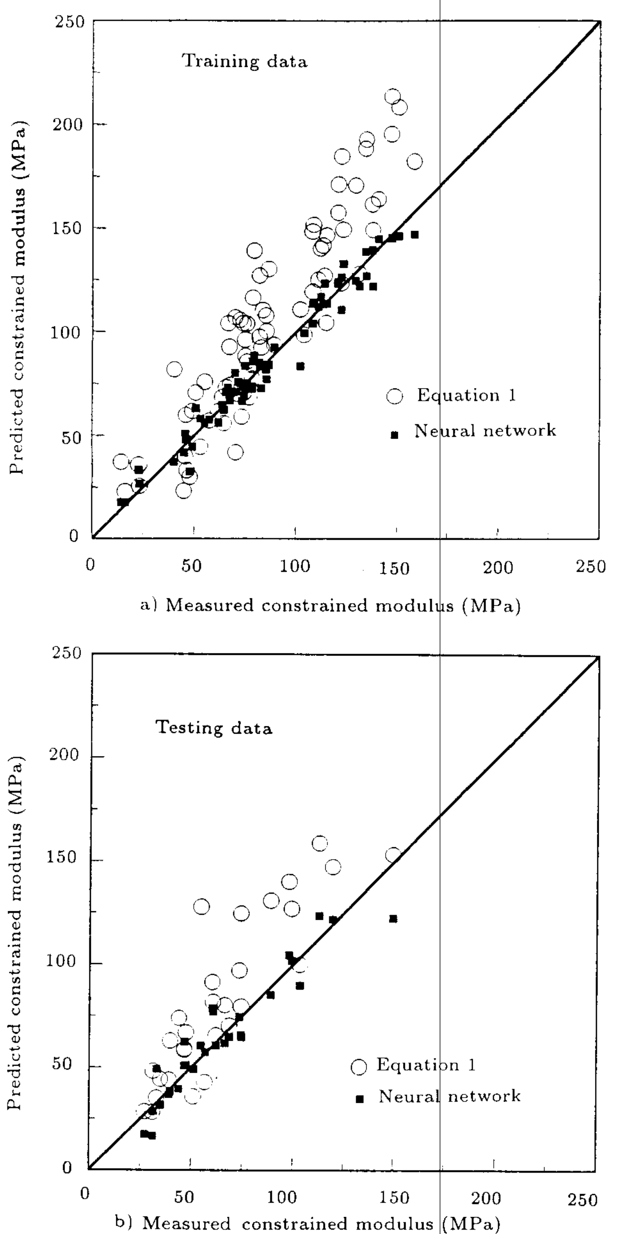

Figure 2. Comparison of the predicted and measured M_o values.

capacity of driven piles in clay based on actual load test records [17].

Performance Prediction

One example of the performance prediction of a multivariate problem is the assessment of liquefaction potential in earthquake-prone regions. Soil liquefaction involves the strength loss of soil during shaking. During earthquakes, the resultant damage to infrastructure and loss of life from soil liquefaction can be very extensive. 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

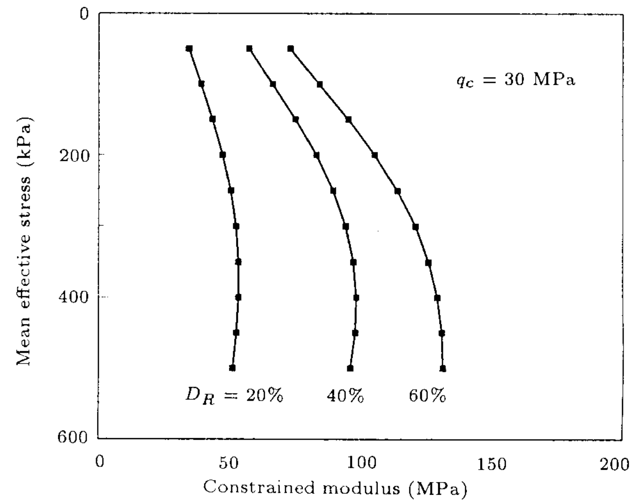

Figure 3. Results of parametric study.

of the soil deposit, the distance from the source of the earthquake and the seismic attenuation properties.

In one common method of evaluating liquefaction potential, the penetration resistance of the Standard Penetration Test (SPT) is used as an index of soil liquefaction resistance [18]. The SPT is an in-situ testing procedure commonly carried out for sandy soil types. The method of Seed et al. [18] 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. A typical empirical boundary separating liquefied and nonliquefied sites is shown in Figure 4. The method is essentially applicable only for earthquakes of magnitude $M = 7.5$. Further calibration of the equivalent dynamic shear stress ratio τ_{av}/σ'_o is required for earthquakes of different magnitudes. In addition, the boundary curve separating the liquefaction and nonliquefaction zones needs to be calibrated for different fines content F of the soil.

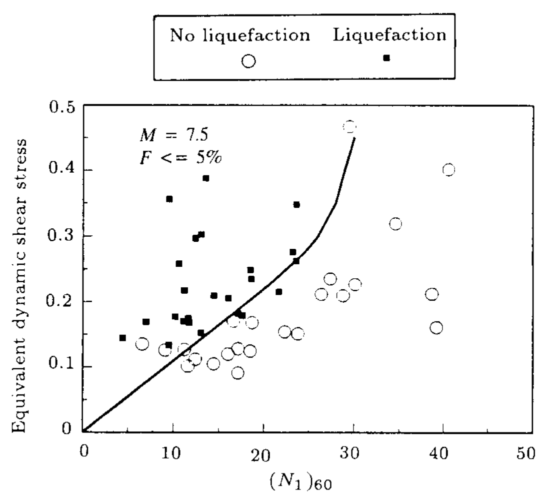

Figure 4. Typical empirical design chart.

Table 3. Soil and seismic data used in testing.

Earthquake	$\sigma_o M$	σ'_o (kPa)	SPT (kPa)	N	a/g	τ_{av}/σ'_o	$F(\%)$	D_{50} (mm)	Field Behavior	NNet. Liquefaction?
Miyagikenoki (1978)	7.4	118.7	66.7	10.0	0.20	0.21	0.0	0.60	Yes	Yes
	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(1980)	6.1	105.9	56.9	5.0	0.10	0.09	13.0	0.18	No	No
	6.1	247.2	105.9	4.0	0.10	0.09	27.0	0.17	No	No

The case records from Tokimatsu and Yoshimi [19] were evaluated using the neural network. A total of 85 case records was considered. This represented 42 sites that liquefied and 43 sites that did not liquefy. The training phase comprised of 59 case records and the testing phase consisted of 26 case records. For brevity, only the data used in the testing phase are shown in Table 3. F is the % fines content and D_{50} is the mean grain size of the soil. The following expression by Tokimatsu and Yoshimi [19] was used to determine the equivalent dynamic shear stress (τ_{av}/σ'_o) at depth z:

$$(\tau_{av}/\sigma'_o) = 0.1(a/g)(M-1)(\sigma_o/\sigma'_o)(1-0.015z), \tag{2}$$

in which σ_o is the total vertical stress, σ'_o is the effective vertical stress, M is the earthquake magnitude and a/g is the normalized peak horizontal acceleration at ground surface. The standardized SPT $(N_1)_{60}$ values were used for all the cases [18]. N_1 is the SPT N value normalized for effective overburden pressure. $(N_1)_{60}$ 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 back-propagation neural network adopted in this study consisted of three layers of neurons. The number of input variables were varied to assess the quality of the neural network predictions. 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. Training was carried out until the average sum squared errors over all the training patterns were minimized. Further details are described in [20]. The number of input variables in the neural network models were varied to determine the most reliable model. The optimal solution was deduced as the model giving the least number of errors. The number of neurons in the hidden layer was found to have minimal effects on the prediction performance of the neural networks.

For brevity, only the most successful model $M8$ is described. The model consisted of 8 input variables and 3 hidden neurons. The input variables were: σ_o, σ'_o, M, $(N_1)_{60}$, a/g, τ_{av}/σ'_o, F and D_{50}. The results of the predictions for the testing phase, using this model, have been tabulated in Table 3, along with the actual field performance. Altogether, there were 2 errors in the training data and 2 errors in the testing data. Overall, 95% of the predictions were correct. In comparison, the Seed et al. procedure gave 14 errors or a 84% success rate. The results indicate that the neural network has been successful in learning the relationship between the input and output data. The results from the testing phase suggests that although the neural network model was not explicitly trained for these data, it was capable of generalization and provided reasonable predictions.

The neural network modeling approach is simpler to apply than the more conventional method. 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. is applicable only for M of 7.5, further calibration of τ_{av}/σ'_o is required for earthquakes of different magnitudes. In addition, the boundary curve separating the liquefaction and nonliquefaction zones needs to be calibrated for different fines content of the soil. A similar approach based on cone penetration data (CPT) has also been reported by Goh [21].

Neural networks can also be used to synthesize data obtained from extensive parametric studies using numerical tools such as the finite element method. An example is the prediction of the maximum lateral wall displacement for braced excavations in clays. Goh et al. [22] have demonstrated the feasibility of training a back-propagation neural network for evaluating wall displacements.

In open cut excavations for buildings and tunnels in soft clays, braced sheet piles or diaphragm walls are generally required as lateral supports to maintain stability. A major consideration in selecting the appropriate braced retaining wall system is to limit the soil and wall movements. Surrounding buildings and services can be damaged if these movements are not controlled.

The magnitude of the wall movements associated with braced excavation systems is often determined using the finite element method, particularly for problems that involve complex soil conditions and construction procedures. Achieving reasonably good estimates of the wall movements requires a good knowledge of the finite element method, which many geotechnical engineers are not familiar with, as well as familiarity with the computer program that is used and its limitations. Since many of these geotechnical finite element programs are not user-friendly, the setting up of the finite element mesh, the input data preparation and the interpretation of the output are rather time-consuming. Hence, several empirical solutions [23-25] have been developed that provide engineers with simpler methods of estimating the maximum wall deflections. These methods are particularly useful for uniform soil conditions and for providing first estimates for preliminary design of more complex problems. The methods are essentially for clay soils and are based on finite element studies, supplemented by measured case records. In many of these methods, the estimation of the wall deflection incorporates a factor related to the factor of safety against basal heave. This enables yielding of the soil and the influence of the underlying strong layers of soil to be considered. The methods also take into consideration other critical factors such as the soil strength and stiffness, the wall geometry and stiffness and the excavation geometry. These methods provide the designer with a reasonable first estimate of the wall maximum displacement δ, assuming average to good workmanship.

The back-propagation neural network model consists of 7 input variables (B, T/B, EI, H, c_u, E_u/c_u and γ) and a single output variable. The excavation geometry parameters are illustrated in Figure 5. EI is the wall stiffness, γ is the soil unit weight, c_u is the soil undrained shear strength and E_u is the soil undrained elastic modulus. The output variable is the maximum lateral wall deflection δ.

The data were drawn from parametric studies using the finite element method (FEM). Details of the parameters and their range of values are shown in Table 4. The variations in the parameters are typical of those which would occur for braced excavations in soft and medium clay. The finite element modeling is described in [24]. The soil stress-strain behavior is represented by a hyperbolic constitutive model. The clay has been assumed to be saturated and incompressible with a Poisson's ratio of 0.49. The total horizontal

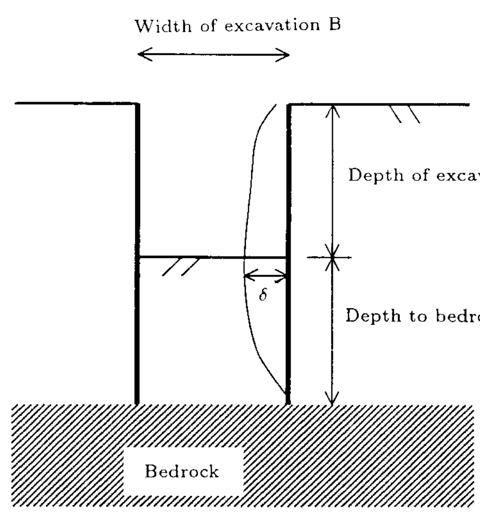

Figure 5. Wall and excavation geometry for braced excavation.

Table 4. Summary of excavation parameters.

Property	Symbol	Units	Range of Values
Excavation width	B	m	11-33
Soil thickness/width ratio	T/B	—	0.18–4.45
Wall stiffness	EI	MNm^2/m	46.5–7000
Excavation height	H	m	1-11
Soil undrained shear strength	c_u	kPa	18-70
Soil modulus /shear strength ratio	E_u/C_u	—	200–300
Soil unit weight	γ	kN/m^3	15–20
Max. wall deflection	δ	m	0.003–0.540

Table 5. Neural network predictions and field measurements.

Case	B (m)	T/B	EI (MNm^2/m)	H (m)	c_u(kPa)	E_u/c_u	γ (kN/m^2)	Measured δ (mm)	Predicted δ (mm)
Lavender	23.5	0.49	1670	6.5	40	200	18	32	31
	23.5	0.37	1670	9.4	50	200	18	36	28
Telecom	27.0	0.78	60	4	25.6	200	15	56–84	65
Vaterland	11.6	1.47	62	7	30	200	17	76	76
[26]	11.6	1.21	62	9.1	30	200	17	114–140	107
San Francisco	40.5	0.59	46.5	4.6	58	250	17.6	20–60	59
[27]	40.5	0.45	46.5	10.4	66	250	17.6	72–150	122

and vertical stresses are assumed to be equal prior to excavation. Excavations to depths of between 1 to 11 m were considered. The strut levels were at depths of 1 m, 3.5 m, 6 m and 8.5 m. In most published case histories as well as the authors' experiences in Singapore, the vertical strut spacing is usually between 2 m and 3 m. As the finite element studies have indicated that the lateral wall deflections are not very sensitive to strut spacing varied within this range, the strut spacing was omitted as an input variable in the neural network model. The strut stiffness was also not considered in the neural network model. For a "normal" braced excavation system, the influence of the strut stiffness on the wall deflection is not as significant as the wall stiffness and strut spacing [23].

For flexible sheetpiles, walls floating in the clay and penetrating into the hard stratum were considered. For diaphragm walls, only walls penetrating into the hard stratum were considered. The retaining walls were also assumed to have sufficient moment capacity so that no yielding or cracking occurred during construction. The data were arbitrarily separated into a training set and a testing set. A total of 196 patterns were used for training and 57 patterns for testing. The convergence performance of the neural network was found to be optimal with 3 neurons in the hidden layer. Further details of the neural network model are found in [22].

Figure 6 shows plots of the FEM maximum deflection values versus the values predicted by the neural network (NN), for the training and testing data. The scatter of the predicted NN values relative to FEM deflections were assessed using regression analysis. High coefficients of correlation for the training and testing data of 0.984 and 0.967, respectively, were obtained. The results indicate that the neural network was successful in learning the relationship between the input and output variables.

Some additional testing data from actual case records were also used to validate the performance of the trained neural network model. The results are summarized in Table 5. The agreement of the NN predicted and measured wall deflections is encouraging.

Using the neural network approach in place of more conventional empirical techniques is more advantageous, since the neural network model provides instantaneous results, once it is properly trained. It is also more direct as there is no need to compute the factor of safety against basal heave. The neural network model will directly relate the various factors affecting basal heave, such as the soil shear strength, depth of excavation and depth to underlying strong layers, to the wall displacement. The neural network model may be improved as additional data are acquired, as it can be readily retrained with patterns which include these new data. Also, it may be used as a quick check on

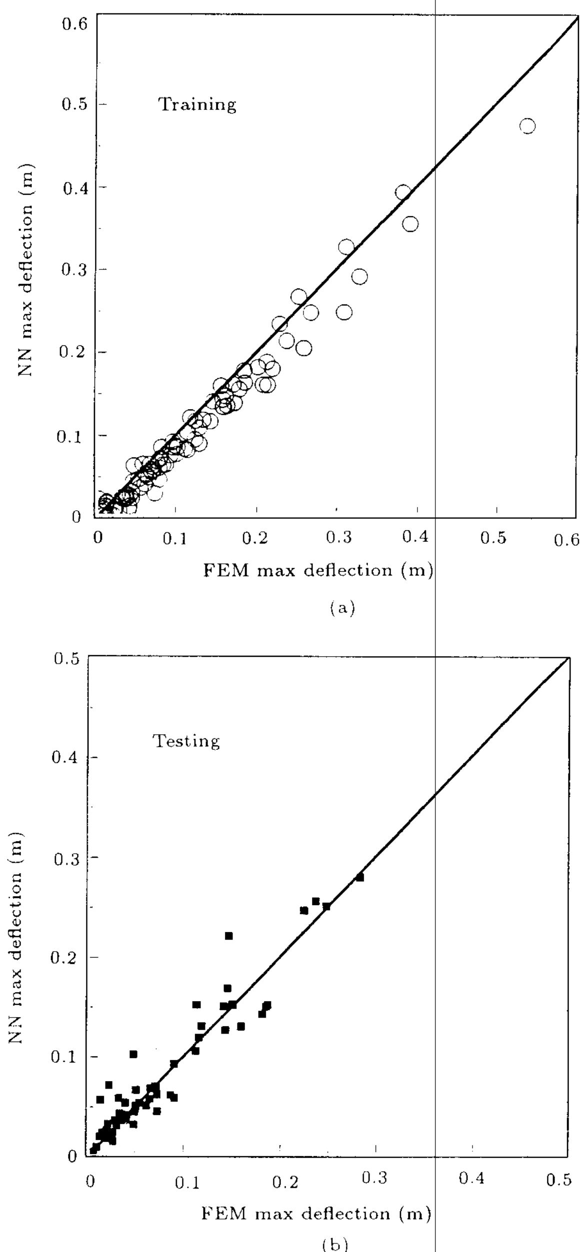

Figure 6. Neural network and FEM predictions.

the solution developed by the time-consuming finite element analysis.

Other applications proposed include the analysis of pile driving records to predict pile load capacity [28], the prediction of pile capacity [13] and the prediction of settlements during tunneling [29].

Constitutive Modeling

Studies conducted by Ghaboussi et al. [30,31] since 1991 have demonstrated the feasibility of using neural networks to model the stress-strain behavior of soils and other materials. In the neural network approach, the representation of material behavior is not based on a-priori assumptions about the material behavior, but is based on the experimental data on which it has been trained. This similar approach has also been reported by other researchers [32,33]. It is envisaged that further refinement would involve the incorporation of these constitutive models into finite element codes.

Pattern Recognition

Another area with scope for development is in applications involving signal pattern recognition. Some success in other civil engineering disciplines have already been reported. An example is the interpretation of ultrasonic data for concrete to detect the presence of flaws [34]. In geotechnical engineering, it is envisaged that the identification of soil types from insitu cone penetration test and dilatometer test data and the interpretation of stress-wave measurements from pile integrity tests, may gain in speed of computation and reliability using a neural network approach. Some preliminary applications to predict pile capacity are discussed in [35,36]. In the work carried out by Teh et al. [36], the neural network was successfully used to predict the static pile capacity using training data based on stress-wave measurements.

SUMMARY

The capability of neural networks to learn multivariate nonlinear relationships by example holds great promises for improving the synthesization of information for the development of empirical design aids for geotechnical engineers. 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.

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