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Neural Networks for Assessing Shear Strength of Soils

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***Abstract*— Over the last few years or so, the use of artificial neural networks (ANNs) has increased in many areas of engineering. In particular, ANNs have been applied to many geotechnical engineering problems such as to predict pile capacity, settlement, liquefaction etc. The correlations between shear strength parameters and other soil properties individually are common among Geotechnical engineers. But establishing a correlation by assessing the shear strength parameters of any type of soil using all other soil properties is as such impossible generally. The existing correlations are mostly one to one in nature or at the most two only. Attempts were made to assess strength parameters of soils using various other engineering and physical properties using the ANN approach. A model has been created using a set of data and the same has been validated. The paper presents the model for assessing the strength parameters modelled with the optimal input physical parameters viz. Grain Size Distribution, Plasticity Index and Dry Density.**

***Keywords*— Angle of Shearing Resistance, Artificial Neural Networks, Cohesion, Correlations, Shear Strength**

I. INTRODUCTION

Geotechnical Engineers often have to solve complex problems involving a number of the interacting factors. The engineering properties of soil exhibit varied and uncertain behaviour due to the complex and imprecise physical process associated with the formation of these materials which is a matter of concern for a Geotechnical Engineer. The shear strength of soils is one of the most important among them. The bearing capacity of shallow or deep foundations, slope stability, retaining wall design and indirectly, pavement design are all affected by the shear strength of the soil in a slope, behind the retaining wall supporting a foundation or pavement. Therefore, due care is taken to evaluate the shear strength parameters.

The shear strength of a soil depends on many factors viz. composition of particles, shape of the grain, degree of interlock, liquidity index etc. Many researchers have developed correlations among these parameters. The correlations between Angle of Shearing Resistance individually with Grain Size Distribution, Plasticity Index, and Density etc. are the most common relations developed by the researchers using the conventional analytical approaches and statistical analysis.

The variability in the geotechnical data used for the correlations makes the analysis complicated and the percentage of reliability is minimal.

Application of neural networks in geotechnical engineering is an emerging area. ANNs have been used successfully in pile capacity prediction, modelling soil behaviour, site characterisation, earth retaining structures, settlement of structures, slope stability, design of tunnels and underground openings and liquefaction [1]. The present study is carried out for predicting shear strength of the soil through computational and knowledge based tool called neural network.

The artificial neural network is trained using actual laboratory tests data. The performance of the network models is investigated by relating the physical and engineering properties of soils. The neural network was trained using a large data base with experimental data. Once the neural networks have been deemed fully trained for its accuracy, the model has been tested for predicting the strength of the soils using a second set of experimental data. The paper presents a model for assessing the strength parameters modelled with the optimal input physical and various other engineering parameters.

II. OVERVIEW OF ANN

Artificial Neural Network (ANN) is a form of artificial intelligence which attempt to mimic the behaviour of the human brain and nervous system. It is a massively parallel system that relies on dense arrangements of interconnections and simple processors. It utilizes a parallel processing structure that has large number of processing units and many interconnections between them. In a neural network each unit is linked to many of its neighbours. The power of the neural network lies in the tremendous number of interconnections. A typical structure of ANNs consists of a number of processing [2, 3] elements or nodes that are usually arranged in layers: an input layer, an output layer and one or more hidden layers. Figure 1 depicts an example of a typical neural network.

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The propagation of information in ANN starts at the input layer where the input data are presented. The network adjusts its weights on the presentation of a training data set and uses a learning rule to find a set of weights that will produce the input/output mapping that has the smallest possible error which is called as “learning” or “training”. Once the training phase of the model has been successfully accomplished, the performance of the trained model is validated using an independent testing set.

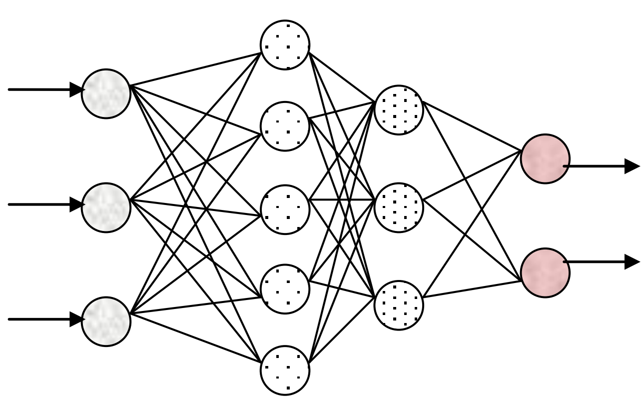

Figure 1 A Typical Neural Network

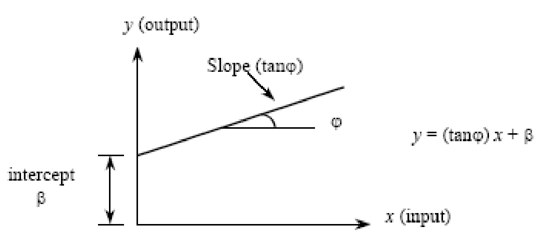

Figure 2 Linear regression model

The ANN modelling philosophy is similar to a number of conventional statistical models in the sense that both are attempting to capture the relationship between a historical set of model inputs and corresponding outputs. For example, suppose a set of x-values and corresponding y-values in 2 dimensional space, where y=f(x). The objective is to find the unknown function f, which relates the input variable x to the output variable y. In a linear regression model, the function f can be obtained by changing the slope tanφ and intercept â of the straight line in Figure 2, so that the error between the actual outputs and outputs of the straight line is minimized.

The same principle is used in ANN models. ANNs can form the simple linear regression model by having one input, one output, no hidden layer nodes and a linear transfer function (Figure 3). The connection weight w in the ANN model is equivalent to the slope tanφ and the threshold è is equivalent to the intercept â, in the linear regression model. ANNs adjust their weights by repeatedly presenting examples of the model inputs and outputs in order to minimize an error function between the historical outputs and the outputs predicted by the ANN model.

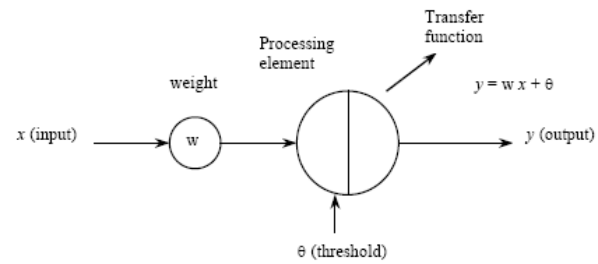

Figure 3 ANN representation of a linear regression model

If the relationship between x and y is non-linear, regression analysis can only be successfully applied if prior knowledge of the nature of the non-linearity exists. On the contrary, this prior knowledge of the nature of the non-linearity is not required for ANN models. In the ANN model, the degree of non-linearity can be also changed easily by changing the transfer function and the number of hidden layer nodes. In the real world, it is likely to encounter problems that are complex and highly non-linear. In such situations, traditional regression analysis is not adequate. In contrast, ANNs can be used to deal with this complexity by changing the transfer function or network structure, and the type of non-linearity can be changed by varying the number of hidden layers and the number of nodes in each layer. In addition, ANN models can be upgraded from univariate to multivariate by increasing the number of input nodes.

III. ANN Applications In Geotechnical Engineering

The engineering properties of soil and rock exhibit varied and uncertain behavior due to the complex and imprecise physical processes associated with the formation of these materials. This is in contrast to most other civil engineering materials, such as steel, concrete and timber, which exhibit far greater homogeneity and isotropy.

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In order to cope with the complexity of geotechnical behavior, and the spatial variability of these materials, traditional forms of engineering design models are justifiably simplified. The prediction of the load capacity, particularly those based on pile driving data, has been examined by several ANN researchers and Neural network to predict the friction capacity of piles in clays and sandy soils have been developed. The problem of estimating the settlement of foundations is very complex, uncertain and not yet entirely understood. This fact encouraged some researchers to apply the ANN technique to settlement prediction and a neural network for the prediction of settlement of a vertically loaded pile foundation in a homogeneous soil stratum has been developed. Neural networks have been used to model the complex relationship between seismic and soil parameters in order to investigate liquefaction potential. Some researchers have proposed a methodology of combining fuzzy sets theory with artificial neural networks for evaluating the stability of slopes. Soil properties and behavior is an area that has attracted many researchers to modelling using ANNs. Developing engineering correlations between various soil parameters is an issue discussed by all researchers. Neural networks have been used to model the correlation between the relative density and the cone resistance from cone penetration test, for both normally consolidated and over-consolidated sands.

IV. Correlations On Shear Strength Parameters

Generally geotechnical designs rely on the observation of the behavior of geotechnical structures under similar conditions. Experiences and judgments also play important role in the evaluation or the characterization of parameters of interest. Despite the great improvement in techniques for modelling the behaviour of soils, there are difficulties. One of them lies in the variability of geotechnical data itself which is large even in nominally uniform soil mass. This variation causes a scatter in the results which is difficult to correct. Applying too many refinements and corrections only serves to make the analysis complicated and may lead to a doubtful result.

Despite all these, many researchers have tried to develop relationship between the shear strength of the soil and Plasticity Index. The existence of these relationships arises because both the Plasticity Index and shear strength reflects the clay mineral composition of the soil. As the amount of clay content increases, the Plasticity Index increases and the shear strength decreases [4].

Figure 4 shows the relationship established by Gibson (1953) between the Angle of Shearing Resistance and the Plasticity Index.

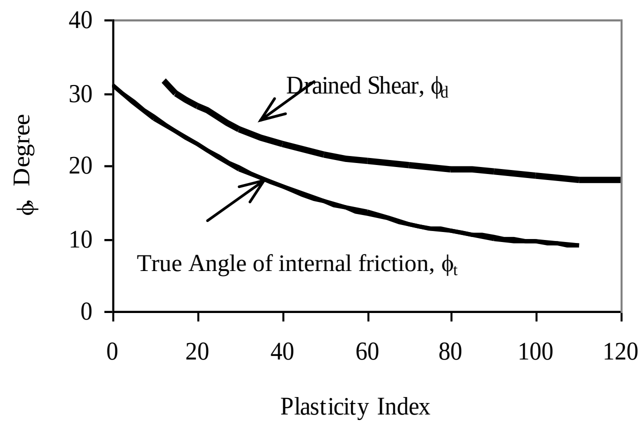

Figure 4 Relationships between Angle of Shearing Resistance and Plasticity Index (after Gibson, 1953) [4]

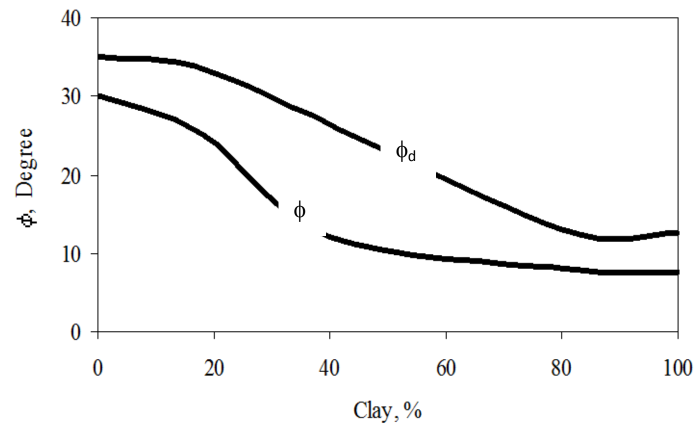

Figure 5 Relationship between clay sizes and Angle of Shearing Resistance (after Skempton) [4]

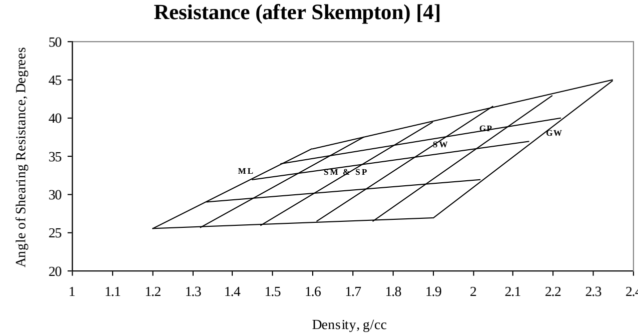

Figure 6 Relationship between Dry Densities and Angle of Shearing Resistance [4]

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Figure 5 shows the relationship between the clay sizes and the Angle of Shearing Resistance. Figure 6 shows the relationship between the dry densities of different types of soils and their respective angle of shearing resistance [4].

It is evident from these relationships that the correlations are established on one to one basis only. But the shear strength of the soil is influenced by various parameters as discussed earlier. Therefore, it is necessary to correlate the shear strength to all the properties at one go which is not possible in the conventional analytical approaches and possible using ANN.

V. ANN Approach

Due to the complexity involved in the statistical correlations, Artificial Neural Network (ANN) which works on a probabilistic modelling is used for establishing a near relationship. The ANN modelling philosophy is similar to a number of conventional statistical models in the sense that both are attempting to capture the relationship between a historical set of model inputs and corresponding outputs. The degree of non-linearity in the set of chosen inputs and corresponding outputs is well taken care of in ANN by varying the number of hidden layers and the number of nodes in each layer. The software, Easy-NN which works on Back Propagation Algorithm, is employed for modelling the assessment of Shear Strength of soil.

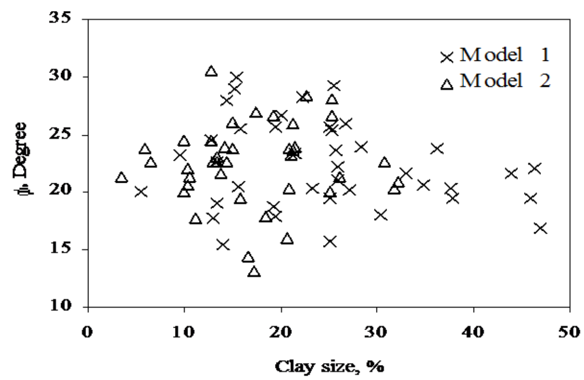
VI. The Model

The study [5] on the assessing shear strength parameters of soil started using a total of 130 data points initially. Then the data points were scrutinized carefully and 80 data points were used finally for the modelling. Primarily the modelling requires careful, significant data scrutiny and placement. Secondarily, the model is trained with the scrutinized data to recognize a pattern so that the model is able to predict the desired output data. The data considered for the study is based on the results obtained from the laboratory investigations of project sites located in the northern region of India.

The soil parameters such as Grain Size Distribution, Consistency Limits (Liquid Limit, Plastic Limit and Plasticity Index) and Density were considered as the input parameters. The model was trained with the scrutinized data points to predict the total and effective shear strength parameters (c, ϕ, c′ and ϕ′) as output parameters. The model so designed consists of two hidden layers.

The maximum error obtained with the model created using 80 data points for predicting True Cohesion (c), Angle of Shearing Resistance(ϕ), Effective Cohesion (c′) and Effective Angle of Shearing Resistance(ϕ′) are 15%, 12%, 9.5% and 4.2% respectively.

But the present study is further refinement of the earlier studies. The data points used for the earlier studies were used for the present study. But these data points were scrutinized according to the ranges of the dry density values. Considering the ranges for the fine grained soils to be less than 17.0 kN/m^3 and the ranges for the Coarse grained soils to be more than 17.0 kN/m^3 and limited to 22.0 kN/m^3 two sets of data points comprising of 40 data each were used finally for the modelling. The relationships between the clay sizes, dry densities and the total angle of shearing resistance and effective angle of shearing resistance of the soil samples considered for the models are presented in Figures 7 to 10.



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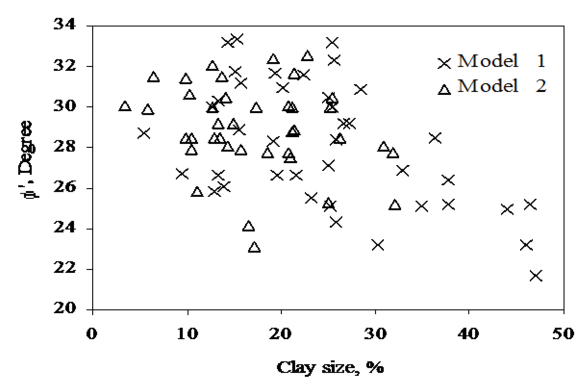

Figure 8 Clay size Vs Effective ϕ

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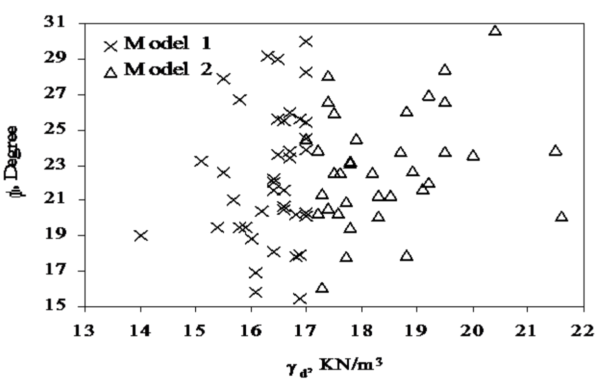

Figure 9 Dry Density Vs Total ϕ

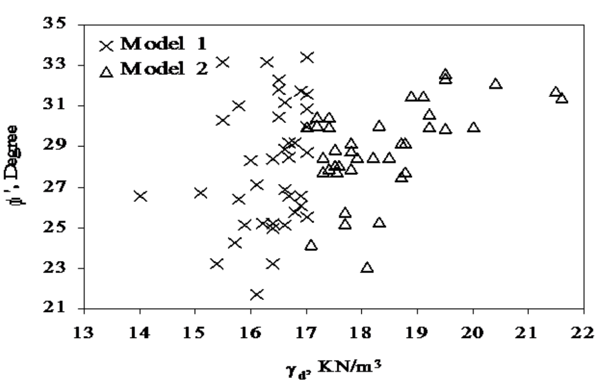

Figure 10 Dry Density Vs Effective ϕ

First, the model was trained with the scrutinized data points. Then the same 40 data points were used for predicting the desired output parameters. The maximum errors for predicting True Cohesion (c), True Angle of Shearing Resistance (ϕ), Effective Cohesion (c′) and the Effective Angle of Shearing Resistance (ϕ′) for the first model with the density values less than 17.0 kN/m^3 were found to be 3.0%, 5.4%, 8.5% and 2.3% respectively.

The maximum errors for predicting True Cohesion (c), True Angle of Shearing Resistance (ϕ), Effective Cohesion (c′) and the Effective Angle of Shearing Resistance (ϕ′) for the second model with the density values more than 17.0 kN/m^3 were found to be 5.5%, 4.8%, 6.7% and 2.4% respectively.

Figure 13 depicts the Error Scatter of both the models for True Cohesion, c. From this figure, it can be seen that 90% of the data are with in 1.8% error in model 1 and 5% in model 2. The average error for predicting cohesion, c for model 1 and model 2 are 0.7% and 2.5% respectively. Figure 14 depicts the actual values versus the predicted values of True Cohesion, c.

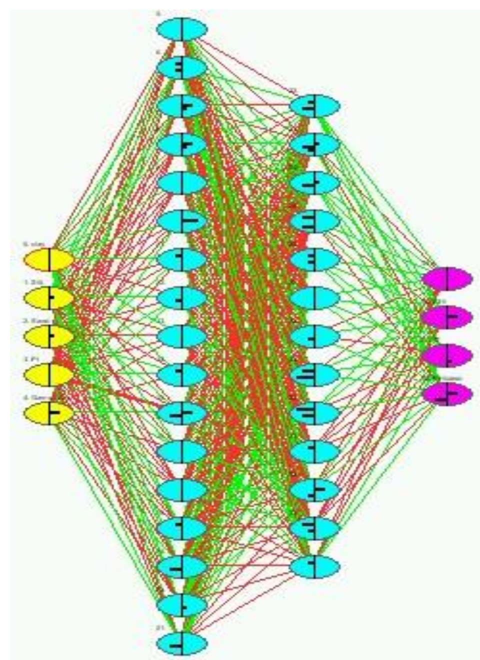

Figure 11 Network - Model 1

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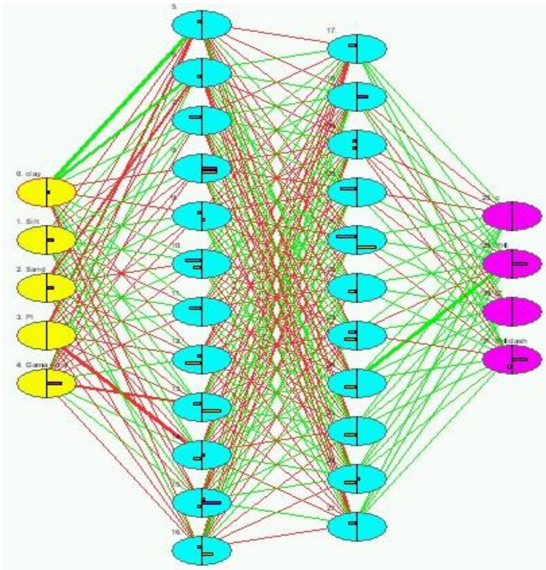

Figure 12 Network - Model 2

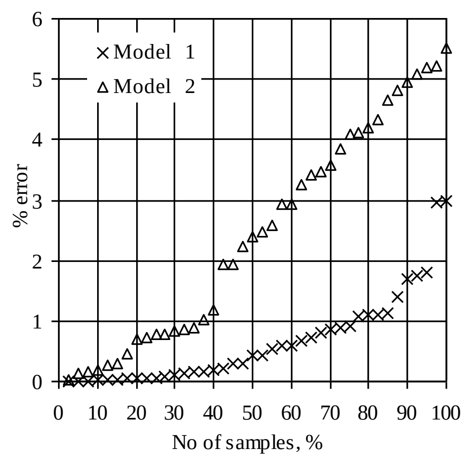

Figure 13 Error Scatter - True Cohesion

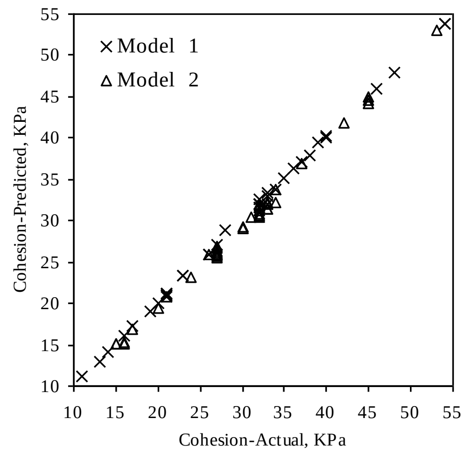

Figure 14 Cohesion–Actual v/s Predicted

Figure 15 depicts the Error Scatter of the model for True Angle of Shearing Resistance(ϕ). From this figure, it can be seen that the maximum error in Model 1 is about 5.4% and 90% of the data are with in 3.2% error. The maximum error in Model 2 is about 4.8% and 90% of the data are with in 4.2% error. The average error for predicting True Angle of Shearing Resistance (ϕ) for model 1 and model 2 are 1.8% and 2.3% respectively. Figure 16 depicts the actual values versus the predicted values of True Angle of Shearing Resistance.

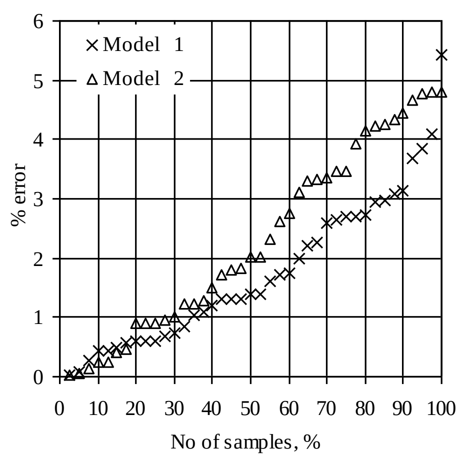

Figure 15 Error Scatter – True ϕ

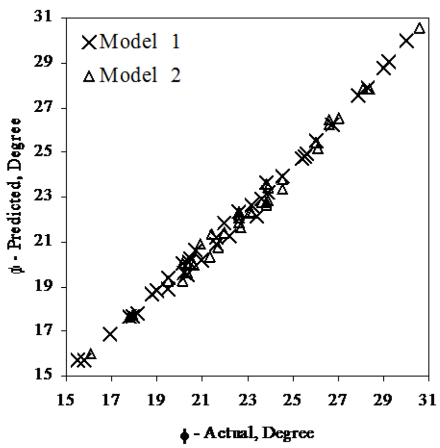

Figure 16 True ϕ –Actual v/s Predicted

Figure 17 depicts the Error Scatter of the model for Effective Cohesion (c′). From this figure, it can be seen that the maximum error in Model 1 is about 8.5% and 90% of the data are with in 6.0% error. The maximum error in Model 2 is about 6.7% and 90% of the data are with in 3.8% error. The average error for predicting Effective Cohesion (c′) for model 1 and model 2 are 3.2% and 1.7% respectively. Figure 18 depicts the actual values versus the predicted values of Effective Cohesion.

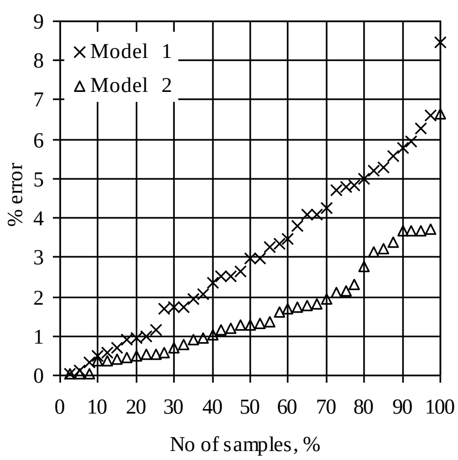

Figure 15 Error Scatter- c′

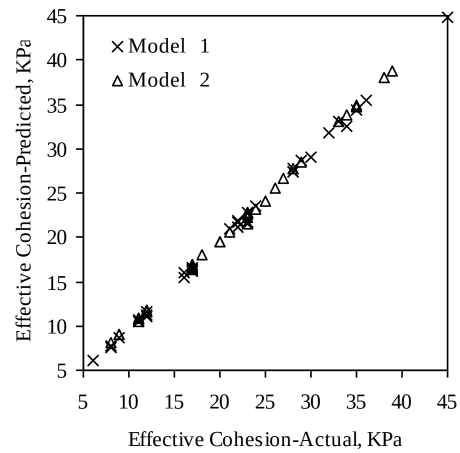

Figure 16 c′ - Actual v/s Predicted

Figure 17 depicts the Error Scatter of the model for Effective Angle of Shearing Resistance(ϕ′). From this figure, it can be seen that the maximum error in Model 1 is about 2.3% and 90% of the data are with in 1.5% error. The maximum error in Model 2 is about 2.4% and 90% of the data are with in 2.1% error. The average error for predicting Effective Angle of Shearing Resistance(ϕ′) for model 1 and model 2 are 0.3% and 1.1% respectively. Figure 18 depicts the actual values versus the predicted values of Effective Angle of Shearing Resistance.

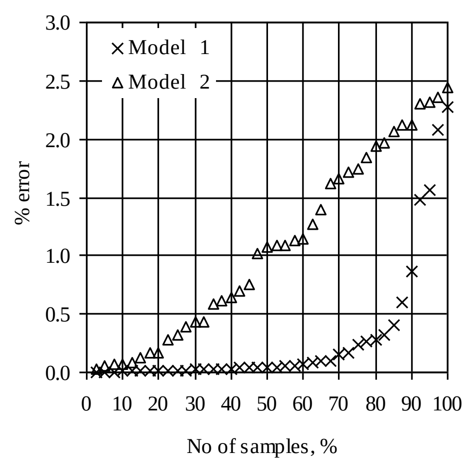

Figure 17 Error Scatter –ϕ′

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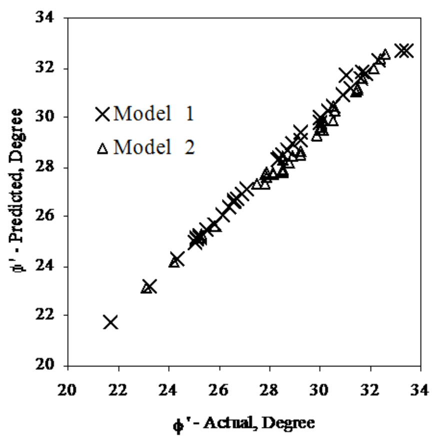

Figure 18 ϕ′ –Actual v/s Predicted

For validating the models, a second set of experimental results consisting of 20 data points each for the model 1 and 2 have been used. The maximum error for predicting True Cohesion (c), True Angle of Shearing Resistance (ϕ), Effective Cohesion (c′) and the Effective Angle of Shearing Resistance (ϕ′) for the 20 data points in Model 1 were found to be 1.1%, 3.1%, 4.3% and 2.1% respectively. The average error for predicting True Cohesion (c), True Angle of Shearing Resistance (ϕ), Effective Cohesion (c′) and the Effective Angle of Shearing Resistance (ϕ′) for the 20 data points in Model 1 were found to be 0.3%, 1.2%, 2.4% and 0.3% respectively.

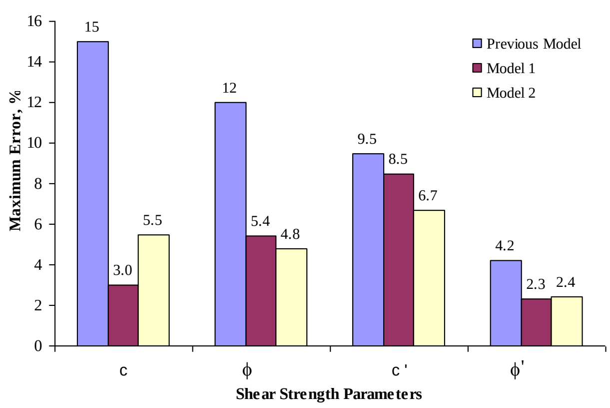

Figure 19 Comparison of Maximum Error

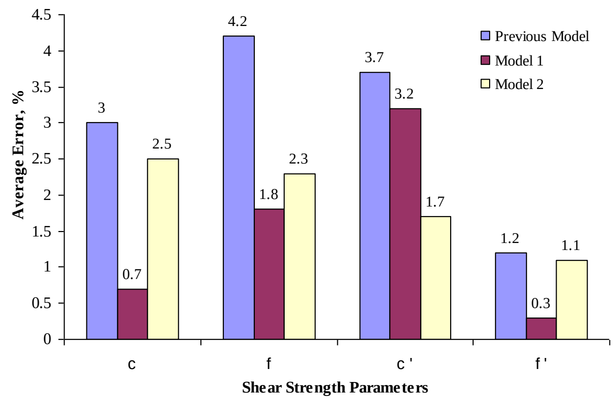

Figure 20 Comparison of Average Error

The maximum error for predicting True Cohesion (c), True Angle of Shearing Resistance (ϕ), Effective Cohesion (c′) and the Effective Angle of Shearing Resistance (ϕ′) for the 20 data points in Model 2 were found to be 2.5%, 1.7%, 3.1% and 1.6% respectively. The average error for predicting True Cohesion (c), True Angle of Shearing Resistance (ϕ), Effective Cohesion (c′) and the Effective Angle of Shearing Resistance (ϕ′) for the 20 data points in Model 2 were found to be 0.9%, 0.4%, 0.7% and 0.5% respectively. The comparison of the maximum and average error obtained for all the models created for assessing the shear strength parameters of soils are presented in Figure 19 and 20.

VII. CONCLUSION

It has been already proved that the Artificial Neural Network can very well be used for predicting the shear strength parameters of soils. But from the present study it is evident that the models used for predicting the shear strength parameters of soils needs proper scrutinization and training. The variability in the data points used for the study influences the percentage of error scatters. The present study confirms the importance of the scrutinization of data points and is much better than the earlier study carried out by the authors.

No doubt that ANN approach is much better than the conventional analytical approach. But one should keep in mind that ANN can predict parameters for which it is formulated and trained. Therefore one should be very careful in using the ANN approach for predicting any soil parameters.

REFERENCES

[1] Abu-Kiefa, M. A. (1998). "General regression neural networks for driven piles in cohesionless soils." J. Geotech. & Geoenv. Engrg., ASCE, 124(12), 1177-1185.

[2] Agrawal, G., Chameau, J. A., and Bourdeau, P. L. (1997). "Assessing the liquefaction susceptibility at a site based on information from penetration testing." In: Artificial neural networks for civil engineers: fundamentals and applications, N. Kartam, I. Flood, and J. H. Garrett, eds., New York, 185-214.

[3] Chitra R and Gupta Manish,(2005), "Applications of Neural Networks in Geotechnical Engineering", Proceedings of the National Conference on `Recent Trends in Geotechnology', Pune, 12 - 13 February, 2005

[4] Chitra R and Gupta Manish,(2012), "Innovative approach by Neural Networks in Geotechnical Engineering", Journal on Civil Engineering & Construction review, July, 2012.

[5] Chitra R., Manish Gupta and A. K. Dhawan (2008), "An ANN Approach for Assessing Strength of Soils", GeoSymposium 2008, National Symposium on "Geoenvironment, Geohazards, Geosynthetics and Ground Improvement - Experiences and Practices – 4G", New Delhi, July 4 & 5, 2008.

[6] Chitra,R., Manish Gupta and A.K.Dhawan (2004) "Assessing Strength of Soils – An ANN Approach". Proceedings of International workshop on "Risk assessment in site characterization and Geotechnical Design", Indian Institute of Science, Bangalore, 26-27 November 2004, pp 182 - 188.

[7] Fausett, L. V. (1994). Fundamentals neural networks: Architecture, algorithms, and applications, Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

[8] Flood, I., and Kartam, N. (1994). "Neural networks in civil engineering I: Principles and understanding." J. Computing in Civil Engrg, ASCE, 8(2), 131-148.

[9] Goh, A. T. C. (1994b). "Seismic liquefaction potential assessed by neural network." J. Geotech. & Geoenv. Engrg., ASCE, 120(9), 1467-1480.

[10] Manish Gupta, Chitra, R. and Dhawan, A.K, (2005), "Prediction of shear strength properties of soils using ANN", Proceedings of National Conference on GEOPREDICT 2005, IIT, Chennai, June 2005.