ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

ARTIFICIAL NEURAL NETWORKS FOR ASSESSING PERMEABILITY CHARACTERISTICS OF SOILS

Dr. Manish Gupta [*], Dr. R. Chitra
[*] Central Soil and Materials Research Station, New Delhi, India

ABSTRACT

Artificial Neural Network (ANN) has been widely used for solving many problems in many areas. Predictions using the neural network are becoming more popular. ANN has been applied in geotechnical engineering also to predict pile capacity, settlement, liquefaction, soil properties and many. Permeability is one of the most important soil properties which is essential in solving large number of engineering problems. Grain size distribution and density are known to influence the permeability of sandy soils. Although the relationships between grain size distribution and permeability has been quantified by some researchers, the influence is not quantified. The correlations between coefficient of permeability and other soil properties individually are common among Geotechnical engineers. But establishing a correlation by assessing the coefficient of permeability of any soil type using all other soil properties is as such impossible generally. The paper presents the method of determining the permeability of soils, factors affecting the permeability of soils, existing correlations practiced and a model for assessing the coefficient of permeability modelled with the optimal input physical parameters.

Keywords: Coefficient of Permeability, Artificial Neural Network, Model, Prediction.

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 behavior 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. 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 solving the Geotechnical problems associated with pile capacity prediction, modelling soil behavior, site characterization, earth retaining structures, settlement of structures, slope stability, design of tunnels and underground openings and liquefaction etc. to name a few. The present study is carried out for predicting permeability of 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 permeability of soil using a second set of experimental data. The paper presents the method of determining the permeability of soils, factors

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

affecting the permeability of soils and the existing correlations practiced in geotechnical engineering. The paper presents a model for predicting the permeability of soil modelled with the optimal input physical parameters.

ARTIFICIAL NEURAL NETWORK – AN OVERVIEW

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 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.

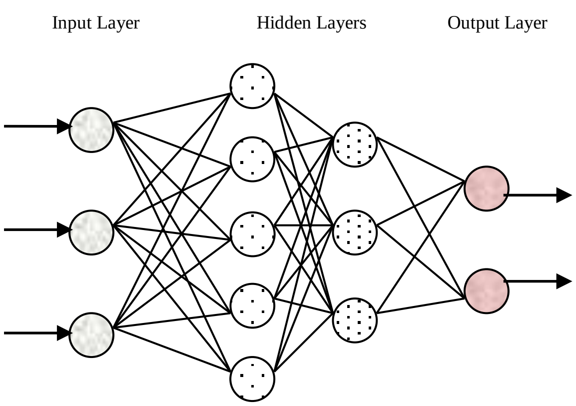

Figure 1 A Typical Neural Network

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.

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.

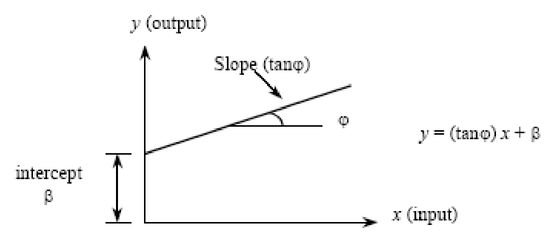

Figure 2 Linear regression model

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.

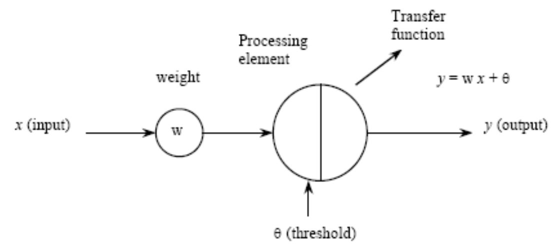

Figure 3 ANN representation of a linear regression model

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

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

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.

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.

DETERMINATION OF COEFFICIENT OF PERMEABILITY

The permeability tests are used to determine the coefficient of permeability (k) of a particular soil. The results of permeability tests on the construction materials of earth and rockfill dams are useful in selecting the type of soil for various zones of the dam. The value of coefficient of permeability is used in drawing the flow nets in the body of the dam which leads to the design of appropriate filter systems. The coefficient of permeability of a soil is determined using the following methods.

Laboratory Methods

Depending on the type of soils two types of laboratory permeability tests are carried out on the construction materials. They are:

- Constant Head test – For more pervious soils
- Falling head test – For impervious soils

Field Methods

The coefficient of permeability (k) of a soil deposit in-situ conditions are determined by:

- Pumping-out tests – influences a large area around the pumping well and give an overall value of the soil deposit
- Pumping-in tests - influences a small area around the hole and give a value of the surrounding hole

FACTORS AFFECTING PERMEABILITY

Permeability is a complex property that is controlled by physical properties of both the soil and the permeating fluid. At a constant temperature of 20°C, the common room temperature, the viscosity and unit weight of water remainconstant. Therefore, physical properties such as grain size distribution, density, void ratio, and soil texture and structure affect the magnitude of permeability.

Effect of Grain Size and Grain Size Distribution

Grain size distribution of granular soils affects their permeability. Poorly graded soils have higher porosity and permeability values than well graded soils in which smaller grains tend to fill the voids between larger grains.

Effect of Density and Void Ratio

Dry density is the ratio of the mass of the solids in a soil to its total volume, the sum of volume of solids and volume of voids. Void ratio (e) is defined as the ratio of the volume of voids to the volume of solids. Density and void ratio are inversely related. Permeability decreases as density increases or void ratio decreases.

Effect of Soil Texture and Structure

Texture and structure relate to size, shape, and arrangement of particles in a soil mass. Particle shape has an important effect on permeability as it

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

influences the size and shape of interconnection between particles. The more angular the grains are, the smaller the voids and more tortuous the flow paths will be. This is because edges and corners of angular grains can fit into voids which means there is a greater degree of interlocking.

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

Figure 4 shows the correlation between the coefficient of permeability and the D_{10} for the sands and gravels. The correlations for clays are difficult due to the clay mineralogy present in clays.

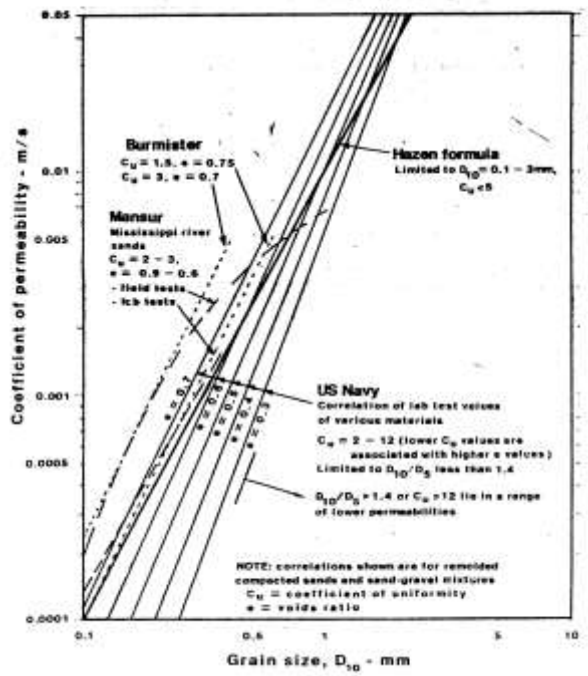

Figure 4 Correlation between k and D_{10}

Figure 5 shows the correlation between the coefficient of permeability and the water content in dry soil mass which depicts the effect of physically mixing or blending of a soil on permeability. Figure 6 shows the correlations between the coefficient of permeability and the dry density and molding water content in dry soil mass and depict the effect of dispersion on permeability. Figure 7 presents the correlations between the coefficient of permeability and the degree of satturation on permeability. The typical ranges of permeability for different soil types are presented in Table 1.

Table 1 Typical Ranges of Permeability

Soil type	Degree of Permeability	k cm/sec	Drainage properties
Clean Gravel	High	1 – 10	Good
Clean Sand, Sand with gravel mix	Medium	1 – 10^{-3}	Good
Fine sand, Silt	Low	10^{-3} – 10^{-5}	Fair - Poor

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Sand – Silt – Clay mixture	Very low	$10^{-4} – 10^{-7}$	Poor - Impervious
Homogeneous Clay	Very low impermeable	Less than 10^{-7}	Impervious

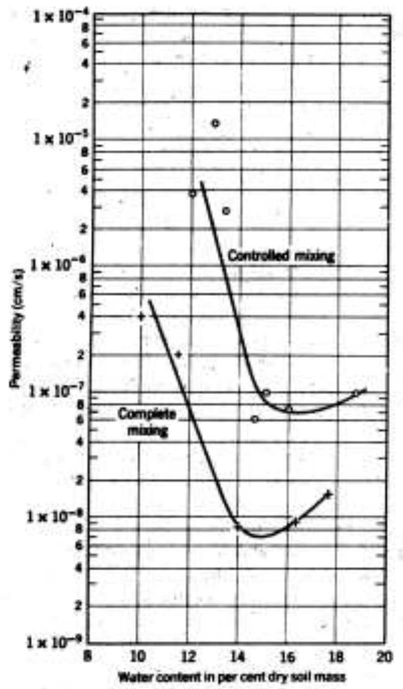

Figure 5 Effect of water content in dry soil mass on k

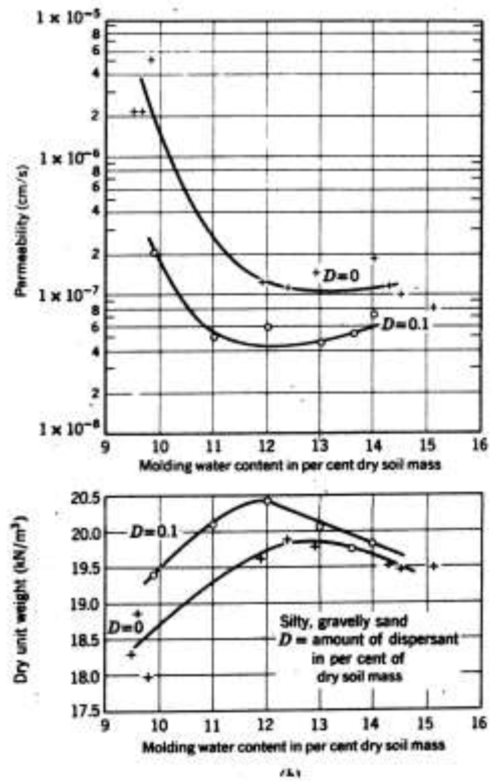

Figure 6 Effect of density and water content on k

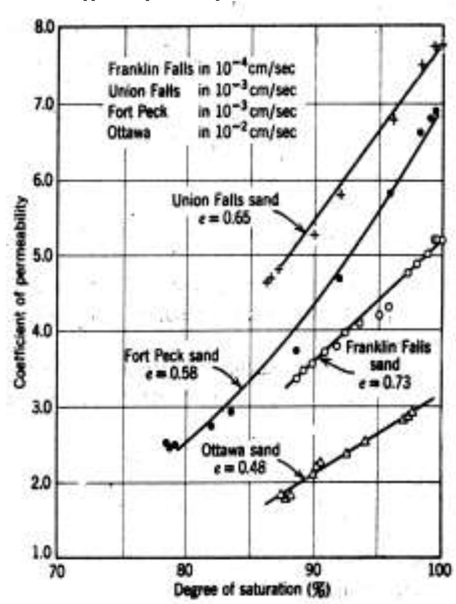

Figure 7 Effect of Degree of Saturation on k

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

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

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 permeability of soil.

THE STUDY

The present study is based on the results obtained from the laboratory investigations of various projects in the northern region of India. Strictly speaking the correlations between the coefficient of permeability and the other soil properties have to be analyzed with respect to the different types of soils as the permeability of the fine grained soils and coarse grained soils are entirely different. But the approach chosen for the present model is based on the back propagation algorithm which takes care of the heterogeneous nature of the input parameters. Moreover to begin with, the present study has been carried out using the properties of all types of soils of meager data points.

THE MODEL

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%. Figure 8 depicts the Error Scatter of the first model for coefficient of permeability, k. From this figure, it can be seen that 96% of the data are with in 3.5% error. Though the maximum error is 4.2% the average error is only 1.6%. It can also be seen that all the data points except one are covered well within the error of 3.5%. Figure 9 depicts the actual values versus the predicted values of coefficient of permeability, k.

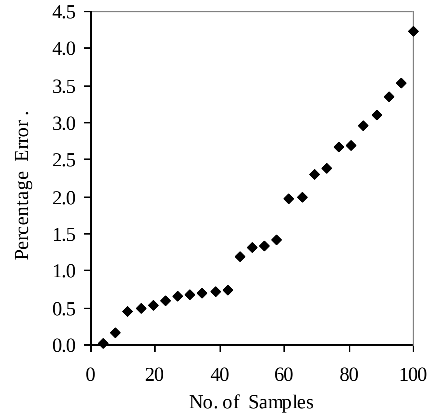

Figure 8 Error Scatter of the First Model

The maximum error for predicting coefficient of permeability, *k* for the second model was found to be 8.7%. Figure 10 depicts the Error Scatter of the second model for coefficient of permeability, *k*. From this figure, it can be seen that 90% of the data are with in 5.4% error. The average error is 3.0%. Figure 11 depicts the actual values versus the predicted values of coefficient of permeability, *k*.

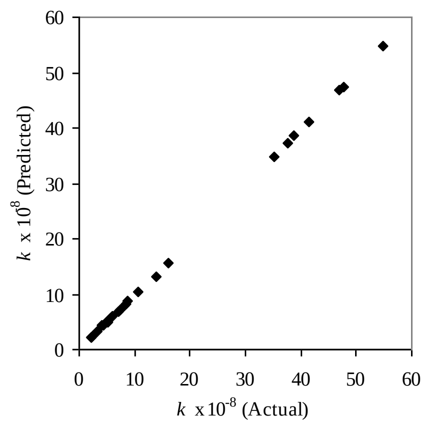

Figure 9 k (Actual) Vs k (Predicted)

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

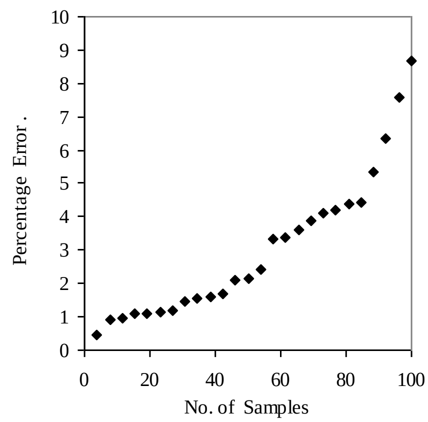

Figure 10 Error Scatter of the Second Model

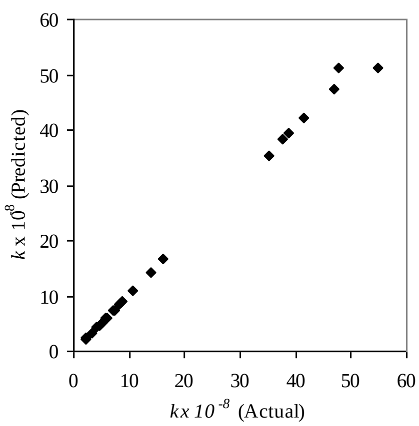

Figure 11 k (Actual) Vs k (Predicted)

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%. Figure 12 depicts the Error Scatter of the first model for coefficient of permeability, *k*. From this figure, it can be seen that 93% of the data are with in 2.7% error. It can also be seen that all the data points except one are covered well within the error of 2.7%. Figure 13 depicts the actual values versus the predicted values of coefficient of permeability by the validated model.

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%. Figure 14 depicts the Error Scatter of the second model for coefficient of permeability, k. From this figure, it can be seen that 93% of the data are with in 4.4% error. It can also be seen that all the data points except one are covered well within the error of 4.4%. Figure 15 depicts the actual values versus the predicted values of coefficient of permeability by the validated model.

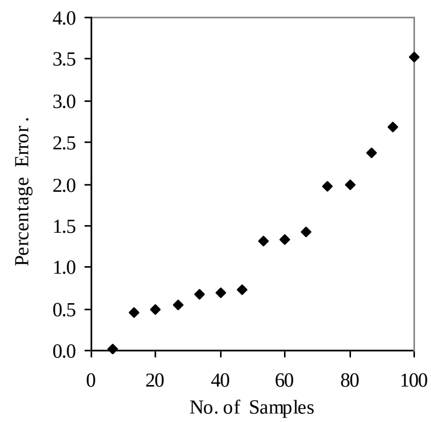

Figure 12 Error Scatter of the First Model

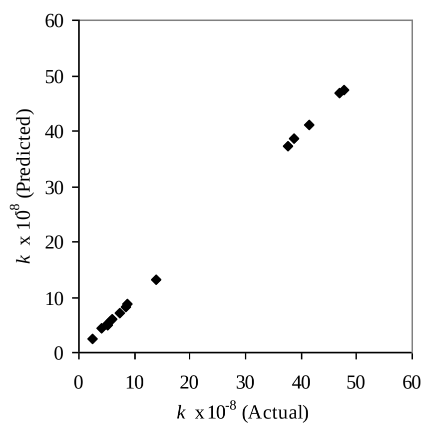

Figure 13 k (Actual) Vs k (Predicted)

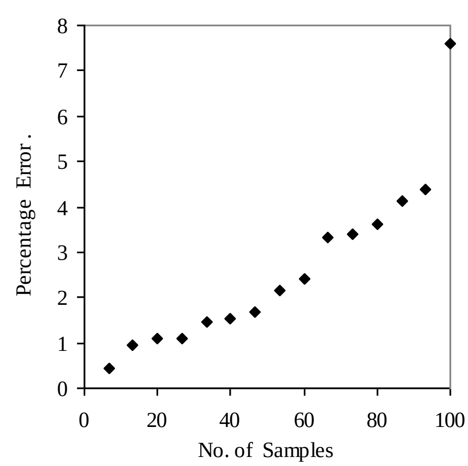

Figure 14 Error Scatter of the Second Model

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

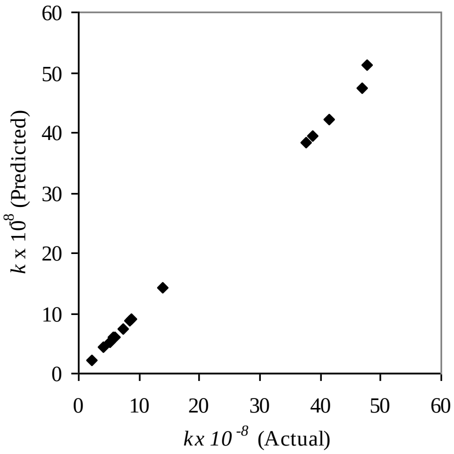

Figure 15 k (Actual) Vs k (Predicted)

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.

CONCLUSION

From the present study it is evident that the Artificial Neural Network can be very well be used for assessing the permeability of soils. 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. The only short coming of the neural network is its inability to trace and explain the step by step logics it uses to arrive at the outputs from the provided inputs. Therefore one should be very careful in using the ANN approach for predicting any soil parameter.

REFERENCES

[1] Alam Singh, G.R.Chowdhary. (1994), Soil Engineering – In Theory and Practice, Volume-I, Fundamentals and General Principles. *CBS Publishers & Distributors*, Delhi.

[2] Assessing Permeability of Soils using ANN, Proceedings of the All India Seminar on Advances in Geotechnical Engineering, Rourkela, 22 - 23 January, 2005.

[3] Carmen, P.C., 1956, Flow of gases through porous media: Academic press, New York. 182 p.

[4] Chitra, R., and Manish Gupta, (2014), Neural Networks for Assessing Shear Strength of Soils, International Journal of Recent Development in Engineering and Technology, Volume 3 Issue 4, October 2014, pp. 24-32.

[5] Das, B.M., 2008, Advanced soil mechanics: Taylor & Francis, New York, NY, 567 p.

[6] Holtz, R.D., Kovacks, W. D. and Sheahan, T. C., 2011, An introduction to Geotechnical Engineering: Prentice-Hall, Upper Saddle River, NJ, 853 p.

[7] Kozeny, J., 1927, Uber kapillare leitung des wassers im boden: Sitzungsber. Acad. Wiss. Wien, Vol. 136, pp. 271-306. 80

[8] Kozeny, J., 1927, Uber kapillare leitung des wassers im boden: Sitzungsber. Acad. Wiss. Wien, Vol. 136, pp. 271-306.

[9] Lambe T.W. and Robert V.Whitman (1984), Soil Mechanics. Wiley Eastern Limited, Delhi

[10] Mitchell, J.K., and Soga, K., 2005, Fundamentals of Soil Behavior: John Wiley & Sons Inc., Hoboken, NJ, 592 p.

[11] Shashi K Gulhati. (1981), Engineering Properties of Soils. Tata McGraw-Hill Publishing Company Limited, Delhi.

[12] Shenbaga R Kaniraj. (1994), Design Aids in Soil Mechanics and Foundation Engineering. Tata McGraw-Hill Publishing Company Limited, Delhi.

[13] Terzaghi, K. and Peck, R. B., 1964, Soil Mechanics in Engineering Practice: John Wiley and Son, New York.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Author Biblography

	**Dr. Manish Gupta** obtained PhD from IIT Delhi and is presently working in Central Soil and Materials Research Station, New Delhi. He has been working in the areas of Rock Mechanics, Concrete Technology, Soil Mechanics, Numerical Modelling and Geosynthetics He has published 85 reaserch papers.
	**Dr. R. Chitra** obtained her PhD from IIT Delhi and is presently working in Central Soil and Materials Research Station, New Delhi. She is working in the field of Geotechncial Engineering, Numerical Modelling and Geosynthetics. She has published 120 reaserch papers. She is recipient of Indian Geotechnical Society Delhi Chapter Leadership Award in recognition of her outstanding contribution to geotechnical engineering.