Undrained shear strength of norwegian clays estimated by neural networks

La détermination de la contrainte de cisaillement au cour d'essai non-drainé des argilles norvegiennes par les reseaux de neurones

P.U.Kurup – *University of Massachusetts Lowell, Lowell, MA, U.S.A.*
N.K.Dudani – *Haley & Aldrich, Boston, MA, U.S.A.*

ABSTRACT: This paper describes an artificial neural network model for estimating undrained shear strength from piezocone penetration test (PCPT) data. The model requires the following five input variables: cone resistance, total vertical overburden pressure, excess pore water pressure at the cone tip, excess pore water pressure measured just above the cone base (reference location), and the hydrostatic pore water pressure. The neural network was trained using partial set of PCPT data from three Norwegian geotechnical test sites (Bakklandet, Glava and Valoya clays). The remaining data was used to verify the predictive capabilities of the model. The undrained shear strengths at these sites were also estimated using some of the existing interpretation techniques. The neural network model was found to give better predictions of undrained shear strength compared to the methods evaluated.

RÉSUMÉ: Dans cet article, les auteurs ont présenté un modèle des réseaux de neurones artificielles pour déterminer la contrainte de cisaillement à partir des données d'essais pénetromètriques au piezocône. Les cinqs données requises pour le functionnement du modèle sont les suivantes: la résistance de point, la charge verticale totale, la surpression interstitielle, autour de point, la surpression interstitielle au dessus du cône (au point de réference), et la pression interstitielle. Le réseau de neurone a été entrainé en utilizant une partie du serie des données obtenues de trois sites d'experimentation géotechnique en Norvège (des argilles de Bakklandet, Glava et Valoya). Les données restantes ont été utilisées pour valider le modèle. En comparaison, autres techniques d'interpretation existantes ont été utilisées pour évaluer les contraintes de cisaillement à ces sites. Les données ont montré que le modèle des réseaux de neurones donnent les résultants qui calent mieux les contraintes de cisaillement au cour d'essai non-drainé que les autres méthodes évaluées.

1 INTRODUCTION

The increasing use of the piezocone penetration test (PCPT) in geo-media characterization has resulted in a growing need for reliable methods to estimate engineering soil properties. Determination of the undrained shear strength (s_u), of cohesive soil deposits is an important step for the analysis and design of safe and efficient geotechnical systems. Several methods (based on bearing capacity approach, cavity expansion models, strain path method, empirical and semi-empirical methods) have been developed for predicting s_u from PCPT data. However most techniques fail to accurately describe the complex process and soil behavior around an advancing probe. The soil elements in front of the tip are subjected to a changing state of stress (involving rotation of the principal stresses) as they slide along the cone face up the shaft. Because of the continuous failure and the varying state of stress, the mode of failure is very much different from any of the laboratory tests used to determine the undrained shear strength. In addition to the above, the strain rates experienced by the soil elements in the vicinity of the cone is very high compared to that in a conventional triaxial or vane shear test. A number of factors such as stress history, rigidity index, sensitivity, soil and stress anisotropy, soil fabric, and strain rate, influence the correlation of PCPT data with s_u. Existing analytical models cannot take into account all the above factors in the evaluation of s_u. This paper examines the feasibility of using neural networks to estimate the undrained shear strength of clays from PCPT data. The neural network was trained using actual PCPT data from three well-referenced (Sandven 1990) Norwegian geotechnical test sites (Bakklandet, Glava and Valoya clays). The reference undrained shear strength values were obtained from laboratory triaxial tests. The model was able to learn the correlation between the PCPT data and s_u. The validity of the model was further verified by presenting it with new data and comparing model predictions with reference s_u values.

2 BACKGROUND

Many methods (analytical and empirical) have been proposed to determine s_u from PCPT data. For this paper the following interpretation models were considered: (1) bearing capacity models; (2) cavity expansion models; (3) strain path method (4) empirical methods (5) artificial neural network model (proposed method).

2.1 *Bearing capacity models*

In bearing capacity models, the cone resistance is assumed to be equal to the collapse load of an axisymmetric deep foundation. Empirical depth factors and shape factors are used to modify the plane strain bearing capacity solution, for axisymmetric deep penetration problems. The cone resistance, q_t during undrained penetration in cohesive soils can be expressed in the following form:

$$q_t = N_c s_u + \sigma_{vo} \tag{1}$$

where N_c = analytical cone factor; and σ_{vo} = total vertical stress. Based on different assumed failure patterns (geometry of the plastified zone), the following values for N_c have been suggested: N_c = 7.4 (Terzaghi 1943); N_c = 9.3 for smooth base, and N_c = 9.7 for rough base (Meyerhoff 1961); N_c = 9.6 (Durgunoglu & Mitchell 1974).

Bearing capacity models have limitations when used to analyze deep penetration problems. The boundary conditions used are not appropriate for deep cone penetration. In shallow penetration problems, the soil moves outwards and upwards to the surface, whereas in deep penetration problems, the displaced soil (inner plastic zone) is accommodated by the elastic deformations of the soil in the outer zone. The method also involves empirical correction factors for depth and shape. It cannot model the continuous process of the cone penetration mechanism.

2.2 *Cavity expansion models*

During the PCPT, some surface heave occurs at shallow depths of penetration. However at larger penetration depths, little surface heave is noticed and it has been argued that the soil moves predominantly outwards. The general form of soil movement at the penetrometer tip has been visualized as that due to the expansion of a spherical cavity from zero radius to an equivalent penetrometer radius. The ultimate cavity pressure required to expand the spherical cavity is often considered an estimate of the cone resistance (at the tip). Many theories for cavity expansion have been developed. Vesic (1977) developed solutions for spherical cavity expansion in an isotropic soil media governed by the Mohr-Coulomb failure criteria. The effects of volume change in the plastic zone were taken into account. For undrained cavity expansion in cohesive soils, the following expression for N_c was derived:

$$N_c = \frac{4}{3}\left(1 + \ln I_r\right) + 2.57 \tag{2}$$

where $I_r = G/s_u$ = rigidity index; and G = shear modulus at 50% peak shear stress.

The cavity expansion theories are one-dimensional theories and do not take into account the two-dimensional nature of the penetration process. It involves assumptions for the rigidity index, and the equivalent spherical cavity radius (during predictions of excess pore pressure distribution). Cavity expansion studies using work hardening elastoplastic soil models have been used by Randolph, et al. (1979), Banerjee & Fathallah (1979), and Chopra, et al. (1992) to analyze PCPT results.

2.3 *Strain path method*

The steady penetration method (Balıgh, 1985; Teh & Houlsby, 1991) hypothesized that due to strict kinematic constraints in deep penetration problems, soil deformations, and strains were independent of the shearing resistance of the soil and the problem was essentially strain controlled. The cone penetration problem was analyzed by considering the flow of an incompressible, inviscid fluid (soil) around a static penetrometer. The strain history for each soil element was determined from the computed flow pattern. The deviatoric stresses were then determined (using appropriate initial stresses) by integration of the appropriate constitutive laws along the streamlines. The mean normal stress was then determined using one of the equations of equilibrium (radial or axial) and integrating from an outer boundary starting from some point sufficiently away from the cone. The stresses often did not satisfy the equilibrium equations, reflecting the error in the assumed flow field. Teh & Houlsby (1991) used a large strain finite element method to correct the inequilibrium by applying incrementally equal and opposite forces with the cone held stationary. The expression for N_c including the effects of cone roughness, rigidity index, I_r, and initial in-situ stresses was given by:

$$N_c = \frac{4}{3}\left(1 + \ln I_r\right)\left(1.25 + \frac{I_r}{2000}\right) \tag{3}$$

2.4 *Empirical methods*

The undrained shear strength may be estimated using the following empirical equation suggested by Lunne, et al. (1985):

$$s_u = \frac{q_t - \sigma_{vo}}{N_{kt}} \tag{4}$$

where N_{kT} = empirical cone factor. N_{kT} values have been reported to vary between 4 and 30 in actual practice. Several factors such as plasticity, stress history, stiffness, sensitivity, fabric are known to be the cause for such wide variations.

Based on cavity expansion theories, Massarsch & Broms (1981) proposed an empirical equation (Equations 5) for estimating s_u using penetration induced excess pore pressures.

$$s_u = \frac{\Delta u}{N_{\Delta u}} \tag{5}$$

where Δu = excess pore pressure (Δu_1 or Δu_2); and $N_{\Delta u}$ = empirical pore pressure factor ($N_{\Delta u1}$ or $N_{\Delta u2}$). The value of $N_{\Delta u}$, may vary between 2 and 20, depending on the soil type, in-situ stress state (K_o), rigidity index (I_r), overconsolidation ratio, sensitivity, and the soil micro and macro fabric. Values for $N_{\Delta u}$ as a function of the plasticity index (I_p), rigidity index (G/s_u), and the Skempton's pore pressure parameter at failure (A_f), for two different filter locations (cone tip and cone base) were given in the form of interpretation charts (Massarsch & Broms 1981).

2.5 *Artificial neural network modeling*

Artificial neural networks (ANN) are data processing paradigms that work similar to the brain in processing information (Kohonen 1988, Aleksander & Morton 1990, Hertz et al. 1991). Just like the neurons in the human brain, neural networks are made of a number of interconnected processing units (neurons) organized in layers. 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. This 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. Back-propagation neural networks have been used in geotechnical engineering because of its simplicity and robustness (Ghaboussi 1992, Goh 1995, Ali & Najjar 1999, Penumadu & Chameau 1997). A feed-forward network, trained by back-propagation, was used in this research.

3 ANN MODEL FOR ESTIMATING SHEAR STRENGTH

A typical back-propagation neural network consists of processing units (neurons) organized in layers. The connection between the neurons in the different layers is as shown in Figure 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 transfer function (tansigmoid) was used by the hidden layer neurons to transform the input values.

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 until the ANN gives the desired output. Once the ANN is trained, the prediction mode simply consists of propagating the data through the network, giving immediate predictions.

The following five input variables were used for the model: cone resistance (q_t) corrected for unequal end area, total vertical overburden pressure (σ_v), pore water pressure at the cone tip (u_1), pore water pressure measured just above the cone base (u_2), and the hydrostatic pore water pressure (u_0). Hence the input layer had five neurons. The only output is the shear strength, and therefore there was only one output neuron (in the output layer). The hidden layer enabled non-linear modeling of the sensor data. The number of neurons in the hidden layer was 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 ten neurons gave good results for estimating the undrained shear strength of the sites. Thus a 5x10x1 network architecture was trained and tested for predicting undrained shear strength from PCPT data. The architecture of the ANN model used in this study is illustrated in Figure 1.

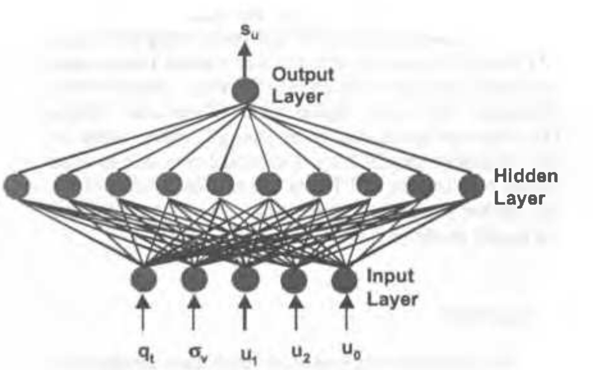

Figure 1. Architecture of the neural network model

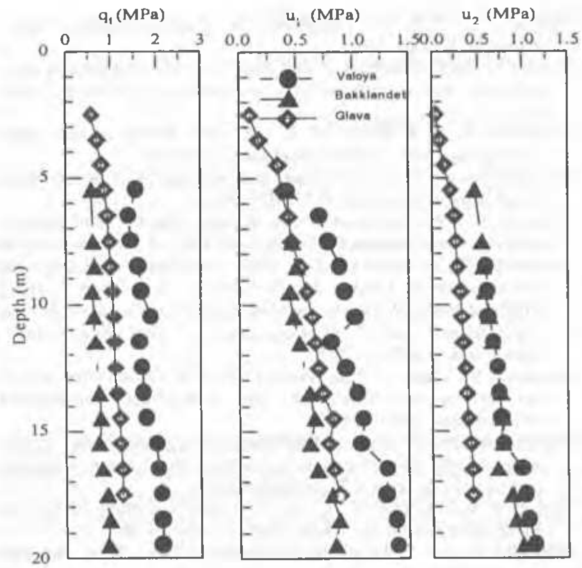

Figure 2. PCPT profiles in Valoya, Bakklandet and Glava sites

3.1 *Training and testing the model*

The neural network was trained using partial set (75% of the complete data set) of PCPT data from three Norwegian geotechnical test sites. The ground water table at the Valoya, Bakklandet, and Glava sites were located at depths of 3.0 m, 4.0 m and 0.5 m respectively. The PCPT profiles are shown in Figure 2 (Sandven 1990).

The entire data set was first normalized with the largest number from the data set (2138 kPa: corresponds to the cone resistance in Valoya clay), so that the input to the ANN model was in the range −1 to +1. Such a transformation was also performed during the testing phase. Training was performed until the average sum squared errors over the entire training pattern reached a minimum. This occurred after approximately 5000 cycles of training. The weight and bias matrices obtained after the training phase are given below.

Weights between the input and the hidden layer neurons (in the form H x I):

$$net.IW\{1,1\} = \begin{bmatrix} 15.0 & -3.5 & 1.6 & -3.0 & -18.5 \\ 5.5 & -3.3 & 2.5 & -3.3 & -9.5 \\ -14.4 & 14.8 & 6.1 & 4.4 & 32.6 \\ -18.8 & -5.1 & -3.8 & 18.4 & -240.4 \\ -15.2 & 13.7 & 7.2 & 0.8 & 31.6 \\ -14.0 & 2.2 & 5.1 & -12.4 & 37.2 \\ 4.7 & 12.1 & 1.2 & 10.2 & 42.3 \\ -2.7 & -4.9 & 2.9 & -13.1 & 12.7 \\ 7.4 & 3.5 & 2.5 & -3.9 & 35.1 \\ 4.5 & -4.8 & 13.8 & 3.1 & -43.7 \end{bmatrix}$$

Bias for the hidden layer neurons (H x 1):

$$net.b\{1\} = \begin{bmatrix} -17.8 \\ -18.7 \\ 16.4 \\ 8.5 \\ 16.1 \\ 0.2 \\ 15.5 \\ 3.3 \\ 18.4 \\ -3.6 \end{bmatrix}$$

Weights between the hidden and the output layer neurons (in the form O x H):

$$net.LW\{2,1\} = [-20.2 \ -20.9 \ 20.2 \ -11.7 \ 8.6 \ 17.2 \ 21.2 \ -26.2 \ 10.9 \ 66.7]$$

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

$$net.b\{2\} = [21.2]$$

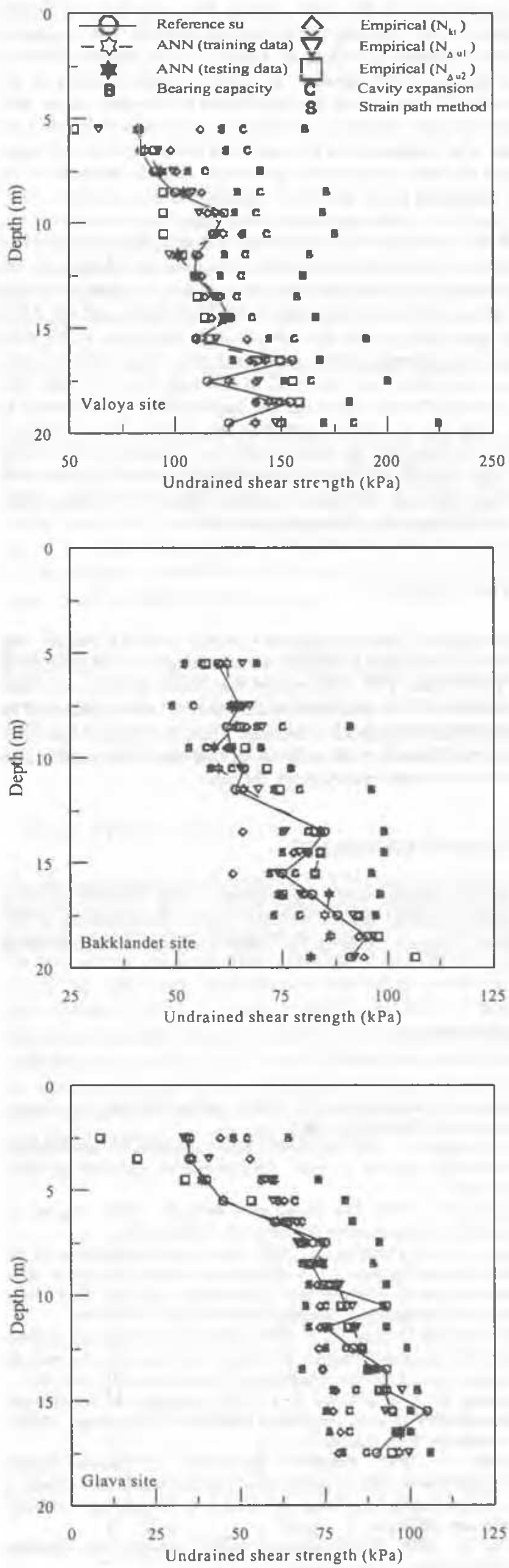

Figure 3. Predicted profiles of undrained shear strength in Valoya, Bakklandet and Glava sites

The ANN model was first tested using the data set that was used for training (75% of the complete data set). The model predictions (using the training data) are compared with the reference s_u values obtained from triaxial tests in Figure 3. It can be seen that the ANN model was able to accurately predict the s_u of the training data. The model was further tested using new data (25% of the complete data set) that was not used in the training phase. The s_u predicted by the ANN (testing data), and those predicted by some of the existing interpretation methods are compared with the reference s_u values in Figure 3. The bearing capacity model because of its smaller N_c value, overpredicted s_u at all three sites. The empirical methods based on the cone factor and the pore pressure factors were found to give reasonably good estimates of s_u (compared to the analytical methods). Overall it can be seen that the ANN model gave very reliable estimates of s_u when compared to the analytical models and the empirical methods. The ANN model described in this paper does not require the PCPT sleeve friction measurements. The advantage of the ANN model over the analytical methods is that the model does not require the rigidity index for input. The influence of the soil rigidity index is reflected on the measured PCPT data, and the ANN model was able to learn the correlation between the PCPT data and s_u. Using simple matrix operations, the weight and bias matrices given above may be used to estimate the s_u of any site from the PCPT data. However the applicability of the model to other sites has not been verified in this paper. Future research will involve training the model with data obtained from several test sites around the world, and comparing model predictions with other strength estimation methods (Olsen 1995) not considered in this paper due to length limitations.

4 CONCLUSIONS

A feed-forward, back-propagation neural network model was developed to estimate undrained shear strength of cohesive soils from PCPT data. The ANN model was found to give very reliable estimates of the undrained shear strength when compared to the interpretation methods evaluated. The advantage of the ANN model over the analytical methods is that the ANN model does not require the soil rigidity index for input.

5 ACKNOWLEDGEMENTS

The authors acknowledge the support of the National Science Foundation, Career Award 9875037 under the direction of Dr. Fragaszy, Program Director for Geomechanics & Geotechnical Systems.

6 REFERENCES

Aleksander, I. & Morton, H. 1990. *An Introduction to Neural Computing*. Chapman and Hall.

Ali, H. & Najjar, Y. 1999. Neuronet - based approach for assessing the liquefaction potential of soils. *Transportation Research Records*, 1633: 3-8.

Baligh, M. M. 1985. The strain path method. *ASCE, Journal of Geotechnical Engineering Division*, 3(9): 1108-1136.

Banerjee, P. K & Fathallah, R. 1979. An eulerian formulation of the finite element method for predicting the stresses and pore water pressures around a driven pile. *Proceedings, 3rd Int. Conf Num. Meth. on Geomechanics, Aachen, West Germany*: 1053-1060.

Chopra, M. B. & Dargush, G. F. 1992. Finite-element analysis of time-dependent large-deformation problems. *International Journal for Numerical and Analytical Methods in Geomechanics*, 16: 101-130.

Durgunoglu, H. T. & Mitchell, J. K. 1974. Influence of penetrometer characteristics on static penetration resistance. *Proceedings, ESOPT I, Stockholm*, 2(2): 133-141.

Ghaboussi, J. 1992. Potential applications of neuro-biological computational models in geotechnical engineering. In G.N. Pande & S. Pietruszezak (eds.), *Numerical Models in Geotechnics*: 543-555. Rotterdam: Balkema.

Goh, A.T.C. 1995. Backpropagation neural networks for modeling comlex-systems. *Artificial intelligence in engineering*, 9(3): 143-151.

Hertz, J., Krogh, A., & Palmer, R. 1991. *Introduction to the Theory of Neural Computation*, Addison-Wesley.

Kohonen, T. 1988. An introduction to neural computing. *Neural Networks*, 1(1): pp. 3-16.

Lunne, T., Christoffersen, H. P. & Tjelta, T. I. 1985. Engineering use of piezocone data in north sea clays. *Proceedings, XI ICSMFE*, 2: 907-912.

Massarsch, K. R. & Broms, B. B. 1981. Pile driving in clay slopes. *Proceedings, 10th ICSMFE, Stockholm*, 3: 469-474.

Meyerhof, G. G. 1961. The ultimate bearing capacity of wedge-shaped foundations. *Proceedings, V ICSMFE, Paris*.

Olsen, R. S. 1995. Prediction of clay strength using the combination of cone and sleeve resistances. *Proceedings, CPT'95, Sweden*, 245-250.

Penumadu, D., & Chameau, J.-L. 1997. Geomaterial modeling using neural networks: Chapter 10. In Garret, J. and Flood, I. (eds.), *Artificial Neural Networks for Civil Engineers: Fundamentals and Applications, Journal of Computing in Civil Engineering - Monograph, ASCE*: 197-223.

Randolph, M., Carter, J. P. & Wroth, C. P. 1979. Driven piles in clay - the effects of installation and subsequent consolidation. *Geotechnique*, 29(4): 361-393.

Sandven, R. 1990. *Strength and deformation properties of fine grained soils obtained from piezocone tests; Ph.D. Dissertation*. Norwegian Institute of Technology, Trondheim, Norway.

Teh, C. I. and Houlsby, G. T. 1991. An analytical study of the cone penetrometer test in clay. *Geotechnique*: 41(1): 17-34.

Terzaghi, K. 1943. *Theoretical Soil Mechanics*, John Wiley and Sons, Inc., New York, NY.

Vesic, A. S. 1977. Design of pile foundations. *Synthesis of Highway Practice 42, Transportation Research Board*. National Research Council, Washington, D.C.