



ESTIMATION OF PLASTIC FINE ALTERED RIVER BED PERMEABILITY USING ARTIFICIAL NEURAL NETWORKS

Mohammad Adil¹, Mirza Muhammad², Raheel Zafar³, Salma Noor⁴
Neelam Gohar⁴, Tanveer Ahmed Khan⁵, Hamza Jamal⁶

¹ Assistant Professor, Department of Civil Engineering, University of
Engineering and Technology, Peshawar, Pakistan

² Senior Designer, Geotech Section, NESPAK and Researcher at University of
Engineering and Technology, Lahore, Pakistan,

³ Researcher, Department of Civil Engineering, University of Engineering and
Technology, Peshawar, Pakistan,

⁴ Assistant Professor, Department of Computer Science, Shaheed Benazir
Bhutto Women University, Peshawar, Pakistan

⁵ Assistant Professor, Civil Engineering Department, Bahauddin Zakariya
University, Multan, Pakistan (tanveerkhan@bzu.edu.pk)

⁶ Researcher, Department of Civil Engineering, University of Engineering and
Technology, Peshawar, Pakistan

E-mail : ¹adil@uetpeshawar.edu.pk, ²mirza_muhammad@yahoo.com,
³13jzciv0026@uetpeshawar.edu.pk, ⁴dr.salmanoor@sbbwu.edu.pk, ⁵
tanveerkhan@bzu.edu.pk, ⁶16pwciv4679@uetpeshawar.edu.pk

<https://doi.org/10.26782/jmcms.2020.11.00006>

(Received: September 19, 2020; Accepted: November 7, 2020)

Abstract

The permeability of the soil is one of the most important properties of an unlined earthen canal or river bed. Using fine plastic particles has experimentally proven to reduce soil permeability, but the experimental study of the effect of a variety of types of plastic fines and their percentages in riverbed soil is tedious work to do. Estimation of permeability of riverbed soil by altering it with plastic fines using Artificial Neural Networks (ANNs) may reduce this effort. Particle size distributions (PSDs) have a significant influence on the permeability of bed soils. Being able to predict the permeability of bed soil by knowing the PSDs may provide an easy approach to know the loss of water by percolation. This study has investigated the quantitative relationships between permeability and PSD indices using ANNs. The aim was to build a mathematical model capable of predicting the permeability of bed soil by PSD indices of choice. A model was built using ANNs including PSD indices as input and permeability as output. The model stated that the coefficients of curvature and uniformity (C_c) and (C_u) and effective particle size (D_{50}) may be used to predict

Mohammad Adil et al

the bed permeability. The computational model was able to predict the effect of variation of PSD indices on bed permeability, thus allowing increasing the efficiency of the river bed, to ensure maximum downstream water supply, lesser seepage and percolation and better productivity. The test result has confirmed the efficiency of the developed ANN tool in predicting the bed permeability for different PSD combinations.

Keywords: River, permeability, plastic fines, neural network

I. Introduction

Particle Size Distribution (PSD) indices have been used for many years to develop empirical equations to predict the permeability of soils, such as those of Hazen (1892), Kozeny (1927), Carmen (1956), Terzaghi and Peck (1964), Kenney et al., (1984), Alyamani and Sen (1993) because the in-situ and laboratory test methods have limitations; like its variation in both vertical and horizontal directions (Jabro, 1992), quality of undisturbed soil samples (Holtz et al., 2011), how well the natural state of the soil in the field is represented by laboratory samples (Degroot, Ostendorf and Judge, 2012), time-consuming and costly field pumping tests (Shepherd, 1989), in situ methods that generally measure horizontal permeability (Degroot, Ostendorf and Judge, 2012).

Linear and non-linear empirical equations, such as those based on PSD characteristics, have been widely used to determine the permeability of soils (Hazen, 1892; Kozeny, 1927; Carman, 1956; Alyamani and Şen, 1993; Terzaghi and Peck, 1997). The Kozeny-Carmen equation is globally accepted and used the equation of permeability that involves easily measurable and readily available soil properties (Odong, 2007). The equation, however, is limited because of the inability to produce correct results when effective size is greater than 3 mm or clayey soil (Carrier, 2003). Errors were caused by grains of extreme size in the whole sample that produce erroneous predictions of soil permeability (Arkin and Colton, 1956). Moreover, a general correlation equation between permeability and gradation incorporating a wide range of soils is not yet available (Boadu, 2000). Even though many predictive and empirical models; that determine key parameters of the soil, have been proposed in the past decades, models; that predict key parameters for fine media, are scarce and a general correlation between the sorting condition/PSD, K and incorporating a wide array of soil is still not available (Qi et al., 2015). Furthermore, these equations do not consider the influence of the entire PSD as well as the effect of soil density on permeability (Onur, 2014).

Recently, there has been an interest in developing models that simulate soil properties since they have been found to improve our understandings of soil processes and evaluate engineering problems (Sarmadian, Mehrjardi and Akbarzadeh, 2009). Particularly, they have been applied to predict permeability and cation exchange capacity (CEC) (Sarmadian, Mehrjardi and Akbarzadeh, 2009), which have shown better predictive performance than multiple regressions (Amini et al., 2005). The advantage of ANNs over traditional regressions pedo-transfer functions (PTFs) is,

Mohammad Adil et al

partly because of their better adaptability, flexibility and greater generalization capabilities (Benardos and Vosniakos, 2007) and their easy application in computational devices; both in the soft and hard form (Hunt *et al.*, 1992; von Twickel, Büschges and Pasemann, 2011). They have been used with great success, for predicting soil parameters; like water percentage at field capacity, CEC and permanent wilting point (Sarmadian, Mehrjardi and Akbarzadeh, 2009). All in all, these characteristics make them a powerful and unique tool for predicting non-linear relationships among variables.

The permeability of soil can be predicted indirectly with great success under certain conditions, using available empirical equations that involve easily measurable and readily available soil properties like PSDs (Ishaku, Gadzama and Kaigama, 2011), making them ideal to assess the potential of ANNs to model/evaluate the soil response at different combinations of mentioned soil properties and to understand important soil processes. An ANN is an approach to create a mathematical model that works analogously to the human brain (Sarmadian, Mehrjardi and Akbarzadeh, 2009). PSD, as a physical property, has a great impact on key soil parameters like permeability and various ANNs have been developed to understand its dynamics (Khanlari *et al.*, 2012; Tizpa *et al.*, 2015). Linear and non-linear empirical equations are famous, but, are limited because of the inability to produce correct results when effective size is greater than 3 mm or clayey soil (Carrier, 2003). These limitations provide the necessary motivation/push for testing and validating ANNs; as an effective alternative for those empirical equations, for modeling and predicting key parameters of soil.

The aim of the research was threefold: first to develop a correlation of permeability with a particle size of the river bed, second to write a simple neural network that can be easily defined mathematically and third, to develop a generalised ANN tool for prediction of permeability from the river soil bed particle size information. To solve these problems, the response; predicted permeability, of ANN models, were compared with experimental results as well as single and multiple inputs were measured.

II. Materials and Methods

II.i. Properties of Riverbed Soil Samples

In this research work, a database of 45 datasets has been compiled through laboratory testing. The database contains properties of riverbed material from three different river sources in Pakistan; Lawrencepur, Chenab, and Ravi. The distribution of collected and prepared samples is shown in table 1. The specific gravity of all samples was obtained according to ASTM D854 specifications. The standard proctor test was performed on all samples in accordance with the ASTM D698 specifications to obtain maximum dry density and optimum moisture content. Sieve analysis and hydrometer analysis according to ASTM D422 specifications were used to obtain particle size distribution for all samples. Index properties (liquid limit and plastic limit) were obtained as per ASTM D4318 specifications and were used along with the characteristics of the particle size distribution curve to obtain the class of each sample

Mohammad Adil et al

as per the Unified Soil Classification System (USCS). Permeability tests were performed on constant head permeability apparatus ASTM D2434 specifications and falling head permeability apparatus ASTM D5084 specifications.

Table 1. Riverbed soil samples and their alterations

Sr. No.	Sample types	Samples	River	Total Nos of samples
1.	Undisturbed	1	1. Lawrencepur 2. Chenab 3. Ravi	3
2.	With varying % of plastic fines	7		21
3.	With varying % of non-plastic fines	7		21
Total Samples				45

The processed properties of these riverbed soil samples i.e., coefficients of curvature and uniformity (C_c) and (C_u) and effective particle size (D_{50}) are plotted against permeability and shown in fig 1. An attempt has been made to correlate the recorded permeability of these riverbed samples (listed in table 1) with particle size properties, using cubic and trigonometric functions, as shown in fig 1. It is clear from the correlation function ($R_{sq} < 1$) that this relationship is not straightforward and requires a more rigorous method (like ANN) to define any relationship.

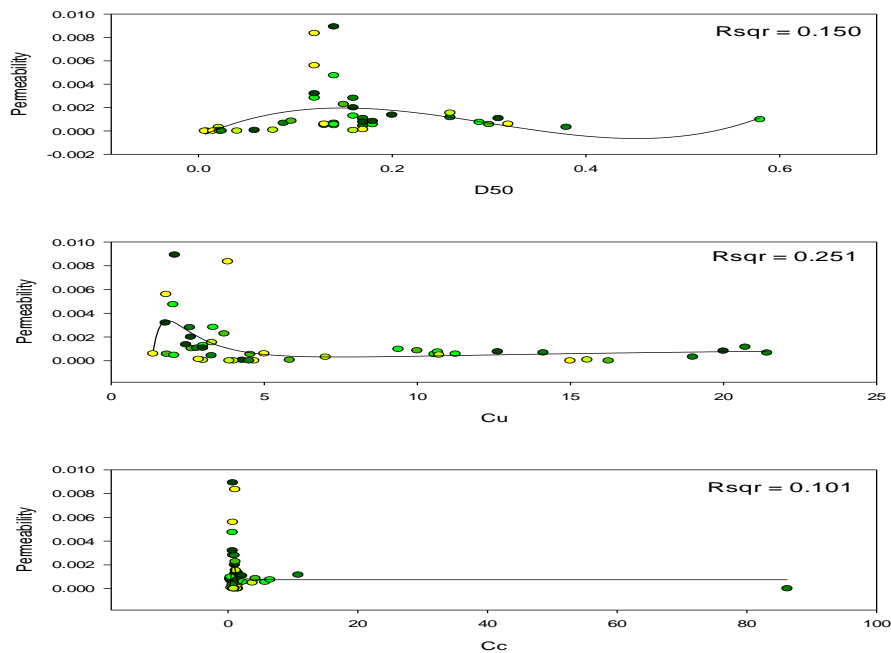


Fig. 1. Permeability of riverbed material plotted with the coefficient of curvature (C_c), coefficient of uniformity (C_u) and effective particle size (D_{50}). Coloured circles only help graphically in differentiating between clustered points.

Mohammad Adil et al

II.ii. ANNs for the permeability of river bed soil

A static multi-layer artificial neural network, based on a Feed-Forward Neural Network (FFNN) has been developed to predict riverbed soil permeability. This type of network uses back-propagation, which compares the output values with obtaining experimental values to compute the value of some pre-defined error-function. Later, by optimization techniques, the error is fed back into the network. Using this information, the optimization algorithm adjusts the weights of each connection to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is smallest. To adjust weights properly, a general method for non-linear optimization, called generalised reduced gradient (GRG) has been used. With GRG, the network calculates the derivative of the error function with respect to the network weights and changes the weights such that the error decreases.

The architecture of the developed ANN includes 2 layers; hidden, and output layer, each of which was formed by a determined number of nodes. Additionally, the input layer has three nodes (effective particle size (D_{50}), coefficient of curvature (C_c), and coefficient of uniformity C_u). The output layer has one node (the permeability of riverbed soil). In the developed network the hidden and output nodes are defined mathematically as follows:

$$y = f(\sum_i w_{ji}x_i + \theta_i) \quad (1)$$

where x and y are the i inputs and outputs respectively of the j th node, w_{ji} are the weights for each input, θ_i is the bias and $f(x)$ is referred to as the activation function (Xing & Pham, 1995).

The data in the input layer has been scaled from 0 to 1 by linear mapping techniques before using in the ANN. In the hidden layers of ANN, a sigmoid function is shown in eq. (2) has been used as an activation function to introduce a non-linearity in the estimated output. Sigmoid is one of the most used activation function in ANN applications (Jain, Mao and Mohiuddin, 1996; Xing & Pham, 1995). All the results from the non-linear sigmoid function were linear.

$$f(x) = 1/(1+e^{-x}) \quad (2)$$

The Microsoft Excel built-in Solver function has been used to optimize and train the ANN. The basic back-propagation method was used for training the network and to calculate the weights between the nodes. This method consists of two passes, a forward pass, and a backward pass. In the forward pass, inputs are provided with fixed weights and an activity pattern is applied to the input nodes of the network while providing fixed weights of the networks. The effect of this activity pattern generates a set of outputs. The output value is subtracted from the recorded value to yield/obtain an error value. This error value is used to adjust the weights, to get almost the same output value as the recorded value. The weights are adjusted according to the

Mohammad Adil et al

generalised delta rule. The number of samples in the input vector was set to 45 samples. The initial weights and bias values were initialized 0.01 and 0.02 for weight and bias respectively of each node in the hidden layer and 0.04 and 0.03 for weight and bias of each node in the output node and later optimize using optimization algorithms.

II.iii. Optimization algorithms for ANN architecture design

The performance; prediction accuracy, of ANNs greatly depends upon selecting the right number of nodes and layers for that ANN. In this research, an algorithm was written and applied to modify the architecture until the optimal architecture was found. The algorithm was designed such that, it will test a pre-defined set of neurons, and iterated each neuron ten times with the GRG Nonlinear method for calculating the global best performance of every neuron. For each iteration, the weights of every neuron were adjusted through the GRG Nonlinear method unless and until the global best solution was obtained.

The GRG Nonlinear optimization algorithm is used for solving nonlinear smooth optimization problems (Lasdon et al., 1974). They are chosen for their acceptable accuracy, efficiency and fast convergence compared to classical algorithms for solving non-linear programs (Lasdon et al., 1974). The nonlinear program to be solved is assumed to have the form minimize

$$f(x) \quad (3)$$

subject to

$$g_i(x) = 0, \quad i=1, \dots, m \quad (4)$$

$$l_i < X_i < u_i, \quad i = 1, \dots, n \quad (5)$$

Where X is n -vector and u_i, l_i are given lower and upper bounds $u_i > l_i$. We assume $m < n$ since, in most cases, $m \geq n$ implies an infeasible problem or one with a unique solution (Lasdon et al., 1974).

A single sigmoid function was involved. When the population was created and passed through the back-propagation, the networks were trained to predict the permeability. In a population of 45 from one individual parse of input data, we took a sample of 36 for training and the remaining 9 testing the response of ANNs. The testing data is used at the end to verify that the training has been successful.

The Mean Square Error (MSE) was calculated (Eq. (6)), for estimating the performance, between the predicted output value and recorded output value.

$$MSE (\%) = (1/n)(\sum_{i=1}^n (Y_i - Y'_i)^2)$$

Where Y_i is the recorded output value of permeability at the i th sample and Y'_i is the predicted output of N samples, from the trained artificial neural network.

III. Results

III.i. ANN prediction model for permeability

3 input variables were used for the prediction of riverbed permeability using ANN, including effective particle size (D_{50}), the coefficient of curvature (C_c) and coefficient of uniformity (C_u). The only output was permeability. Among 45 measured data sets, 36 sets (80 %) have been used for training and the remaining 9 (20%) have been used for testing the model. Figure 4 shows an almost perfect prediction of riverbed permeability based on the input parameters; however, in the testing cases, the predictions exhibit a higher scatter.

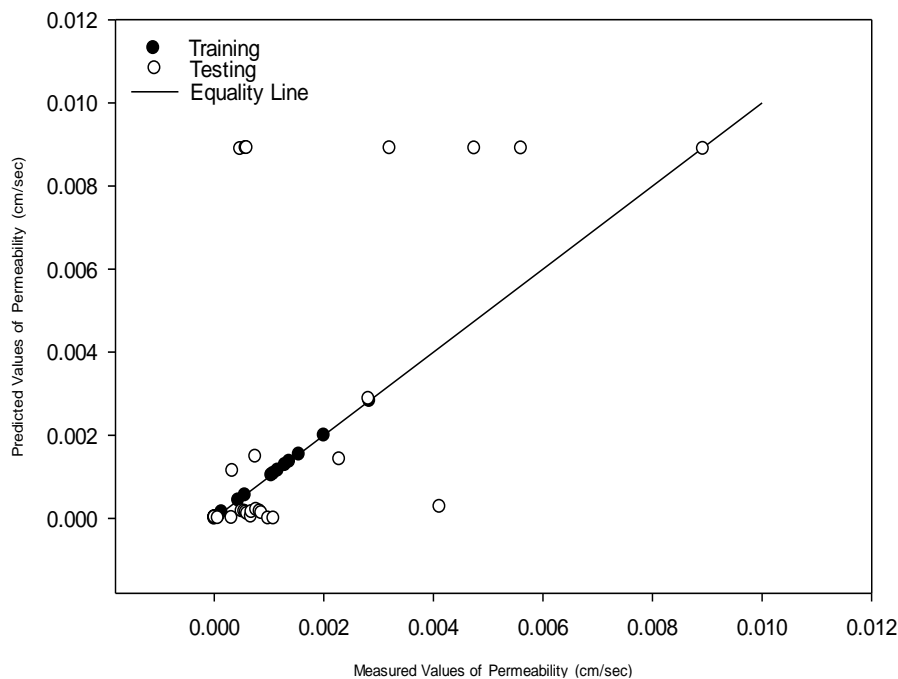


Fig. 2 : Comparison between the predicted values of riverbed permeability and the experimental data

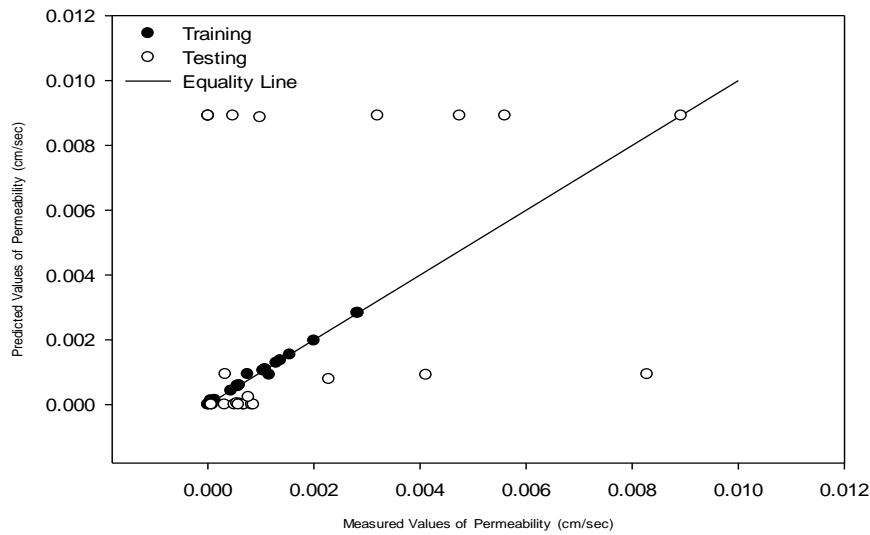


Fig. 3: Comparison between the predicted values of riverbed permeability and the experimental data (21 samples)

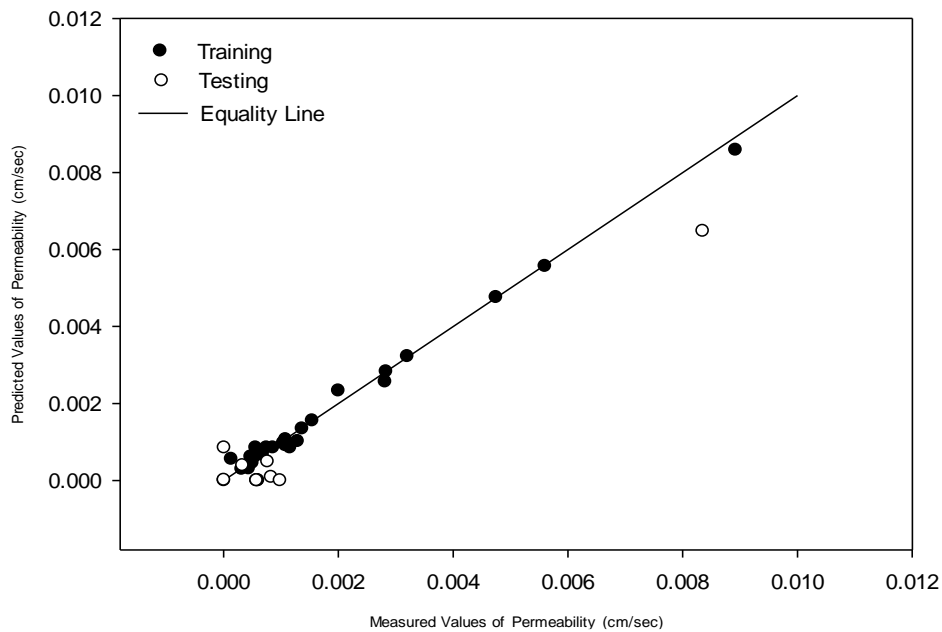


Fig. 4: Comparison between the predicted values of riverbed permeability and the experimental data (36)

III.ii. Architectures of the ANN models

The algorithm tested a pre-defined set of neurons/nodes; 2-29 neurons, in the hidden layer and iterated each neuron ten times with the GRG Nonlinear method for calculating the global best performance of every neuron. In accordance with figures 6,7 and 8, mostly for every neuron, the optimization algorithm obtained the best possible solution after 3rd iteration. The output of the optimization algorithm was composed of two nodes and used by the architecture of ANNs to model the riverbed permeability. The algorithm was allowed for networks from 2 to 29 neurons. The best architecture was composed of 19 (for 36 cases i.e trial 3) (at 10 neurons for trial 2 & at 14 neurons for trial 1) neurons as evident from figure 7, figure 8 and figure 9.

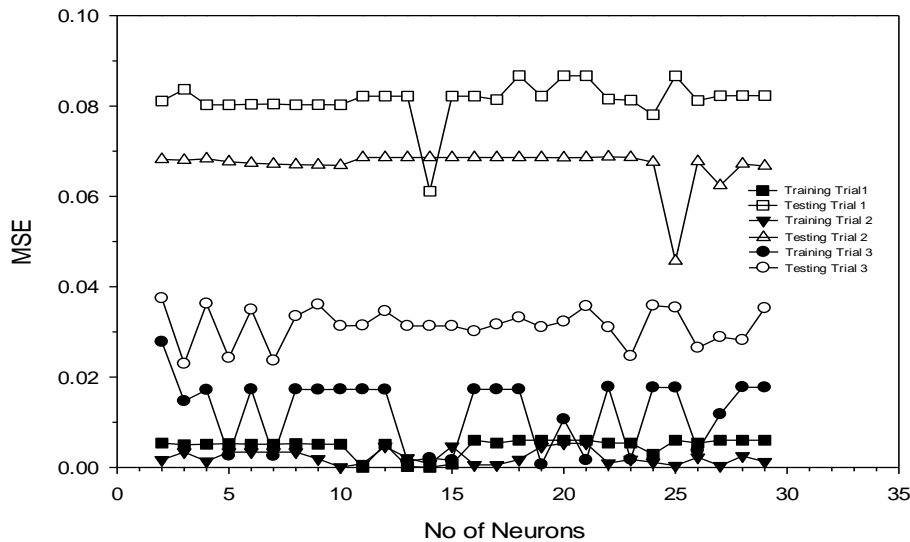


Figure 5: No. of neuron vs MSE

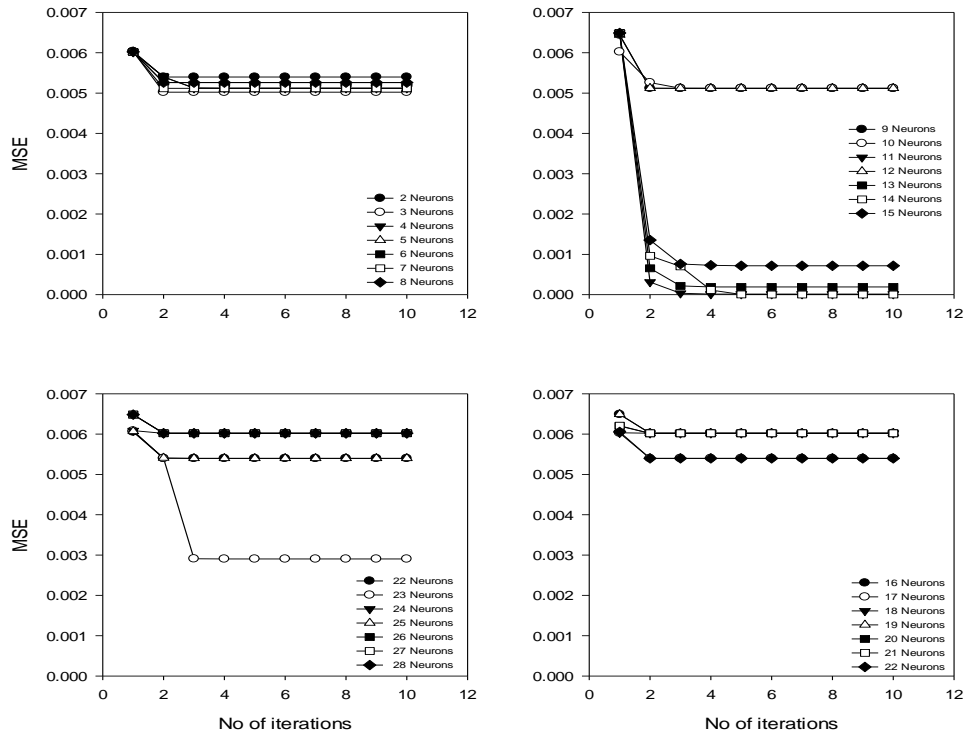


Figure 6: No. of iteration vs MSE (16 samples)

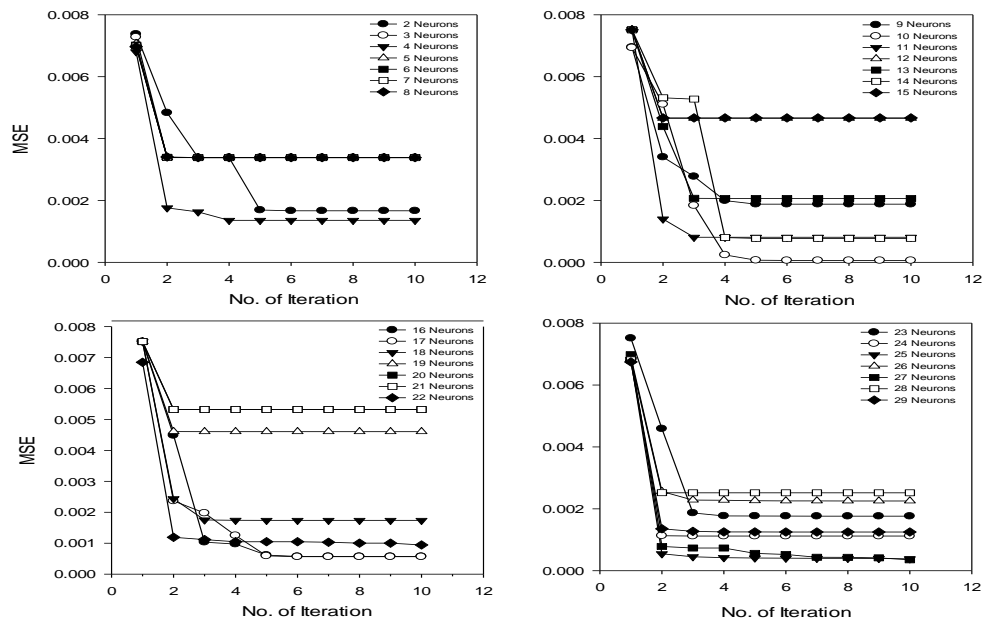


Figure 7: No. of iteration vs MSE (21 samples)

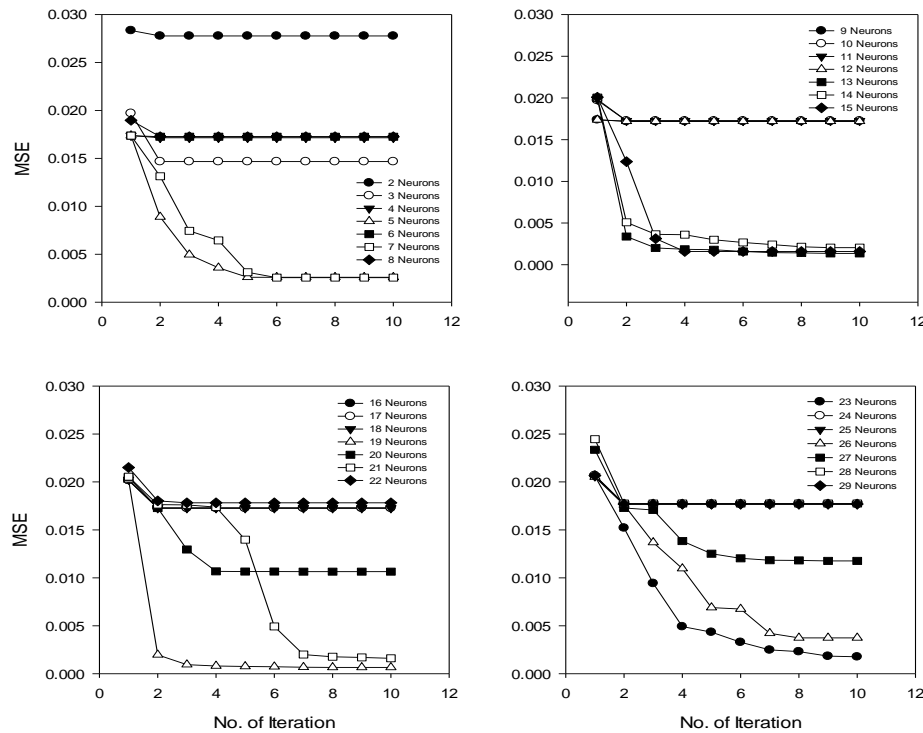


Figure 8: No. of iteration vs MSE (36 samples)

III.iii. Validation of the ANNs

The architecture obtained with the optimization algorithm was trained for the prediction of river bed permeability (Fig. 8) using D_{50} , C_c , and C_u as input parameters. As is clear from the figure 8, the model was able to effectively predict the riverbed permeability. However, the performance of the model varied when it is tested with new data (the 1/5 of data not used in the network training). The best architecture has MSE of 6.5E-04 and 0.0369 for training and testing respectively, which confirms the model efficiency in the prediction of riverbed permeability.

IV. Discussions

It is evident from the results of this research that ANNs can use to predict riverbed permeability and can be used to improve understanding of soil processes.

We have developed an algorithm to automate the ANNs architecture design for developing models that simulate engineering problems and predict the response in a systematic manner/approach. The developed algorithm optimized the ANN architectures to reduce computational time and improve their generalisation abilities.

Mohammad Adil et al

We have shown that PSD can be used to develop models that can predict riverbed permeability. This research confirms the suitability of ANNs in modeling the complex behaviour of most geotechnical engineering materials. Furthermore, the results suggest that ANNs could be used as a mathematical representation of soil response to variation in index properties. The performance; predicted permeability, was perfect in the training set but showed slight variation when it is tested with new data (the 1/5 of data not used in the network training). There are several possible reasons for why the model fit is not perfect in the validation and testing sets, which points out to the deficiencies in model extrapolation, and uncertainty, improvements in these issues will greatly enhance the usefulness of ANNs models. In this research, all these factors were captured in the mean square error.

As is clear from the results, input variables; D_{50} , C_c , and C_u have significant influence/impact on the ANN prediction model and can be used to accurately predict the riverbed permeability. Furthermore, the individual impact/importance of these input variables can be evaluated by performing sensitivity analysis.

V. Conclusions

In this research, we show that ANNs can be used to model the soil responses to variation in PSD indices and predict the permeability with great success. We have developed an algorithm to automate the ANNs architecture design, which reduces computational time and improves their generalisation abilities. Thus, confirming the suitability of ANNs in modeling the complex behaviour of most geotechnical engineering materials. Furthermore, the ANN model was able to estimate the responses validation and testing sets, but predictions tended to be better within the training sets, highlighting the deficiencies in model extrapolation, and uncertainty.

Conflict of Interest:

There is no conflict of interest regarding this article

References

- I. Abdul Farhan, Farman Ullah, Fawad Ahmad, Mehr E Munir, : Effect of Thin Layer on Bearing Capacity in Layered Profile Soil, *J. Mech. Cont.& Math. Sci.*, Vol.-14, No.-3, May-June (2019) pp 597-608.
- II. Alyamani, M. S. and Şen, Z. (1993) ‘Determination of Hydraulic Conductivity from Complete Grain-Size Distribution Curves’, *Ground Water*. Blackwell Publishing Ltd, 31(4), pp. 551–555. doi: 10.1111/j.1745-6584.1993.tb00587.x.

Mohammad Adil et al

- III. Amini, M. et al. (2005) 'Neural network models to predict cation exchange capacity in arid regions of Iran', *European Journal of Soil Science*. Blackwell Science Ltd, 56(4), pp. 551–559. doi: 10.1111/j.1365-2389.2005.0698.x.
- IV. Arkin, H. and Colton, R. R. (1956) *Statistical Methods*, 4th Edition. New York: Barnes and Noble Inc.
- V. ASTM D854-14 (2014), "Standard Test Methods for Specific Gravity of Soil Solids by Water Pycnometer," ASTM International, West Conshohocken, PA, 2014, 10.1520/D0854-14, www.astm.org
- VI. ASTM D698-12 (2012), "Standard Test Methods for Laboratory Compaction Characteristics of Soil Using Standard Effort (12 400 ft-lbf/ft³ (600 kN-m/m³)), " ASTM International, West Conshohocken, PA, 2012, 10.1520/D0698-12E02, www.astm.org
- VII. ASTM D422-63 (2007), "Standard Test Method for Particle-Size Analysis of Soils," ASTM International, West Conshohocken, PA, 2007, 10.1520/D0422-63R07, www.astm.org
- VIII. ASTM D4318-17 (2017), "Standard Test Methods for Liquid Limit, Plastic Limit, and Plasticity Index of Soils," ASTM International, West Conshohocken, PA, 2017, 10.1520/D4318-17, www.astm.org
- IX. ASTM D2434-68 (2006), "Standard Test Method for Permeability of Granular Soils (Constant Head) (Withdrawn 2015)," ASTM International, West Conshohocken, PA, 2006, 10.1520/D2434-68R06, www.astm.org
- X. ASTM D5084-16a, (2016a), "Standard Test Methods for Measurement of Hydraulic Conductivity of Saturated Porous Materials Using a Flexible Wall Permeameter," ASTM International, West Conshohocken, PA, 2016, 10.1520/D5084-16A, www.astm.org
- XI. Benardos, P. G. and Vosniakos, G.-C. (2007) 'Optimizing Feedforward Artificial Neural Network Architecture', *Eng. Appl. Artif. Intell.* Tarrytown, NY, USA: Pergamon Press, Inc., 20(3), pp. 365–382. doi: 10.1016/j.engappai.2006.06.005.
- XII. Boadu, F. K. (2000) 'Hydraulic conductivity of soils from grain-size distribution: new models', *J. Geotech. Geoenviron.*, 126, 739–746, 2000.
- XIII. Carman, P. C. (1956) *Flow of gases through porous media*. London: Butterworths Scientific Publications.
- XIV. Carrier, W.D., (2003) 'Goodbye, Hazen; hello, Kozeny-Carman', *Journal of Geotechnical and Geo environmental Engineering*.
- XV. Degroot, D. J., Ostendorf, D. W. and Judge, A. I. (2012) 'In situ measurement of hydraulic conductivity of saturated soils', *Geotechnical Engineering Journal of the SEAGS & AGSSEA*, 43, pp. 63–71.

- XVI. Hazen, A. (1892) Some Physical Properties of Sands and Gravels: With Special Reference to Their Use in Filtration. Available at: <https://books.google.com.pk/books?id=DW1cGwAACAAJ>.
- XVII. Holtz, R.D., Kovacks, W. D. and Sheahan, T. C., (2011) ‘An introduction to Geotechnical Engineering’: Prentice-Hall, Upper Saddle River, NJ, 853 p.
- XVIII. Hunt, K. J. et al. (1992) ‘Neural networks for control systems—A survey’, *Automatica*, 28(6), pp. 1083–1112. doi: [https://doi.org/10.1016/0005-1098\(92\)90053-I](https://doi.org/10.1016/0005-1098(92)90053-I).
- XIX. Ishaku, J. M., Gadzama, E.W. and Kaigama, U. (2011) ‘Evaluation of empirical formulae for the determination of hydraulic conductivity based on grain-size analysis’, *Journal of Geology and Mining, Research* Vol. 3(4) pp. 105-113.
- XX. Jain, A. K., Mao, J. and Mohiuddin, K. M. (1996) ‘Artificial neural networks: a tutorial’, *Computer*, 29(3), pp. 31–44. doi: 10.1109/2.485891.
- XXI. Jobro, J.D. (1992), ‘Estimation of hydraulic conductivity of soils from particle size distribution and bulk density data’, *Journal of the American Society of Agricultural Engineers*, 35(2), 557–560.
- XXII. Khanlari, G. R. et al. (2012) ‘Prediction of shear strength parameters of soils using artificial neural networks and multivariate regression methods’, *Engineering Geology. Elsevier B.V.*, 131–132, pp. 11–18. doi: 10.1016/j.enggeo.2011.12.006.
- XXIII. Kenney, T.C., Lau, D. and Ofoegbu, G.I., (1984), ‘Permeability of compacted granular materials’, *Canadian Geotechnical Journal*, Vol. 21, pp. 726-729
- XXIV. Kozeny, J. (1927) ‘Über kapillare Leitung des Wassers im Boden’, *Akad. Wiss.Wien*, 136, pp. 271–306.
- XXV. Kavin kumar C, Heeralal M, Rakesh J Pillai, : NUMERICAL ASSESSMENT OF RAINFALL INDUCED SLOPE FAILURE, *J. Mech. Cont.& Math. Sci.*, Vol.-15, No.-1, January (2020) pp 328-338
- XXVI. Odong, J. (2007) ‘Evaluation of empirical formulae for determination of hydraulic conductivity based on grain-size analysis’, *Journal of American Science*, 3(3), pp. 54–60. doi: 10.7537/marsjas040108.01.
- XXVII. Onur, E. M. (2014) ‘Predicting the Permeability of Sandy Soils from Grain Size Distributions’, p. 137.
- XXVIII. Qi, S. et al. (2015) ‘A new empirical model for estimating the hydraulic conductivity of low permeability media’, *Proceedings of the International Association of Hydrological Sciences*, 368(August 2014), pp. 478–483. doi: 10.5194/piahs-368-478-2015.

- XXIX. Sarmadian, F., Mehrjardi, R. T. and Akbarzadeh, A. (2009) 'Modeling of Some Soil Properties Using Artificial Neural Network and Multivariate Regression in Gorgan Province, North of Iran', *Australian Journal of Basic and Applied Sciences*, 3(1), pp. 323–329.
- XXX. Shepherd, R. G. (1989) 'Correlations of Permeability and Grain Size', *Ground Water*. Blackwell Publishing Ltd, 27(5), pp. 633–638. doi: 10.1111/j.1745-6584.1989.tb00476.x.
- XXXI. Terzaghi, K. and Peck, R. B. (1997) 'Soil Mechanics in Engineering Practice Third Edition', *New York*, 48(1–2), pp. 149–150. doi: 10.1016/S0013-7952(97)81919-9.
- XXXII. Tizpa, P. *et al.* (2015) 'ANN prediction of some geotechnical properties of soil from their index parameters', *Arabian Journal of Geosciences*, 8(5), pp. 2911–2920. doi: 10.1007/s12517-014-1304-3.
- XXXIII. Von Twickel, A., Büschges, A. and Pasemann, F. (2011) 'Deriving neural network controllers from neuro-biological data: implementation of a single-leg stick insect controller', *Biological Cybernetics*, 104(1), pp. 95–119. doi: 10.1007/s00422-011-0422-1.
- XXXIV. Xing, L., & Pham, D. T. (1995), *Neural networks for identification, prediction, and control*. New York: Springer-Verlag New York, Inc.