Unconsolidated Undrained Shear Strength Of Remoulded Clays By Anns Technique

Jain Rajeev
Associate Professor
S.A.T.I. VIDISHA (M.P.)
India

Sharma Pramod
Associate Professor
S.A.T.I. VIDISHA (M.P.)
India

Bhandari Sanjay
Professor
S.A.T.I. VIDISHA (M.P.)
India

Abstract

In many civil engineering practices like design of earthen dam, railway embankment, slope stability analysis etc unconsolidated undrained shear strength parameters of remolded natural and artificial soils are used. Under variable constituent composition, determination of these parameters in the laboratory becomes laborious and time-consuming task. The strength parameters are function of a number of state and index properties, which are relatively easy to determine and are invariably determined for soil characterization. In the present work attempt is made to predict unconsolidated undrained shear strength parameters cohesion 'c' and angle of shear resistance 'ϕ' of remoulded clayey soils from basic soil parameters applying General Regression Neural Networks (GRNN) and multilayer perceptrons (MLPs) neural network techniques. A large data base of input and output parameters were prepared in the laboratory to train the model. It is found that both GRNN and MLPs predict 'c' and 'ϕ' close to the experimentally determined value. With input parameters, GRNN has found better than MLP in terms of performance parameters Mean Square Error (MSE) and the coefficient of determination (R^2).

Keywords

Clays; Shear Strength; Neural Network; Cohesion; Angle of shear resistance; Dry density.

1. Introduction

One of the most important engineering properties of soil is its ability to resist sliding along internal surfaces within a mass. The stability of structures built on soil depends on the shearing resistance offered by the soil along probable surfaces of slippage. The shear strength of geotechnical materials is generally represented by the Mohr-Coulomb theory. According to this theory, the soil shear strength varies linearly with the applied stress through two shear strength components known as cohesion, 'c' and angle of shearing resistance, 'ϕ'. The values of these empirical parameters for any soil depend on several factors. The fine-grained soils such as clays having high plasticity, exhibit low 'ϕ' and high 'c'. On the other hand, as the grain in the soil increases, the 'ϕ' value increases and the 'c' value decreases. If the cohesion intercept and angle of shearing resistance are determined using the total stresses, they are named as total or undrained cohesion intercept 'c' and angle of shearing resistance 'ϕ'.

Many times when the natural soils are poor in some of the properties they, are modified by mixing other types of soils to them. For example, the strength and stability of highly compressive clayey soils can be enhanced by mixing coarse materials like sand and stone dust in different proportions. [26]. A review of literature reveals that the components of shear strength namely cohesion and angle of shearing resistance depend on index and state parameters of the soil. These parameters are affected by mixing of coarse particles in to the soils; consequently, shear strength parameters are also changed. Further, variation in degree of saturation, compaction energy also influences the strength parameters of the soils. Hence determination of shear strength parameters for artificial soils prepared by mixing different quantity of coarse material under (i.e. artificial soils) changing moisture and compaction energy requires testing of huge quantity of samples and thus becomes laborious and time consuming task [9] [13].

Accurate determination of 'c' and 'ϕ' is a major concern in the design of different geotechnical structures such as computation of bearing capacity of foundations, stability analysis of slopes against slope failures and landslides, lateral pressure acting on earth retaining walls, underground chambers and open excavations etc. In many situations, the short-term stability is more critical than the long term because the subsoil consolidates with time under loading and the strength increases. Under such situations, where no water dissipates during construction due to low permeability of soil; the applicable strength of soil is unconsolidated undrained shear strength. The unconsolidated undrained shear parameters can be determined either in the field or in the laboratory. The triaxial compression and direct shear tests are the most common tests for determining the 'c' and 'ϕ' values in the laboratory. The triaxial test is more suitable for clayey soils. The direct shear test is commonly used for sandy soils and requires simpler test procedure in comparison with the triaxial test. The tests employed in the field include vane shear test or any other indirect method [2] [11].

It is not always possible to conduct the tests on every new situation. In order to cope up with such problems, numerical solutions have been developed to estimate the shear strength parameters. The fact that most of the available empirical models are based on limited experimental data and raises doubts on their generality. On the other hand, despite the multivariable dependency of soils, such correlations are mostly developed using only one soil index property. Incorporation of simplified assumptions into the development of the statistical and numerical methods may also lead to very large errors.

The alternative approaches, which have demonstrated superior predictive ability when compared with traditional methods is the Artificial Neural Network (ANNs) techniques. These techniques have been applied successfully to virtually every problem in geotechnical engineering and are receiving increasing attention in geotechnical engineering as a powerful, flexible, statistical modeling technique for describing complex problems [8] [12] [14] [15].

In view of this, an attempt has been made in the present work to develop models to predict unconsolidated undrained shear strength parameters namely cohesion and angle of shearing resistance through basic soil parameters like index properties and the soil state parameters using General Regression Neural Network (GRNN) and Leivenberg Marquardt Back propagation (LMB) for natural and artificial soils (mixed with materials namely sand and stone dust).

The data sets for training and testing have obtained by conducting laboratory tests on nine types of soils: four natural and five artificial. The input parameters are percentage of fines (silt and clay fraction), fine sand content, coarse sand content, degree of saturation, liquid limit and the dry density. The output parameters are 'c' and 'ϕ'. Mean Square Error (MSE), coefficient of determination (R^2) and nearness of output values with experimental values measured the network performance.

2. Brief Review of ANNs in Geotechnical

ANNs models have also been developed to, predict unconfined compressive strength of artificial cohesive soils from basic soil properties i.e. water content, void ratio, saturated density, specific gravity and permeability [4], prediction of shear strength parameters of normally consolidated plastic clays from index properties i.e. water content and plasticity index [3], prediction of cohesion of different soils from physical properties namely; fine content, D_{30}, coefficient of uniformity, liquid limit, water content and dry density [10], prediction of undrained shear strength from SPT data and the index properties of cohesive soils i.e. natural water content, plasticity index and liquid limit [16], prediction of unconfined compressive strength of compacted soil from different particle size of soils i.e. % clay, % fine silt (0.002-0.02 mm), % coarse silt (0.02-0.1mm), % fine sand (0.1-0.25mm), % middle sand (0.25-0.5mm), % coarse sand (0.5-2.0mm), % gravel (> 2.0mm) [6], prediction of angle of shearing resistance of fine grained soils by soft computing methods; Genetic expression programming, Adaptive neuro fuzzy and ANNs from physical properties % fine grained, % coarse grained, liquid limit and bulk density of soils etc [7].

These studies encouraged authors to apply ANNs methods in predicting shear strength parameters 'c' and 'ϕ' of natural and artificial soils from the basic soil properties. The proposed work demonstrates that the ANNs models are able to evaluate the unconsolidated undrained shear strength parameters on remolded soils

3. Database Used in Development of Models

In order to achieve the above objectives a large database is generated by conducting various tests on nine types of soil; four natural soils and the five artificial soils. The artificial soils were prepared by mixing sand and stone dust with one of the natural soil in different proportions.

The tests conducted on each type of soil are sieve analysis, hydrometer analysis, liquid and plastic limit, specific gravity, compaction test at various compactive efforts and unconsolidated undrained triaxial shear test. The soil samples for triaxial test were prepared in the compaction mould at different compactive efforts by varying the number of blows from 05 to 25 and moisture contents.

For a specific number of blows and water content two soil moulds were prepared. One of the moulds was kept in water for 24 hours. Three tubes of 38 mm diameter were inserted in each of the mould to obtain samples of desired size. The triaxial tests were performed on both the samples under unconsolidated undrained condition. The shear parameters cohesion and the angle of shearing resistance were determined for each soil for different values of moisture content and the dry densities. Thus, in total for six types of soil, 900 values of shear parameters have been obtained. In the ANN models developed here in, 30% data was used for testing the models and the remaining data are divided in to 70% for training and 30 % for validation.

The input parameters for the study considered are; soil fractions below 75 micron (F1=38%-93%), soil fractions between 75 micron to 4.75 mm (F2=5.3%-47.47%), liquid limit (w_L=26%-73%), plasticity index (PI=13.0-42.0), dry density (γ_d=1.32gm/cc-1.80gm/cc) and degree of saturation (S_r=13.22%-100%) and the output parameters are cohesion ‘c’ (30.0kn/m^2-243.6kn/m^2) and angle of shearing resistance‘ϕ’ (1.0 degree-28.3 degree). Two types of ANN models namely; Levenberg-Marquardt back-propagation and General Regression neural network are developed and performance of these models have been compared with respect to coefficient of determination (R^2) and Mean square error (MSE).

The neural network toolbox MATLAB 7.0 was used for training and testing the all models.

4. Neural Networks Development

4.1 Multilayer Layer Perceptrons Neural Network

The MLPs that are trained with Levenberg-Marquardt back-propagation algorithm has been used [5]. MLPs are perhaps the best-known type of feed forward networks. It has generally three layers: an input layer, an output layer and an intermediate layer or hidden layer. The performance of the model mainly depends on the network architecture and parameter setting. According to a universal approximation theorem a single hidden layer network is sufficient for the MLPs to uniformly approximate any nonlinear function [1].

Selection of number of hidden layer, number of neurons in hidden layers, learning rate moment, momentum coefficient, epochs, and activation function type plays an important role in the model performance. In the present work herein, about 70% of the available data (632 data sets of 900 data sets) was used for training and validation session and about 30% (268 data sets of 900 data sets) was used for testing session. In order to obtain optimum number of hidden layer/s in Train-LMB model four networks with one, two, three, and four hidden layers were trained. The network with one hidden layer, lead to minimum MSE value in comparisons with two, three and four hidden layers. The model was trained, fed neurons at minimum MSE in the hidden layer. The neural network was trained by varying learning rate moment (0.01, 0.03 and 0.05) and momentum coefficient (0.5 and 0.7) and number of optimum neurons (obtained at minimum MSE). The cross validation approach is used to determine the best network structure in this study. For the development of the LMB model, a script was written in the MATLAB environment using Neural Network Toolbox 7.0 (Math Works, 2007).

In an overall sense, model was developed with single hidden layer with 190 hidden neurons, 0.03 learning rate moments(l_r) and 0.7 momentum coefficients (m_c) gave better performance as compare to other values of m_c, l_r. R^2 and MSE values are shown in Table 1. The results obtained from LMB model have compared with experimental results of cohesion and angle of shear resistance shown in figure 1(a) to 1(d).

Table 1; R^2 and MSE Values

Performance	Training ‘c’	Training ‘ϕ’	Testing ‘c’	Testing ‘ϕ’
R^2	0.9678	0.9549	0.9549	0.9450
MSE	9.1321		10.3	

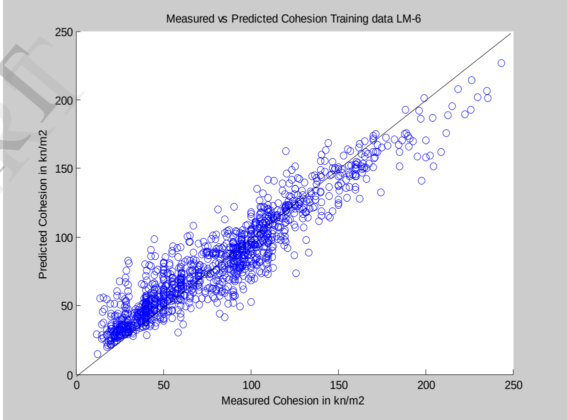

Figure 1(a); Comparison of predicted and measured cohesion ‘c’ (Training Data Set)

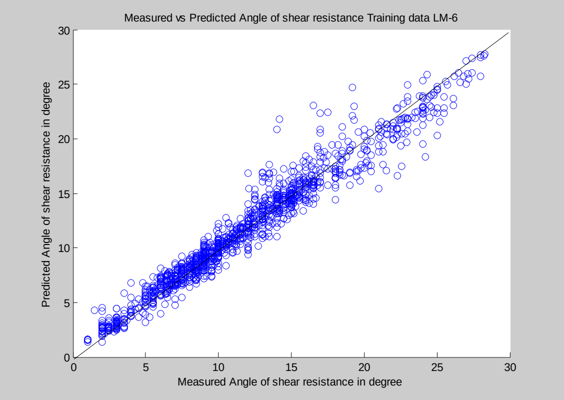

Figure 1(b); Comparison of predicted and measured angle of shear resistance‘ϕ’ (Training Data Set)

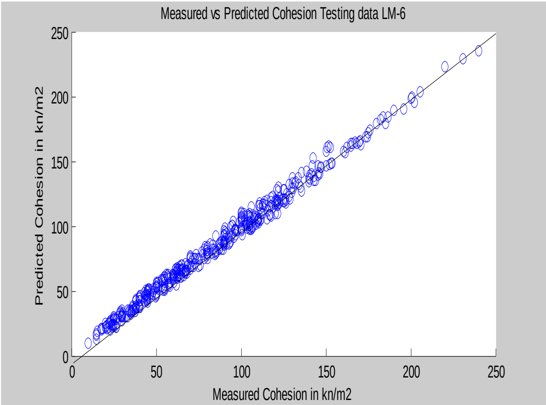

Figure 1(c); Comparison of predicted and measured cohesion ‘c’ (Testing Data Set)

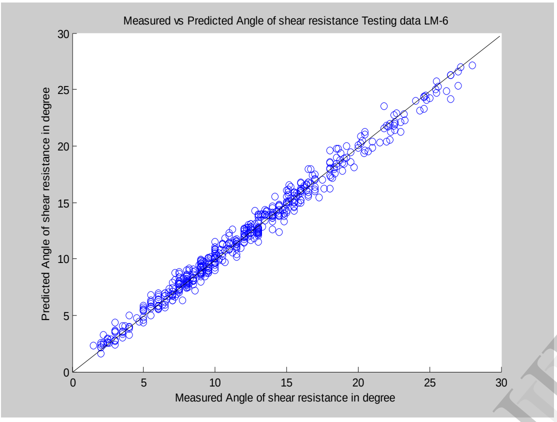

Figure 1(d); Comparison of predicted and measured angle of shear resistance‘ϕ’ (Training Data Set)

4.2 General Regression Neural Network

GRNN Algorithm

GRNN has four layers including the input layer, two hidden layers, and one output layer. The first hidden layer consists of the radial units. These radial units represent clusters rather than each training case. The center of the clusters can be assigned using sub sampling or Kohonen algorithm _Kohonen 1989_. The number of node in the first hidden layer can be as many as the number of cases. The second hidden layer consists of units that help estimate the weighted average. The second hidden layer always has exactly one more node than the output layer. Since two output is considered in the present study ‘c’ and ‘ϕ’ the second hidden layer has only three nodes [17].

In the present study, 690 training data base and 210 data base were used to training and testing the network respectively. GRNN trained with 690 nodes in the hidden layer with varying radius from 0.1 to 0.5. The network with 0.1 radiuses gave best performance (maximum R^2 and minimum MSE) compare to train with other radiuses. R^2 and MSE values are shown in Table 2. The results obtained from GRNN model have compared with experimental results of cohesion and angle of shear resistance shown in figure 2(a) to 2(d).

Table 2; R^2 and MSE Values

Performance	Training		Testing	
	‘c’	‘ϕ’	‘c’	‘ϕ’
R^2	0.9990	0.9934	0.9911	0.9865
MSE	6.5299		8.7694	

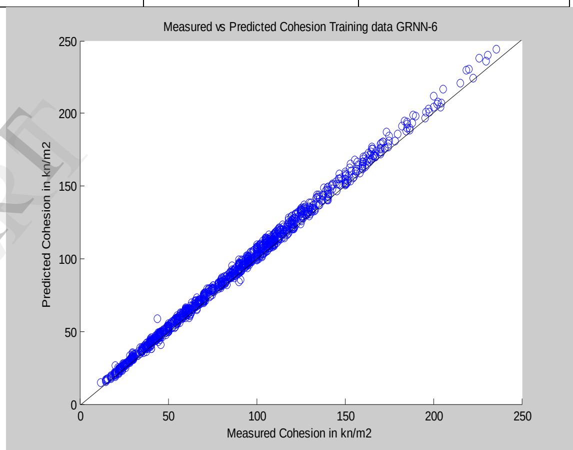

Figure 2(a); Comparison of predicted and measured cohesion ‘c’ (Training Data Set)

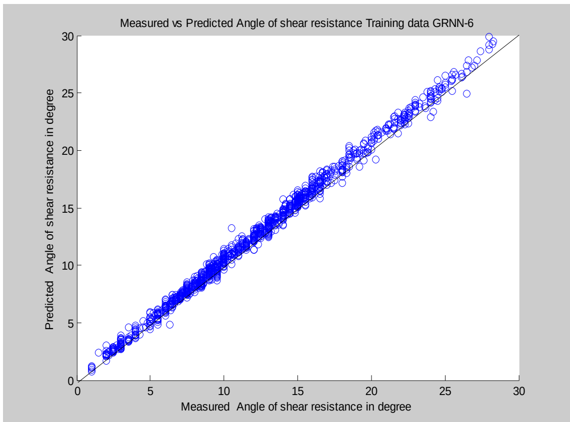

Figure 2(b); Comparison of predicted and measured angle of shear resistance ‘ϕ’ (Training Data Set)

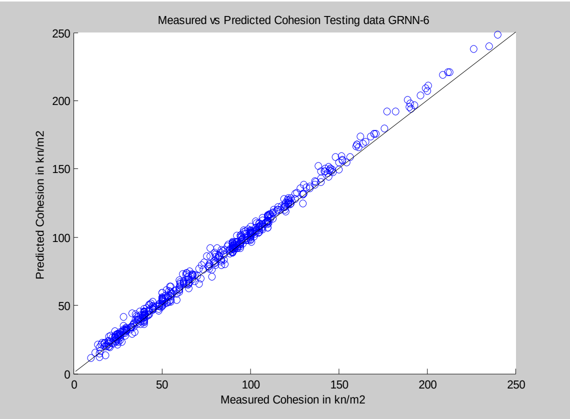

Figure 2(c); Comparison of predicted and measured cohesion 'c' (Testing Data Set)

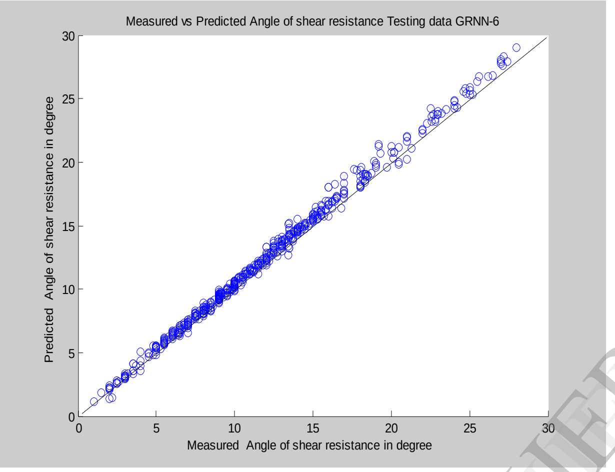

Figure 2(d); Comparison of predicted and measured angle of shear resistance 'ϕ' (Testing Data Set)

Conclusions

Neural networks models have been developed for the prediction of shear strength parameters under unconsolidated undrained conditions of clayey soil using data obtained from laboratory experiments. The present study demonstrate that the developed models using the basic physical properties (i.e. γ_d, w_L, PI, S_r, F1 and F2) is capable of effectively capturing the shear strength parameters ('c' and 'ϕ'). Commercial software, MATLAB 7, was used to develop two different feedforward-type ANN models: LMB and GRNN. To examine the strengths and weaknesses of the developed models, the predicted values were compared with the experimental values with respect to the R^2 and MSE values. Thus, a higher R^2 value and lower MSE were considered a better fit of the development data set.

In the present study, The LMB neural network was trained by varying learning rate moment (0.01, 0.03 and 0.05) and momentum coefficient (0.5 and 0.7) and 190 number of optimum neurons (obtained at minimum MSE) and GRNN model was trained at 690 nodes with varying radius (0.1 to 0.5).

The higher R^2 value and lower MSE values were found in GRNN model with 0.1 radius and 690 hidden nodes compare to LMB model, so it indicate the GRNN model is a better than LMB model for predict the shear strength parameters.

REFRENCES

1. Cybenko, J., 1989 "Approximations by superposition of a sigmoidal function." *Math. Cont. Sign. Syst*., Vol. 2, pp. 303-314.

2. El-Maksoud, 2006 "Laboratory determining of soil strength parameters in calcareous soils and their effect on chiseling draft prediction", Proc. Energy efficiency and agricultural engineering international conf., Rousse, Bulgaria,

3. Goktepe, A.B., Selim, A., Gokhan, A., and Tan, O., 2008 "Shear strength estimation of plastic clays with statistical and neural approaches", Building and Environment, vol.43, pp. 849–860.

4. Gunaydin, O., Gokoglu, A., Fener, M., "Prediction of artificial soil's unconfined compression strength test using statistical analyses and artificial neural networks", Advances in Engineering Software, vol. 41, pp. 1115–1123, 2010.

5. Hegan, M. T. and Menhaj,M. B.,1994 "TrainingFeedforward Networks with the Marquardt Algorithm, IEEE T. Neural Network, 5, 989-993.

6. Kalkan, E., Akbulut, S., Tortum, A., 2009 "Prediction of the unconfined compressive strength of compacted granular soils by using inference systems", Journal of Environ Geol, vol. 58, pp.1429–1440.

7. Kayadelen, C., Gunaydin, O., Fener, M., and Ozvan, A., 2009 "Modeling of the angle of shearing resistance of soils using soft computing systems", Expert Systems with Applications, vol.36 pp. 11814–11826.

8. Korayen, 1996 "Prediction of soil shear strength and penetration resistance using some soil properties", Mis.J. Agr. Res, vol.13, no.4, pp. 119-140.

9. Lee, L.T., 2004 "Predicting geotechnical parameters for dredged materials using the slump test method and index property correlations," DOER Technical Notes Collection (ERDC TN-DOER-D-X), U.S. Army Engineer Research and Development Center Vicksburg, pp. 1-15.

10. Mollahasani, A., Alavi, A. H., Gandomi, A.H., and Rashed, A., 2011 "Nonlinear neural-based modeling of soil cohesion intercept", KSCE Journal of Civil Engineering 15(5) pp. 831-840.

11. Murthy, S., 2008 "Geotechnical engineering principals and practices of soil mechanics", second edition, Taylor and Fracis, CRC Press, UK.

12. Panwar and Seimens, 1972 "Shear strength and energy of soil failure related to density and moisture", T. ASAE, vol.15, pp.423-427.

13. Saarilahti, M., 2002 "Modeling of the seasonal variation of the trafficability on forest sites", Soil interaction model appendix report no 1, University of Helsinki, Department of Forest Resource Management, pp. 13-14, May.

14. Sahin, M. A., Jaksa, M. B., and Maier, H.R., 2001 "Artificial neural network applications in geotechnical engineering", Journal of Aus. Geomech. Vol. 36, no.1, pp. 49-62.

15. Sahin, M. A., Jaksa, M. B., and Maier, H.R., 2002 "Predicting the settlement of shallow foundations on cohesion less soils using back-propagation neural networks" ASCE Journal of Geotechnical and Geo environment, pp. 785-793, September.

16. Sivrikaya, O., 2009 "Comparison of Artificial Neural Networks Models with Correlative Works on Undrained Shear Strength", Journal of Eurasian Soil Science, Vol. 42, No. 13, pp. 1487–1496.

17. Zaman, M., Solanki, P., Ebrahimi, A., and White, L., 2010 "Neural network modeling of resilient modulus using routine Subgrade soil properties" Journal of Geomechanics, ASCE,Vol. 10, No. 1, pp. 1-12, February 1.