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PREDICTING SOIL PROPERTIES USING NEURAL NETWORKS

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Abstract- Artificial Neural Networks (ANN) has been used in many areas of engineering and science for assessing the behaviour of the materials over the past few years. Particularly, ANN has been applied in many geotechnical problems such as prediction of pile capacity, liquefaction, settlement etc. Attempts are being made by many researchers to predict many soil properties, such density, shear strength parameters, consolidation properties, permeability etc. The correlations between the physical properties and the engineering properties very common for the practising Geotechnical Engineers. However, it is very difficult to establish correlations using all the soil properties to predict shear strength and permeability of the soil. The existing correlations are mostly one to one in nature or at the most two only. The paper presents the attempts made to predict the shear strength parameters and the soil permeability using the soils' physical properties and the other engineering properties using ANN approach. A very valuable set of data have been using for creating a model for the prediction and the same set of data has been used for validating the model.

Keywords—Artificial Neural Networks, Grain Size, Cohesion, Angle of Shearing Resistance, Shear Strength, Permeability

I. INTRODUCTION

Complex problems in the geotechnical engineering are being solved using a number of 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.

Permeability is a very important engineering property of soils. Determination of permeability is essential in a number of soil engineering problems, such as settlement of buildings, yield of wells, seepage through and below the earth structures etc. It controls the hydraulic stability of soil masses. The permeability of soils is also required in the design of filters used to prevent the piping in hydraulic structures. Permeability of soils is influenced by various factors such as Particle Size, Structure of soils, Shape of Particles, Void ratio, Properties of water and degree of saturation. Several methods are adopted for determining the coefficient of permeability in the field and laboratory generally depending upon the site conditions and type of soils. Indirect methods are also used to evaluate the coefficient of permeability of soils without conducting any test. With the analytical approaches for evaluating the coefficient of permeability, it is difficult to correlate more than one factor in the approach.

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

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structures, settlement of structures, slope stability, design of tunnels and underground openings and liquefaction [Abu-Kiefa]. 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 and permeability modelled with the optimal input physical and various other engineering parameters.

I. 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 [Agrawal et.al and Chitra et.al.] elements or nodes that are usually arranged in layers: an input layer, an output layer and one or more hidden layers. Fig. 1 depicts an example of a typical neural network.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.

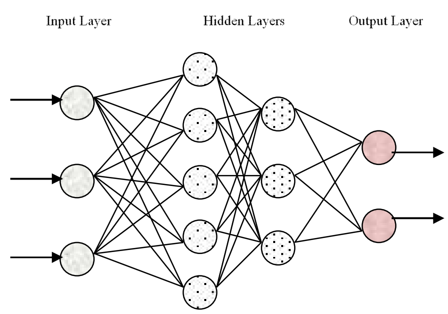

Fig. 1 A Typical Neural Network

II. 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. 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.

III. 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]. Fig.2 shows the relationship established by Gibson (1953) between the Angle of Shearing Resistance and the Plasticity Index. Fig. 3 shows the relationship between the clay sizes and the Angle of Shearing Resistance.

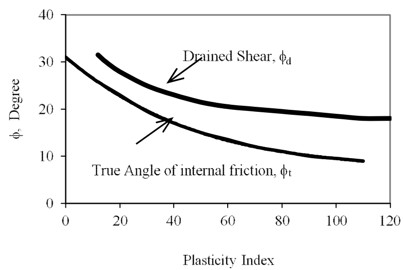

Fig. 2 Relationships between Angle of Shearing Resistance&Plasticity Index (Gibson, 1953) [4]

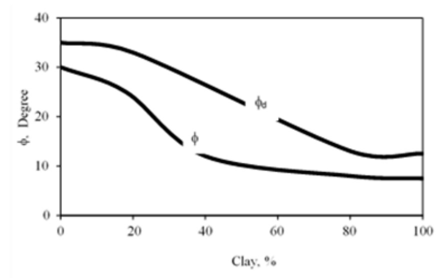

Fig. 3 Relationship between clay sizes and Angle of Shearing Resistance (Skempton) [4]

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.

IV. CORRELATIONS ON COEFFICIENT OF PERMEABILITY

Attempts were made by many researchers to predict permeability empirically from grain size distribution indices, void ratio, porosity, viscosity etc. Computation from the particle size or its specific surface and computation from the consolidation test data are the most common among them. Some of the correlations are given below.

Allen Hazen's Formula:

$$k = C.D_{10}^2$$

Where k = Coefficient of permeability, cm/sec
D_{10} = Effective size, cm
C = Constant with a value 100 and 150

Kozeny – Carman equation:

$$k = \frac{g\rho_w}{\left(C_s \mu S^2\right)T^2} \cdot \frac{e_3}{1+e}$$

Where k = Coefficient of permeability, cm/sec
ρ_w = Mass density of water, g/cc
C_s= Shape factor which can be taken as 2.5 for granular soils
μ = Coefficient of viscosity, poise
e = Void ratio
g = 9.81 cm.sec^2
T = Tortuosity, with a value of √2 for granular soils and
S = Surface area per unit volume (Specific area), cm^2/ cm^3

Terzaghi and Peck (1964) equation:

$$k = \frac{g}{v} C_t \left[\frac{n - 0.13}{(1-n)^{1/3}} \right]^2 D_{10}{}^2$$

Where k = Coefficient of permeability, cm/sec
g = the acceleration due to gravity, cm/sec^2
v = kinematic viscosity, mm^2/sec
C_t = sorting coefficient,
ranging between 6.1×10^{-3} and 10.7×10^{-3}
n = porosity
D_{10} = grain size corresponding to 10% passing, mm

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 prediction of the soil properties.

V.1. Prediction of Shear Strength Parameters

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 present study is refinement of the earlier studies. The 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.

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.Figs.4and 5 depicts the Error Scatter for True Cohesion, c and True Angle of Shearing Resistance(ϕ) respectively. Figs. 6 and 7 depicts the Error Scatter of the model for Effective Cohesion (c′) and Effective Angle of Shearing Resistance(ϕ′) respectively.

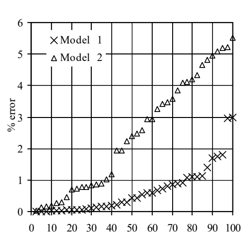

Fig. 4 Error Scatter-True c

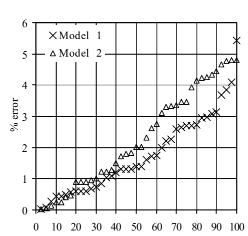

Fig. 5 Error Scatter-True ϕ

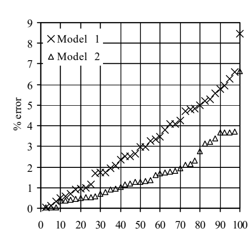

Fig. 6 Error Scatter- c′

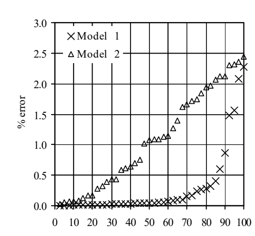

Fig. 7 Error Scatter- ϕ′

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.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 maximum and average error obtained for all the models created for assessing shear strength parameters of soils are presented in Figs.8 and 9.

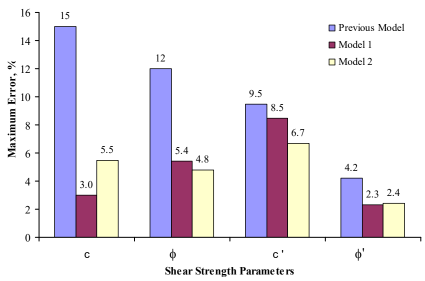

Fig. 8 Comparison of Maximum Error

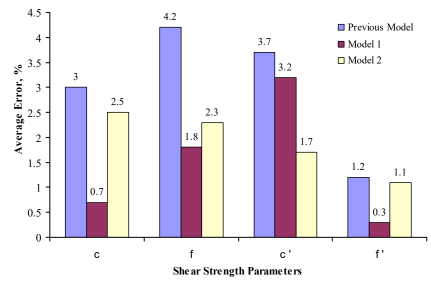

Fig. 9 Comparison of Average Error

V.2. Prediction of Permeability

A total of 40 data points were used for the modelling initially. The data points were scrutinized after and 26 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. Two models with the soil parameters such as Grain Size Distribution, Plasticity Index and Density as the input parameters in the first and parameters such as effective particle sizes viz. D10, D15 and D85, Plasticity Index and Density as the input parameters in the second were considered. The model was trained with the scrutinized data points to predict the coefficient of permeability, k as output parameter. The model so designed consists of two hidden layers.

First, the model was trained with a total of 26 scrutinized data points. Then the same 26 data points were used for predicting the desired output parameter. The maximum error for predicting coefficient of permeability, k for the first model was found to be 4.2%. Fig. 10and 11 depicts the Error Scatter of the first and second model for coefficient of permeability respectively.

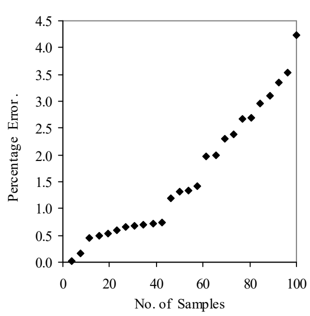

Fig. 10 Error Scatter of the First Model

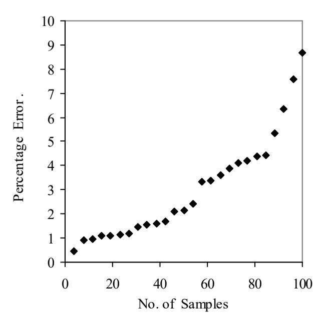

Fig. 11 Error Scatter of the Second Model

For validating the model, a second set of experimental results consisting of 15 data points has been used. The maximum error for predicting coefficient of permeability, *k*for the first model was found to be 3.5% and the average error is only 1.5%. The Error Scatter of the first model for coefficient of permeability, *k*indicates that 93% of the data are within2.7% error. It is also observed that all the data points except one are covered well within the error of 2.7%. The maximum error for predicting coefficient of permeability, k for the second model was found to be 7.6% and the average error is only 2.6%. The Error Scatter of the second model for coefficient of permeability, indicate that 93% of the data are within 4.4% error. It is also observed that all the data points except one are covered well within the error of 4.4%.

The maximum error for predicting the second model with the input parameters as effective particle sizes is twice than that of the first model with the input parameters as grain size distribution. Though the effective particle sizes viz. D10, D15 and D85 are read from the grain size distribution curves of the respective soils only, the error is disreputable. The variability in the input parameters increases the percentage of error scatter. Moreover, the coefficient of permeability is largely influenced by the size of the particles, shape of the particles, molding water, method of mixing, degrees of saturation, void ratio etc. But it is very difficult to express some of these terms in to the mathematical expression in order to predict the coefficient of permeability using any approach. But still the assessment of permeability of soils using ANN has proved to be effective in the present study by combining most of the parameters which influence it.

VI. 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.

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