Predicting geotechnical properties using the artificial neural network model

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Abstract – In this research triaxial testing is being carried out on a medium dense sand samples. Geotechnical properties such as coefficient of earth pressure at rest (K_0), shear strength, axial strain at failure were observed respectively. Vertical and confining pressures were applied on normally and overconsolidated samples and values for aforementioned geotechnical properties were observed. These geotechnical parameters have primary importance in designing soil retaining structures in terms of economy and safety. More realistic values for soil parameters can be obtained within proposed artificial neural network (ANN) models rather than overestimated and under estimated geotechnical properties predictions. Over consolidation ratio (OCR) and the effective stress friction angle (Φ) are considered as input variables in the proposed ANN models. Models give predictions for lateral earth pressure coefficients during normal consolidation and over consolidation. This paper presents a new approach using an Artificial Neural Network technique that could be an alternative methodology against conventional statistical techniques to estimate geotechnical properties. Results obtained in this study provide information for researchers interested in applying ANN to predict geotechnical properties.

Keywords – artificial neural networks, effective stress friction angle, geotechnical properties, lateral earth pressure coefficients, non-linear modelling, over consolidation ratio.

Introduction

The coefficient of earth pressure at rest is used with retaining wall and pile design (Chan et al. 1995; Ingold 1979; Lee and Lee 1996; Michalowski 2005). The relationships between K_0 and OCR are investigated for primary loading-unloading-reloading conditions. The study reviews laboratory data which are on 61 medium dense sand samples. Simple empirical methods for predicting K_0 for normally consolidated and overconsolidated soils are evaluated. K_{onc} is the coefficient of earth pressure at rest for normally consolidated soil. Overconsolidation because of rebound results in higher values of K_0 than the K_{onc}. K_{ou} is coefficient of earth pressure at rest for unloading. There is a significant relation between K_{ou} and overconsolidation ratio (OCR). Empirical approaches depend on statistical analysis of test data were mentioned by Jaky (1944) and Mayne and Kulhawy (1982) for K_{onc} and K_{ou} respectively (see Eq. 1 and Eq. 2). This study focused on generating new approach using an Artificial Neural Network technique that could be an alternative methodology against conventional statistical techniques and empirical formulas to estimate K_{onc} and K_{ou}.

$$K_{onc} = 1 - \sin(\Phi) \tag{1}$$

$$K_{ou} = (1 - \sin(\Phi))OCR^{\sin(\Phi)} \tag{2}$$

I. Triaxial Compression Strength Testing

In the Triaxial Test the sample was reconstructed in a cylindrical form, covered by an impermeable membrane, subjected to an hydraulic pressure within a special cell and then tested to failure under an axial load.

The purpose of the test is to ascertain the shear strength of the sample and determine the relationships between stresses and strains.

Engineering properties of soils at experimental determination of the experimental conditions should be adapted as possible to field conditions. The advantage of the Triaxial Test over the Direct Shear Test is in the recreation of real conditions (Bishop and Henkel 1957; Venkatramaiah 2006; Helwany 2007)

II. Artificial neural networks (ANN) methodology

An ANN takes a set of known patterns as inputs and produces output which closely matches with the actual output of the input patterns (Hu et al. 2005). ANN structure is made up of three layers of neurons; input layers, hidden layers, and output layers. All of the known external data and variables are named as input and input neurons are separately exist at the first layer of ANN structure. The values of the input data are multiplied by the appropriate weights and summed up within the hidden layer in accordance with the backpropagation algorithm. Finally this sum is converted into an output value using transfer function (Ramirez et al. 2005). The main role of the hidden neuron is to sum up the weighted inputs ($x_i w_{ij}$) and combine it with a bias b_j to determine a net value (Abdul-Wahab and Al-Alawi 2008; Chang and Hsiao, 2004), before the net value (net_j) is passed to the output layer, hyperbolic tangent sigmoid transfer functions (see Equation 4) are applied on the weighted summation over the inputs (Demuth and Beale 1998). This is responsible for the non-linear quality of the network (Hamzacebi et al. 2009). Neuron output is calculated as;

$$o = f\,(W.X + b) \tag{3}$$

Where W is the weight matrix and X is the input matrix, n is the number of inputs and f is the transfer function;

$$net_j = \sum_{i=1}^{n} x_i w_{ij} + b_j \tag{4}$$

$$o = f\,(net) \tag{5}$$

$$f(net_j) = \frac{2}{\left(1 + e^{-2 \times net_j}\right)} - 1 \tag{6}$$

$$o = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{7}$$

Non-linear transformation in the output layer is used to constrain prediction between the minimum and the maximum values of the target variable (Gumrah et al.

2000; Kuo et al. 2004; Mitra et al. 1998). Output neurons repeat the same procedure applied by hidden neurons. The processed values from the hidden layer nodes are conveyed to the output layer nodes. The signals received from all the hidden nodes and the bias node are again summed up at the output node. Then this summation is processed by the transfer function and compared with the target values. Weights are calculated by minimizing the error function (E). This is done by using iterative optimization algorithms such as backpropagation (BP) that compute derivatives of training error with respect to those weights and biases, the gradient descent method is used for this aim (Almasri and Kaluarachchi 2005; Demuth and Beale 1998; Karul et al. 2008; Suen and Eheart 2003). BP algorithm is essentially a gradient descent technique that minimizes the network error (Dorum et al. 2010; Noori et al. 2010). According to Maier and Dandy (2000), error function and new connection weights are calculated as;

$$E = \sum_{P_T} \sum_{N_O} \left((R_{pre.})_i - (R_M)_i \right)^2 \tag{8}$$

$$w_{ij}^{\ new} = w_{ij}^{\ old} - \eta \frac{\partial E}{\partial w_{ij}} \tag{9}$$

Where N_O is the number of output neurons, P_T is the number of training patterns, $(R_M)_i$ and $(R_{pre.})_i$ are measured and predicted outputs, w_{ij} is the weight from the i^{th} neuron in the previous layer to the j^{th} neuron in the current layer and η is the learning rate.

III. Research Findings

It is obvious that there is a significant relation between K_{onc} and Φ (see Fig. 1). Similar close relation exists between K_{ou} and other two parameters, mostly with OCR and also with Φ (see Fig. 5, 6 and 10). There are some empirical models to calculate K_{onc} and K_{ou} in literature. These models are created based on series of experiments and statistical analysis of gathered data. The main goal in this study is to use artificial intelligence techniques to approach measured values of K_{onc} and K_{ou} as much as possible. Results from proposed ANN models and existing empirical model results were depicted on separated figures together with the measured values.

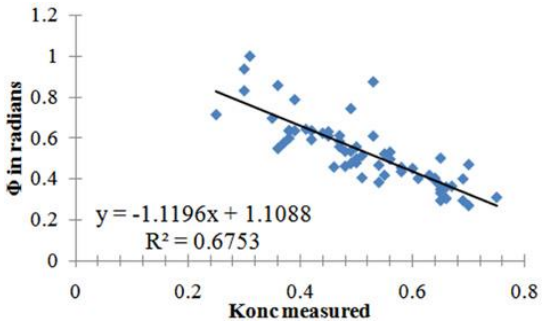


Fig. 1 Relation between K_{onc} and Φ (in radians).

Measured values of K_{onc} were compared with the empirically predicted values as seen in Fig. 2. ANN structure of the K_{onc} prediction model consists of two hidden layers with three and two hidden nodes, respectively (see Fig. 3).

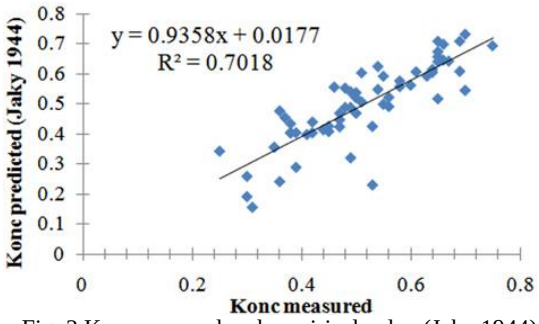


Fig. 2 K_{onc} measured and empirical value (Jaky 1944).

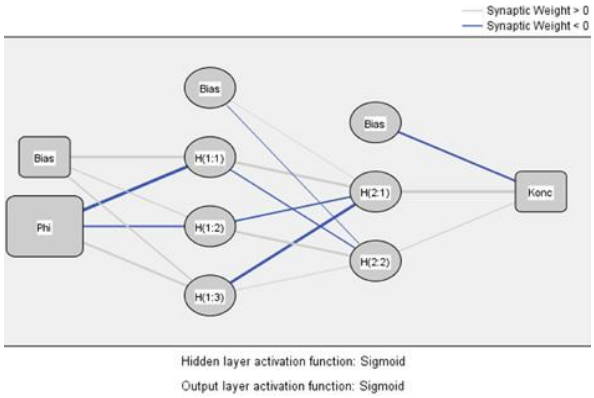


Fig. 3 ANN architecture of the K_{onc} prediction model.

Performance of the ANN model can be evaluated in terms of determination coefficient (R^2) (see Eq. 10).

$$R^2 = \frac{\sum_{i=1}^{N} (K_{0M_i} - \overline{K_{0M}})(K_{0pre_i} - \overline{K_{0pre}})}{\left(\sum_{i=1}^{N} (K_{0M_i} - \overline{K_{0M}})^2 \right)^{0.5} \left(\sum_{i=1}^{N} (K_{0pre_i} - \overline{K_{0pre}})^2 \right)^{0.5}} \tag{10}$$

Where $\overline{K_{0pre.}}$ is the mean predicted K_0 value, $\overline{K_{0M}}$ is the mean measured actual K_0 value, and N is the number of measurements. Determination coefficient between K_{onc} measured and empirical value (Jaky 1944) was calculated as 0.7018. If Fig. 4 is reviewed it is seen that the R^2 is 0.741. Hence the proposed ANN model is more realistic in terms of performance.

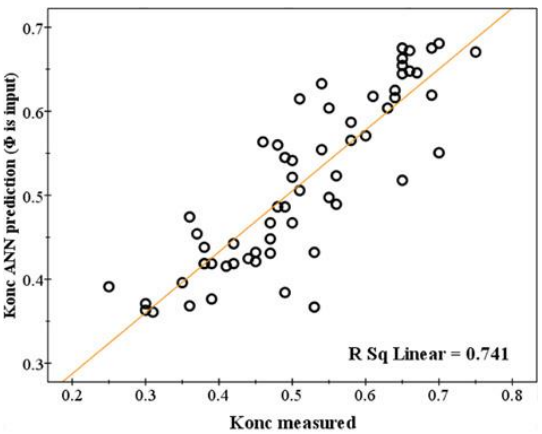


Fig. 4 ANN predictions for K_{onc}.

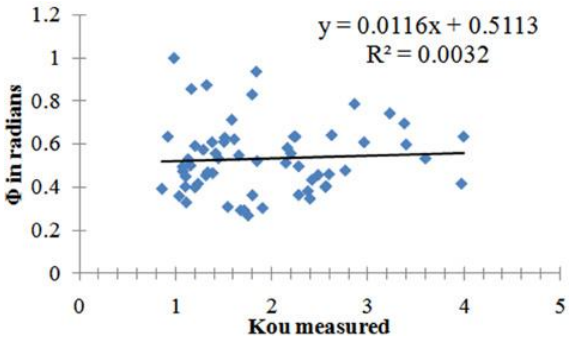


Fig. 5 Relation between K_{ou} and Φ (in radians).

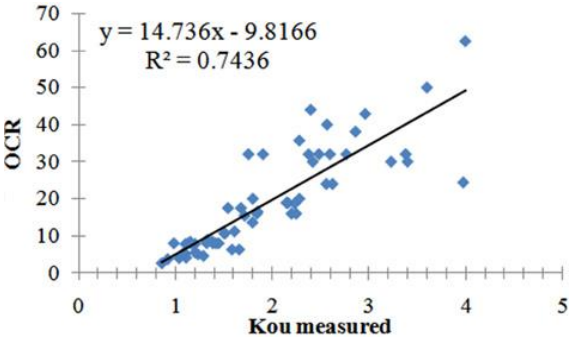


Fig. 6 Relation between K_{ou} and OCR.

Measured values of K_{ou} were compared with the empirically predicted values as seen in Fig. 7. See ANN structure of the Kou prediction model in Fig. 8).

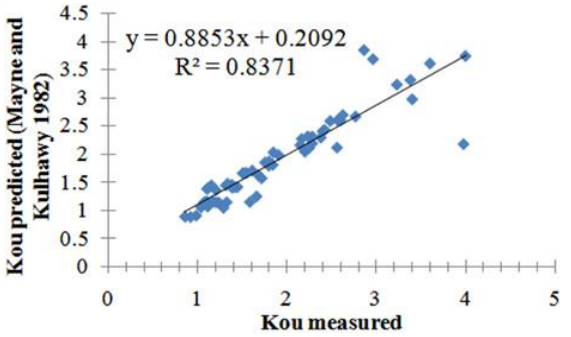


Fig. 7 K_{ou} measured and empirical value (Mayne and Kulhawy 1982).

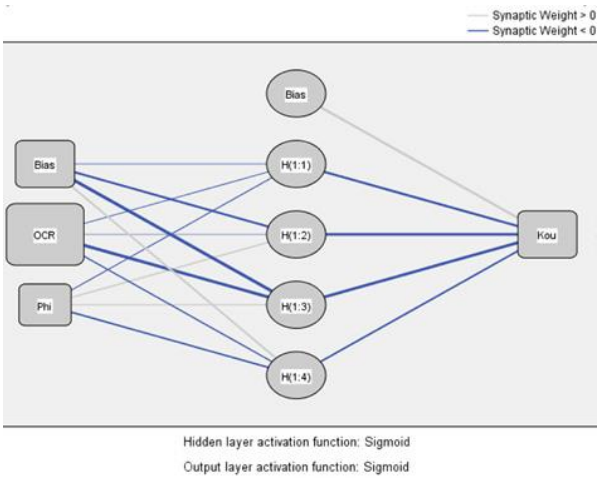


Fig. 8 ANN architecture of the K_{ou} prediction model.

Determination coefficient between Kou measured and empirical value (Mayne and Kulhawy 1982) was calculated as 0.8371 (see Fig. 7). If Fig. 9 is inspected it is seen that the R^2 is 0.965. Hence there is no doubt that the developed ANN model is more reliable in terms of performance.

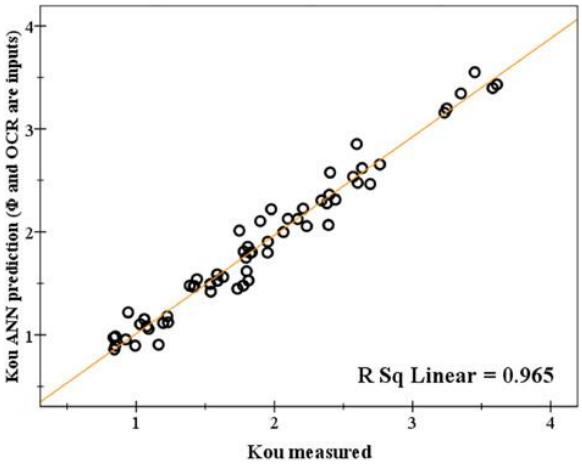


Fig. 9 ANN predictions for K_{ou}.

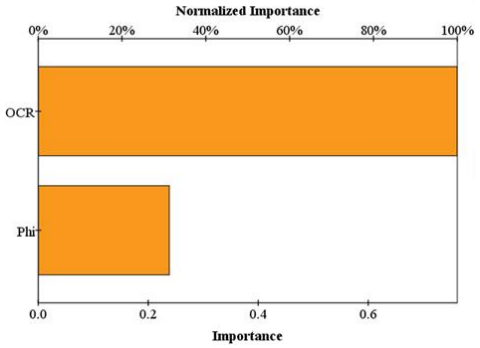


Fig. 10 Calculated importance of independent input parameters for ANN prediction of K_{ou}.

Conclusion

The aim of this paper was to find the value of K_0 for normally consolidated and overconsolidated soils with the help of artificial neural network (ANN) approach. Data obtained from experiments were used to generate a model based on ANN. Multilayered perceptrons (MLPs) architecture were used to train by backpropagation algorithm.

Two distinct approaches were used in this research in order to predict K_{onc} and K_{ou} as close as possible to their measured values.

First approach was to use empirical equations which were given in the literature for estimation of K_0 of normally consolidated and overconsolidated soils. Second approach was to use ANN model. When the results are investigated, it is clear that proposed ANN models give more reliable results for K_{onc} and K_{ou} when compared with the results from empirical models. Results also showed that, overconsolidation ratio is an important factor on K_0 for unloading stage and the effect of Φ is limited with respect to OCR.

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