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# Artificial Neural Network Modelling for Estimation of Suction Capacity

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**Abstract:** The objective of this study was to estimate the suction capacity in clays by using neural networks on the basis of some simple soil properties. For this purpose, a total of 168 data sets obtained from water suction tests were used in the Artificial Neural Networks (ANNs). These tests were carried out on seven different clay samples by using odometer test equipment. One hundred twenty six data sets were used in the training stage and remaining 42 data sets were used in the testing stage. The best model was determined by using a trial and error approach in which the ANN models were trained with different hidden layer nodes and with different combinations of network parameters. The neural network predictions were compared with the water suction test results. It is seen that, there is a good agreement between the prediction results and the results of experiments. The results of this study demonstrate that the neural network model can serve as an alternative predictive tool for determination of water suction capacity of clay soils.

**Key words:** Artificial neural network, dry unit weight, plasticity index, suction capacity, water content

## INTRODUCTION

Soil suction is one of the most important parameters that control mechanical properties of clay soils such as strength, stiffness and hydraulic conductivity. In order to predict a soil's behaviour, the suction capacity of that soil must be measured. Suction capacity is dependent on some soil properties such as fabric, dry unit weight, consistency limit, water content. Several methods have been purposed for determination of soil suction[1].

ANNs are flexible mathematical structures that are capable of identifying complex non-linear relationships between input and output data sets. ANN models are adaptive and capable of generalization. ANN models can handle imperfect or incomplete data and can capture non-linear and complex interactions among variables of a system. Because of its unique learning, training and predicting characteristics, the ANN model has great potential in geotechnical engineering application. Recently, ANNs have been applied to many geotechnical engineering problems[2-6].

This study reports the application of ANN to estimate suction capacity of clay soils. ANN models were established by using 168 individual data sets obtained from suction tests. Back propagation algorithm was applied. The optimal ANN model was determined. The results of ANN model and the results of suction tests are compared and the conclusions are derived and presented.

**Artificial neural networks:** ANNs are numerical modelling techniques that try to simulate the behaviour of the human brain and nervous system[5]. A neural network consists of a large number of simple Processing Elements (PEs) that are variously called nodes, units, cells or neurones. These PEs are arranged in different sections or layers. A typical ANN consists of an input layer, hidden layer(s) and an output layer (Fig. 1).

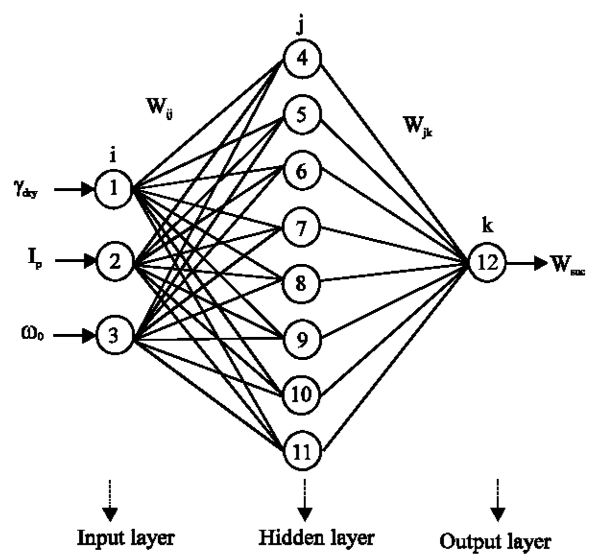


Fig. 1: The architecture of artificial neural network

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The layer that gets the input(s) is called as input layer. The layer that produces the network output is called as output layer. All other layers are called as hidden layers. Each layer has a weight matrix, a bias vector and an output vector. Each layer is connected to other layers through the weight lines that come from each PE. The hidden and output layer nodes process their inputs by multiplying each of their inputs by the corresponding weights, summing the product and then processing the sum using a non-linear activation function to produce a result[3,7].

The sum of the inputs and their weights lead to a summation operation as:

$$NET_j = \sum_{i=1}^{n} w_{ij} \; x_j + \theta_j \qquad (1)$$

Where, $w_{ij}$ is established weight, $x_j$ is input value, $\theta_j$ is bias and $NET_j$ is input to a node in layer j.

The sigmoid function is commonly used as the activation function and it can be formulated mathematically as:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (2)$$

Thus, target output is formulated as in Eq. 3.

$$OUTPUT_j = f(NET_j) = \frac{1}{[1+e^{(-NET_j)}]} \qquad (3)$$

Where, $NET_j$ is input to a node in layer j, $OUTPUT_j$ is output.

The neural network learns by adjusting the weights between the nodes in response to the errors between actual output values and target output values. Several learning rules have been developed. The back propagation learning rule is the most popular one. Training a feed-forward network with the back-propagation learning rule is most frequently used in function approximation and pattern recognition[3]. It can be used to adjust the weights and biases of networks in order to minimize the mean-squared error of the network. This is done by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error. Derivatives of the error vector are calculated for the network's output layer and then back-propagated through the network until derivatives of error are available for each hidden layer. Training refers to the process that repeatedly applies input vectors to the network and calculates errors with respect to the target vectors and then finds new weights and biases with the learning rule. It repeats this cycle until mean-squared error falls beneath an error goal, or a maximum number of epochs have occurred. At the end of this training phase, the neural network presents a model that can be able to predict a target value for a given input value.

## MATERIALS AND METHODS

In this study, a three layer feed forward-back propagation neural network was used to estimate the suction capacity on the basis of the simple soil properties as plasticity index, initial water content and dry unit weight. For this purpose, seven different clay samples were used. Suction capacity tests were made on these clay samples by using odometer test equipment. Clay samples were prepared with compaction method for different dry densities and different initial water contents. Suction tests were made for two groups according to initial conditions. At the first group, dry densities of samples were fixed and initial water contents were changed. At the second group, initial water content of samples was fixed and dry densities were changed. Results related with these test groups are given in Table 1.

The entire 168 individual test data sets were used separately in two stages. One hundred twenty six data sets were used in the training stage and the remaining 42 data sets were used in the testing stage. The training data were used to determine the connection weights and to develop the model. The testing data were used for testing the generalization capability of the model. The input layer was formed from three nodes representing the input variables (plasticity index, $I_P$; dry unit weight, $\gamma_{dry}$; initial water content, $w_0$) and the output layer was a single node, corresponding to measured value of the suction capacity, $W_{suc}$. Before presenting the input and output variables for ANN model training, they were normalized using Eq. 4.

$$x_{norm} = \frac{(x_{actual} - x_{min})}{(x_{max} - x_{min})} \qquad (4)$$

Where, $x_{norm}$ is the normalized value for input node x; $x_{actual}$ is the actual value for input node x; $x_{actual}$ is the minimum value for input node x in the database; $x_{max}$ is the maximum value for input node x in the database.

Levenberg–Marquardt optimization was used in the training stage. The optimal geometry was determined by using a trial and error approach. In order to obtain

Table 1: Ranges of the data used for the ANN model inputs and target

| Data type | Model variables | Minimum value | Maximumvalue |
|---|---|---|---|
| Input | Dry unit weight $\gamma_{dry}$ (kPa) | 11.5 | 16 |
| | Initial water content $\omega_0$ (%) | 15 | 40 |
| | Plasticity index $I_p$ (%) | 21 | 67 |
| Target | Suction capacity $W_{suc}$ (%) | 11 | 90 |

optimal network parameters, ANN models with different combinations of learning rates and momentum terms were trained. In order to find out most reliable model, different number of hidden nodes were tried based on the mean square error and the coefficient of determination. Therefore, 20 networks with different number of hidden nodes were used in the training phase.

## RESULTS AND DISCUSSION

Table 2 shows the variation of mean squared error and coefficient of determination for models with different numbers of hidden nodes.

The model with 8 hidden nodes gave the maximum coefficient of determination value in the testing stage with setting minimum mean square error goal. Therefore, it was chosen as the final model. This model has a learning rate of 0.2, a momentum term of 0.8. In this model, 10 h transfer function for hidden layer nodes and output layer node was used. Connection weights and biases for the final model are given in Table 3.

Figure 2 shows the comparison between the results of suction tests and the neural network prediction of suction capacity for testing stage of ANN model with 8 hidden nodes.

The comparison of experimental and estimated suction capacity values shows that there is a good agreement between the ANN and suction capacity test results.

Table 2: The variation of mean-squared error and coefficient of determination for models with different numbers of hidden nodes

| | Training stage | | Testing stage | |
|---|---|---|---|---|
| No. of hidden nodes | MSE | Coefficient of determination $R^2$ (%) | MSE | Coefficient of determination $R^2$ (%) |
| 1 | 13.03 | 95.22 | 12.18 | 95.38 |
| 2 | 1.86 | 99.34 | 1.52 | 99.45 |
| 3 | 1.70 | 99.40 | 1.45 | 99.47 |
| 4 | 1.39 | 99.51 | 1.29 | 99.54 |
| 5 | 0.99 | 99.65 | 0.84 | 99.70 |
| 6 | 0.46 | 99.84 | 0.70 | 99.75 |
| 7 | 0.46 | 99.84 | 0.76 | 99.73 |
| 8 | 0.33 | 99.88 | 0.66 | 99.77 |
| 9 | 0.77 | 99.73 | 1.66 | 99.42 |
| 10 | 0.23 | 99.92 | 0.87 | 99.70 |
| 11 | 0.27 | 99.91 | 0.75 | 99.74 |
| 12 | 0.14 | 99.95 | 0.90 | 99.68 |
| 13 | 0.12 | 99.96 | 0.93 | 99.70 |
| 14 | 0.25 | 99.91 | 1.85 | 99.35 |
| 15 | 0.16 | 99.94 | 1.09 | 99.63 |
| 16 | 0.12 | 99.96 | 0.94 | 99.67 |
| 18 | 0.08 | 99.97 | 1.16 | 99.60 |
| 20 | 0.09 | 99.97 | 2.58 | 99.13 |
| 25 | 0.00 | 1 | 34.84 | 90.01 |
| 50 | 0.00 | 1 | 41.12 | 87.21 |

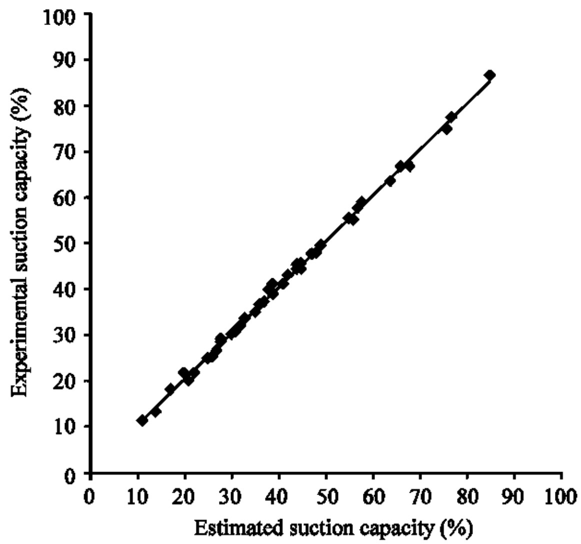

Fig. 2: The comparison between the neural network prediction of suction capacity and experimental results

Table 3: Weight and bias values for the final ANN model

| Hidden layer nodes | $w_{ji}$ (weight from node i in the input layer to node j in the hidden layer) i=1 | i=2 | i=3 | Hidden layer bias $\theta_j$ |
|---|---|---|---|---|
| j=4 | 42.0654 | -0.38947 | 3.9186 | -50.4251 |
| j=5 | 1.6185 | 2.8034 | -7.5052 | 11.0024 |
| j=6 | 0.40737 | -0.16684 | -7.0087 | 2.6177 |
| j=7 | -0.039936 | -3.6858 | -4.1288 | 5.0035 |
| j=8 | 0.40655 | -0.16622 | -7.0284 | 2.6239 |
| j=9 | 0.53396 | 1.3011 | -0.79919 | 0.74917 |
| j=10 | -0.0064197 | -0.29614 | 2.5168 | -6.161 |
| j=11 | 0.29395 | 0.79914 | -1.1287 | -0.76382 |

| Output layer node | $w_{ji}$ (weight from node i in the hidden layer to node j in the output layer) i=4 | i=5 | i=6 | i=7 | Output layer bias $\theta_j$ |
|---|---|---|---|---|---|
| | -704.6838 | -627.4433 | 37.2956 | 0.045224 | |
| j=12 | I=8 | I=9 | I=10 | I=11 | 568.127 |
| | -37.265 | -0.31753 | 645.0142 | -0.33838 | |

In this study, a feed forward-back propagation neural network model for prediction suction capacity of clays is presented. The prediction was based on some simple soil properties as plasticity index, initial water content and dry unit weight. Neural networks having different number of hidden nodes were tested. Neural network predictions and experimental results were compared. It can be seen from the results that, suction capacity values computed by ANN are relatively close to the values obtained from suction tests on clays. It is shown that, the neural network model presented in this paper can effectively estimate the suction capacity. Although this work looks very specific, it may offer a solution for different soil problems.

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