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Knowledge Based Prediction of Standard Penetration Resistance of Soil Using Geotechnical Database

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Abstract

The current study aimed at predicting standard penetration resistance (N) of soil using particle sizes and Atterberg's limits. The geotechnical database was created subsequent to the field and laboratory testing. The sample collection points were distributed in a mesh grid pattern to have uniform sampling consistency. Artificial Neural Networks (ANN) were trained on the database to build a knowledge-based understanding of the interrelation of the given soil parameters. To check the efficacy of the model, the validation was carried out by predicting standard penetration resistance (N) for another 30 samples which were not included in the training data (444 samples). The trained ANN model has been found to predict N values in close agreement with the N values measured in the field. The novelty of the research work is the standard penetration prediction employing basic physical properties of soil. This proves the efficacy of the proposed model for the target civil engineering application.

Keywords: Prediction of SPT; Geotechnical Database; ANN in Geotechnics; SPT Correlation; Soil Gradation.

1. Introduction

Geotechnical investigations are mandatory for any civil engineering project. These investigations have an important role before the project's implementation. Feasibility studies lead to planning, design and finally execution phase. Preliminary soil investigations lead to the selection of the most suitable site or route for the proposed development project. The current study was aimed at the evaluation of economical primary examination consuming less time with equitable accuracy. The standard penetration resistance number (N) has been in the spotlight of researchers. Its numerous correlations have been evaluated with soil's physical and engineering properties. The study employed reverse operation by predicting N from index properties in contrast to most of the available studies. Like the fame of SPT as a field operation, Artificial Neural Networks have also made their place for the establishment of interrelations between available parameters. As presented in the literature review section, its applications include slope stability analysis, soil classification, design of earth supported and earth retaining structures. Artificial Neural Network (ANN) is a knowledge-based technique of artificial intelligence that attempts to replicate the human nervous system. ANN technique involves the generation and training of models using available data sets. The currents study used the soil gradation and Atterberg's limits, as input and the N is the model's output. The optimized ANN model successfully predicted the N values with an optimum accuracy yielding a coefficient of determination up to 0.94.

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2. Literature Review

The Standard Penetration Test (SPT) is an in-situ test and is considered one of the most august tests for soil investigation. The earliest credits for introducing SPT are attributed to Mohr and Terzaghi, as reported by Davidson [1]. Mohr is believed to have introduced the test in 1927 as reported by Hvorsolv, the SPT working Party, who credits Terzaghi for the SPT invention. Almost every soil exploration program in Turkey contains SPT as one of its principal components [2, 3]. Similarly, it is considered a keystone for soil exploration works in North America [4]. Mori reported that more than 90% of preliminary soil investigations are performed using SPT [5]. Inaccessible areas usually require the determination of N via indirect methods [6]. A spatially interpolated map for the allowable bearing capacity in a region based on SPT N values using GIS software has also been developed [7, 8]. Narimani (2018) has appraised the empirical correlation between SPT and pressuremeter test considering the relatively cheaper cost of SPT [9].

In developing countries, the standard penetration test is an extensively used tool for soil investigations. The SPT evaluates the strength of soils by measuring the penetration resistance (N) of the standard rod. It was initially developed for coarse-grained soil, but numerous researchers have developed correlations of N with most of soil's physical and mechanical properties. The said correlations have enhanced its scope to all types of soils and the determination of several soil parameters through these correlations. Site-specific correlations of N with shear wave velocity (Vs) by statistical regression have been reported [10]. Unconfined compressive strength (UCS) is a reliable test for fine-grained soils, Behpoor and Ghahramani (1990) has evaluated the relationship of N with the UCS and modulus of elasticity (E) for the soils having $N < 25$ [11]. Arshid and Kamal (2020) [12] appraised a similar relationship for refilled soils using relative compaction and moisture content. Wrzesiński et al. (2018) appraised the shear strength evaluation of fine-grained cohesive soils using artificial neural networks [13]. A Risk model for the prediction of subsidence along railway lines based on Artificial Neural Networks (ANN) employing Multi-Layer Perceptron (MLP) and support vector machine (SVM) has been developed by Le and Oh (2018) [14]. ANN model to predict settlement of pile has been appraised by Baziar et al. (2015) [15].

For the computation of geotechnical properties, several numerical, statistical or empirical models have been developed. These models in geotechnical engineering contain certain limitations due to spatial variations and uncertainties associated with soil. The nonlinear behaviour of the soil limits the suitability of regression models for its evaluation under various scenarios. Kurup and Griffin (2006) [16] stated that mathematical models work on soil behavior only, ignoring the composition of the soil, which affects their accuracy. Constitutive modeling is unable to properly simulate the behavior of geomaterial for reasons pertaining to excessive empirical parameters, complex formulation, and idealization of material behavior [17]. The limitations of numerical, statistical, or empirical methods/models attract researchers to use artificial neural networks, which are general, flexible and do not require a physical model to start the process [18, 19].

An inference method called Reverse Engineering Gene Networks with Artificial Neural Networks (RegnANN) has been reported to yield better results [20]. Moreover, it can classify patterns and tolerate the presence of chaotic components. ANN has been employed to predict or model the soil parameters yielding higher accuracy. So it is now considered a better alternative to the numerical, statistical, or numerical models for the evaluation of various parameters of geomaterials. Numerous researchers have employed this knowledge-based artificial intelligence technique to crack geotechnical engineering problems; prediction of organic matter present in soil [21], estimation of permeability, compaction and lateral earth pressure [22], light structural foundation[23] determination of an appropriate number of testing points [24], pile foundation, soil nails [25], soil resistivity [26] decision making for geotechnical drilling vessels [27], Prediction of soil type and SPT-N [28, 29], Prediction of shear wave velocity and SPT-N [30].

In contrast to the mathematical models, which incorporate several assumptions to overcome the lack of physical understanding, the ANNs utilize the input-output data only and delineate the structure of the model itself. So, the ANN model does not require to assume the structure of the model in advance. Mathematical models require an advance assumption of the structures which influence the accuracy of their results; hence mathematical models fail to simulate the complex behaviour of most geotechnical engineering problems. With the enrichment of the database, ANNs can always be updated to obtain better results by feeding the additional data. Figure 1 presents an overview of the function of ANN; it consists of three modules. One or more hidden layers are implanted between the input and output layers. The input layer contains input parameters, while the required output is set in the output layer [31].

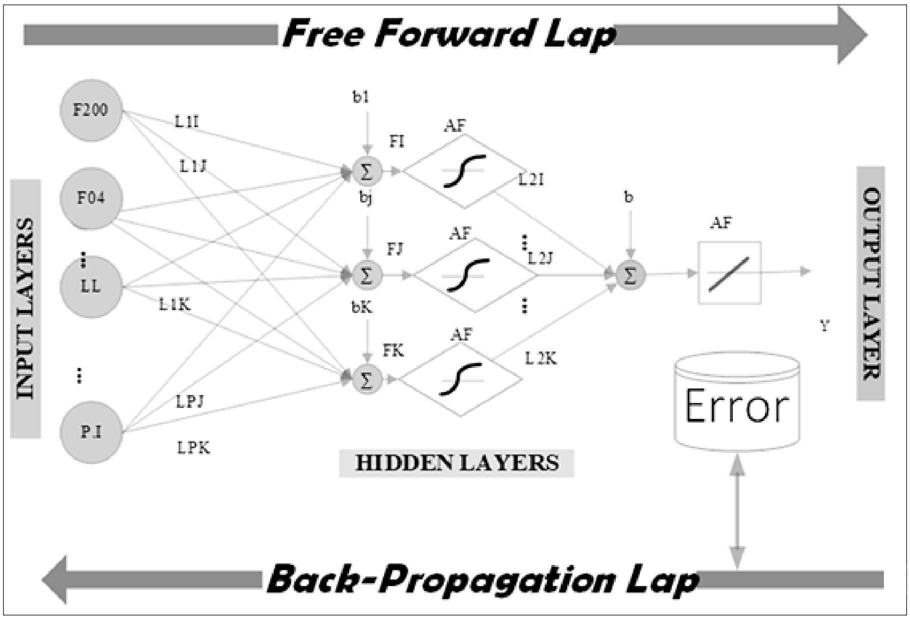


Figure 1. ANN Concept Diagram

The available data is fed to the trial ANN model, and it processes the data by knowing the input and outputs of the fed data. ANN model establishes the interrelations between the nodes in the input layer and output layer by adjusting their weights in backward and forward cycles. The weights of connections between the input, hidden, and output layers are adjusted in each backward cycle to arrive at the known output. The process is expressed mathematically in Equations 1 and 2 [32]. The output predicted from the ANN can be calculated by Equation 1:

$$\mathrm{N} = \sum \mathrm{wixi} + \theta\mathrm{i} \tag{1}$$

where N is the output predicted from the ANN, wi= are the weights for the layer ith, xi=are the input values for the layer ith, and θi=are the bias values for the layer ith.

Back Propagation neural network is the most widely used network in practice; it was developed by Rumelhart et al. [33]. An activation function. To enable the prediction models to arrive at pre-fed output values, an activation function performs the task by assigning calculated weighted input values. A variety of default activation functions are available to work with ANN; however, these functions could be customized to meet any specific requirement. In the present study, training of the ANNs was achieved through the multi-layer free forward back-propagation process (MLFFBP). This process employs the Levenberg-Marquardt back-propagation method [34]. The resulting error can be calculated by the following Equation 2:

$$\mathrm{E(w)} = \frac{1}{2}\sum\nolimits_{\mathrm{i}} [\mathrm{T}^2 - \mathrm{N}^2] \tag{2}$$

where T is the target (defined in the database), and N is the output (predicted by the ANN) value. To minimize the error obtained from Equation 2, the back-propagation technique (DETA RULE) proposed by [35, 36] was employed. Furthermore, to avoid the problem of local minima [37], each database was divided into three further subsets, i.e. (Training, Validation, and Testing). Figure 2 shows the sequence of activities aimed at the prediction of N.

3. Research Methodology

The Photohar is a plateau located in the northern part of Punjab province in Pakistan. The plateau is a geographic term describing an elevated landform having a relatively planar topography. Mountainous ranges enclose its Northern and Southern sides. The Southern rage is descending from the surface, and the Northern range is ascending in elevation. The Eastern and Western sides are enclosed by the major rivers, the Indus on the West, and the Jhelum on the East. The elevation of the hilltops are as high as 1200 m above mean sea level, while the elevation descends to 300 m above mean sea level along the river banks. Owning to an alluvial deposit, the surface shows a number of local ridges and valleys. Photohar stretches from latitude 32.166-34.150 N and longitude 71.166-73.916 E and covers an area of about 23,000 Km^2. The stratigraphic succession exposed in the study area ranges in age from Precambrian to Quaternary. Warwick and Wardlaw (2007) reported that the plateau's geologic setting also inhibits extensive variation [38]. The sedimentary rocks exposed on the Potwar Plateau and adjacent Kohat Plateau are Eocene limestone, evaporites, and red beds; Miocene to Pleistocene fluvial sediments and terrace gravel and loess; and Holocene alluvium [39, 40].

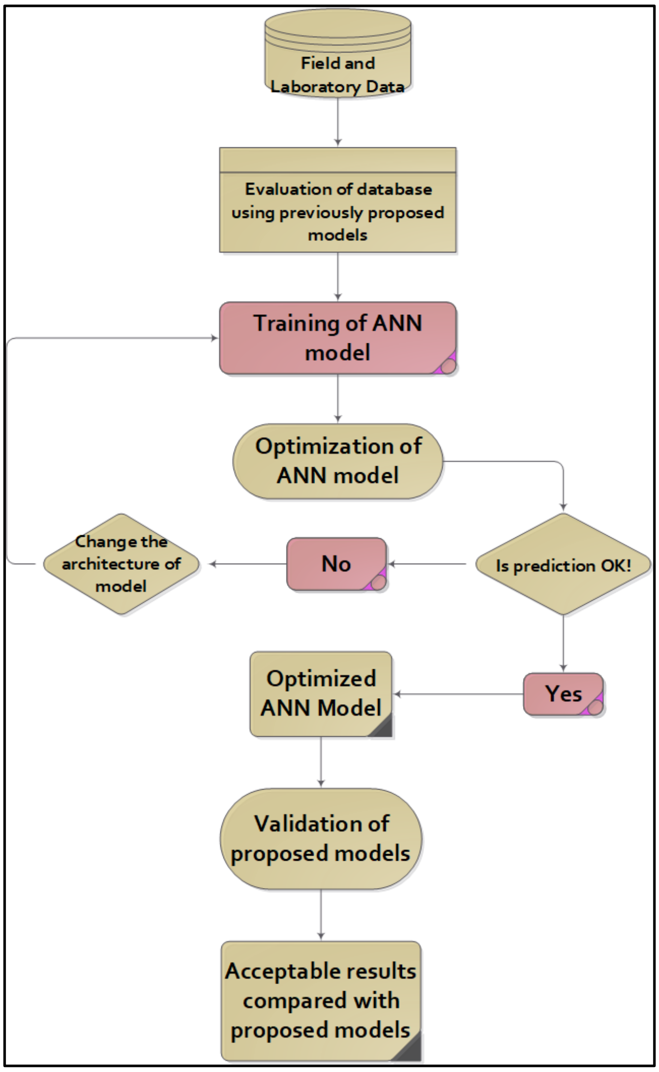


Figure 2. ANN flow chart

3.1. Experimental Program

The study area locator map and data collection points are shown in Figures 3 and 4. Seventy-four (74) data stations were marked and distributed in the mesh grid pattern throughout the Photohar plateau of northern Punjab, Pakistan. The sampling stations were precisely selected to lie on natural deposits and in confirmation to the area's general topographic and geological setting.

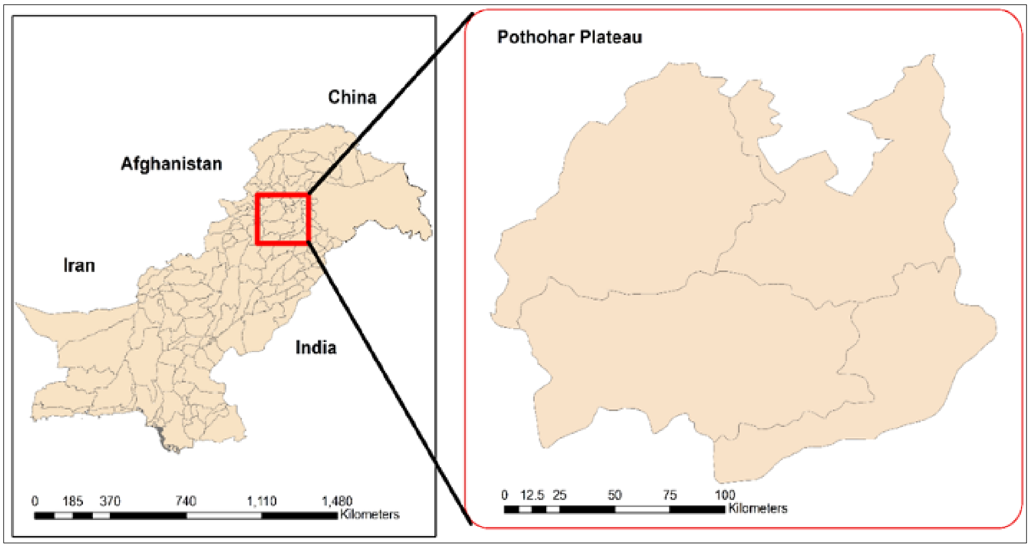


Figure 3. Study area locator map

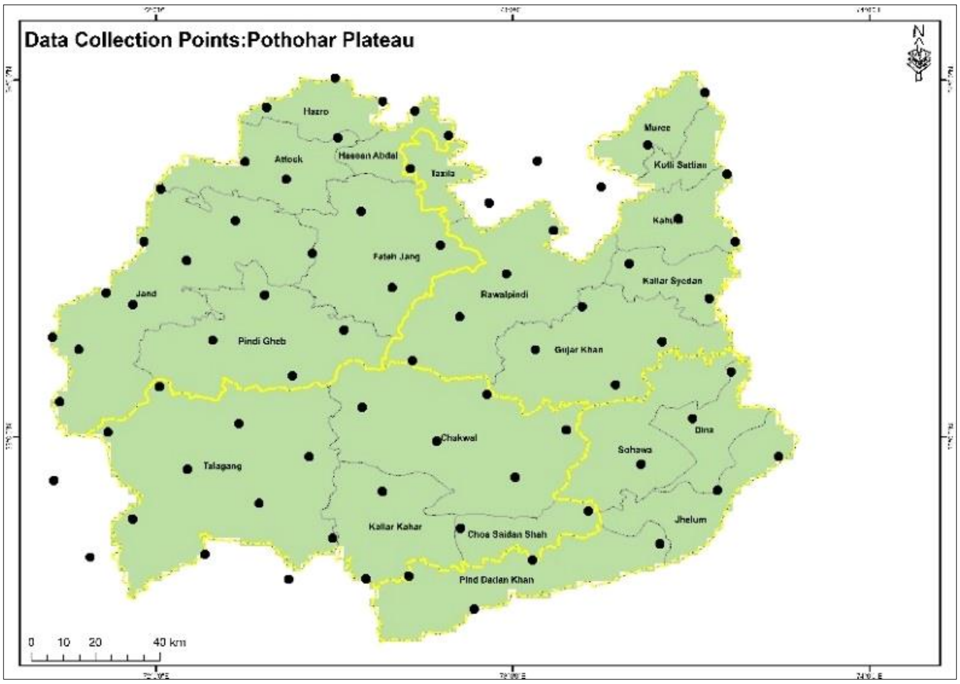


Figure 4. Distribution of data collection points

As the study targets to ease out the feasibility and planning stages of projects, hence the depth of exploration was limited to 4.5 m. SPTs were performed at 1.5 m, 3 m, and 4.5 m depth at each data station. Samples were extracted for gradation and Atterberg's limits. Seventeen Hundred and Seventy-Six (1776) tests were performed, comprising 444 SPT, 444 Gradation (G), and Atterberg's limit (ALs). SPT has been standardized by the American Society of Testing and Materials (ASTM) under designation D 1586 [41]. The test comprises boring a standard diameter hole using an appropriate boring technique depending on the characteristics of the site's soil. The number of blows applied for each 0.15 m (0.5 ft.) penetration are recorded, and the number of blows for the last 0.3 m (1 ft.) penetration is termed as standard penetration resistance number (N). The cathead hammer release system was used in the current study. Figures 5 and 6 present the experimental procedure and samples.

Figure 5. Standard Penetration Test assembly

Figure 6. Samples prepared for sieve analysis test

Many different testing factors can influence the accuracy of the SPT readings. For example, borehole diameter, rod lengths, and hammer efficiency could influence the measured N value. Correction factors for these parameters are available; however, the measured SPT-N values were used to train ANN models. These corrections were considered to have no effect on the prediction mechanism; however, the user may apply the appropriate correction to the predicted SPT-N values according to the actual working conditions. Liquid Limit (LL) is the water content, in percent, at which semiliquid soil turns to plastic. The Plastic Limit (PL) is the water content, in percent, of soil at the boundary between the plastic and semi-solid states [42].

The proportion of various grain sizes present in the soil is termed as its gradation. The plot of the grain sizes and their percentage finer than the designated grain sizes is called the Grain Size Distribution (GSD) of the given soil as described by ASTM D 6913 [43]. The stress-strain behaviour of soil is largely dependent on the GSD of the soil; hence it is almost an integral part of almost all soil exploration works. The GSD is also an important factor for the engineering classification of soils and permeability assessments. The GSD characteristics lead to selecting or rejecting the specific materials for any specific civil engineering project. Almost all the engineering types of soils are present in the region, ranging from GP to CL. The fine-grained inorganic soils have light brown to reddish brown colour shades. Consistency is in the range of medium stiff to hard. The maximum liquid limit as determined is 48.14, while the maximum plastic limit is 27.77, along with the presence of non-plastic silts. AASHTO subgrade ratings range from A-1-a to A-7. Clean coarse-grained soils are poorly graded, while silty and clayey gravels and sands are also found in the region. Coarse soils are having loose to very dense relative density. The results of field and laboratory explorations led to presenting a potential SPT-N Values model using less expensive and less time-consuming laboratory testing and field exploration.

3.2. Preparation of Databases

After the execution of the field and laboratory tests of the samples collected from the locations shown in Fig 3, the soil parameters were evaluated and used to create a database for the selected knowledge-based models. The selected parameters for the generation of models were the percentage passing of the 63, 50, 40, 20, 10, 5, 2, 1, 0.5, 0.25, 0.16, 0.08 mm sieves and Atterberg's Limits (LL, PL). The results were arranged systematically to form a database containing three subsets. The soil parameters representing 1.5 m deep formation were arranged in subset 1, while subset 2 and subset 3 contain parameters for 3.0 m and 4.5 m depths. The ANN model for 1.5 m depth had 16 input parameters, while the ANN model for 3.0m depth had 17 inputs, while the ANN model for 4.5 m depth had 18 parameters in the input layer, as shown in Table 1. The additional parameters for 3.0 m and 4.5 m depth were incorporated to further improve the performance of the models. The statistical outlines of the databases used for training purposes are shown in Table 1.

Table 1. Input Parameters for ANN Models

		Database at 1.5 m				**Database at 3.0 m**				**Database at 4.5 m**			
Sieve #	Units	Min	Max	St.Dev	COV	Min	Max	St.Dev	COV	Min	Max	St.Dev	COV
80	(mm)	86	100	2.75	0.025	88.54	100	1.37	0.01	0	100	9.21	0.09
63	(mm)	79.75	100	3.81	0.04	78.8	100	3.71	0.04	0	100	11.11	0.11
50	(mm)	59.52	100	7.5	0.08	52.15	100	9.15	0.09	0	100	14.23	0.15
40	(mm)	43.54	100	11.25	0.12	20.33	100	14.3	0.15	0	100	21.12	0.23
20	(mm)	9.09	100	20.64	0.22	0.066	100	28.03	0.33	0	100	32.94	0.41
10	(mm)	2.56	100	23.77	0.27	0.066	100	31.13	0.38	0	100	35.14	0.46
5	(mm)	1.1	100	25.13	0.29	0	100	32.13	0.41	0	100	35.94	0.49
2	(mm)	0	100	26.21	0.31	0	100	33.18	0.43	0	100	36.82	0.52
1	(mm)	0	100	26.47	0.32	0	100	33.53	0.44	0	100	36.82	0.53
0.5	(mm)	0	100	27.38	0.34	0	100	34.03	0.46	0	100	37.28	0.56
0.25	(mm)	0	99.5	29.19	0.4	0	100	33.35	0.52	0	100	35.72	0.62
0.16	(mm)	0	99.3	30.53	0.45	0	100	34.05	0.56	0	100	36.07	0.67
0.08	(mm)	0	99	32.65	0.51	0	100	35.43	0.63	0	100	37.22	0.75
LL	%	0	46.12	14.16	0.73	0	48.14	14.43	0.92	0	37.56	14.25	0.97
PL	%	0	26.96	9.54	0.71	0	27.77	10.23	0.9	0	26.83	10.21	0.96
PI	%	0	21.25	5.27	0.9	0	20.37	4.72	1.07	0	16.03	4.6	1.09
SPT-1.5	NO.	2	100	33.07	0.76	2	100	33.07	0.76	2	100	33.07	0.76
SPT-3.0						9	100	36.18	0.63	9	100	36.18	0.63
SPT-4.5										8	100	36.31	0.55

3.3. The Architecture of ANN Models

In this study, a fully customized Matlab-based tool developed by Ahmad was used for training the neural network models. Eighteen (18) different ANN models were trained at three levels (i.e., 1.5, 3.0, and 4.5 m) to predict the N value. For each depth, six ANN models with different architectures were trained. Six model having different number of hidden layers and number of neurons were developed 16-1(16)-1 (inputs-hidden layers (neurons)-output), 16-1(32)-1, 16-2(16)-1, 16-2(32)-1, 16-3(16)-1 and 16-3(32)-1, were developed. In this study, sigmoid and hyperbolic activation functions are used between the input and middle layer, and hyperbolic activation functions are employed between the middle and output layer of the ANN. Different Activation functions are presented in Table 2, and the Architecture of different ANN models has been presented in Table 3.

Table 2. Different Activation functions for ANN

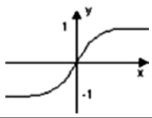
Activation Function	Formulae	Domain	Shape
Logistic/Sigmoid	$f(x) = \frac{1}{1 - e^{-x}}$	(0, +1)	
Hyperbolic	$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$	(-1, +1)	

Table 3. Architecture of ANN Models

Models		1	2	3	4	5	6
Structure of Model	Input Layer	16	16	16	16	16	16
	Hidden Layer 1	16	32	16	32	16	32
	Hidden Layer 2	0	0	16	32	16	32
	Hidden Layer 3	0	0	0	0	16	32
	Output Layer	1	1	1	1	1	1
Transfer Function	Hidden Layer 1	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
	Hidden Layer 2	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
	Hidden Layer 3	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
	Output Layer	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic

3.4. Normalization of Databases

The performance of an ANN depends upon the quality of the database, as the database consists of parameters having different measuring units. Therefore, these units must be converted to unitless entities to bring these to the same dais. This process is termed data normalization. To ease out the learning process of ANN models, it is advisable to assign the upper and lower limits for the subject parameters. In this work, all the parameters were normalized between [0.1-0.9] by using the following Equation 3:

$$N = \frac{\Delta N}{\Delta n} n + \left(Nmax - \frac{\Delta N}{\Delta n} nmax \right) \tag{3}$$

where n is the actual value, N is the new normalized value, Δn is the total variance of n, nmax is the maximum n value, Nmax is the new desired maximum value of N and ΔN is the new desired difference between the maximum and minimum N value. In our case, we use the parameters Nmax=0.9 and ΔN=0.8 to end up with normalized values in the range [0.1, 0.9]. The same equation, Equation 3, in rearranged form, is used to denormalize the output results predicted by the ANN.

4. Results and Discussion

The performance of the proposed ANN models was assessed using the mean arithmetic error (MAE), mean square error (MSE), and coefficient of correlation (R). For the testing data subset 1, the MAE values ranged from 12.73 to 17.72, the coefficient of correlation (R) between 0.61 and 0.75, and the mean square error ranged between 3.22 and 4.74. Model 1.5-N5, which has three hidden layers and sixteen neurons, performed best for subset 1, i.e., 1.5 m depth. Figures 7 and 8 show the results of the models for subset 1.

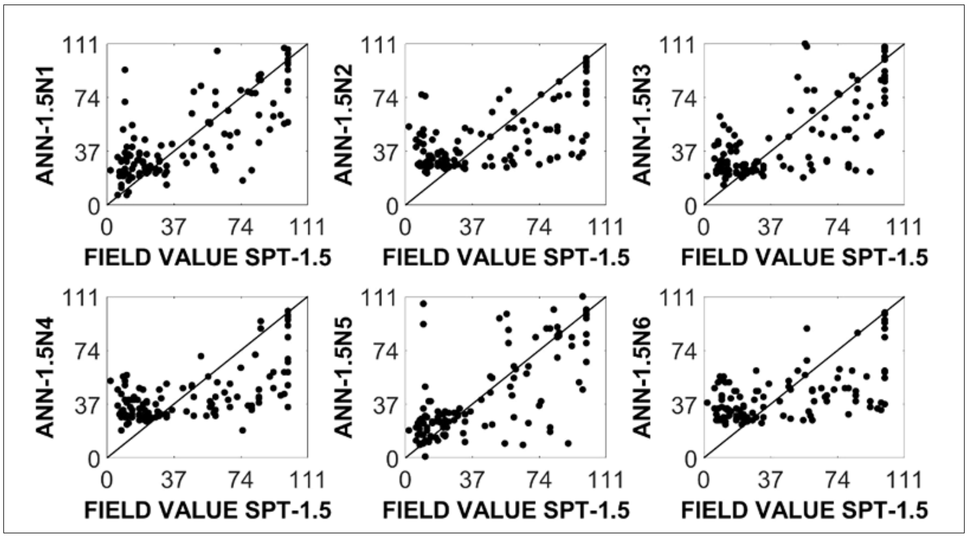


Figure 7. Comparison of Models at 1.5m

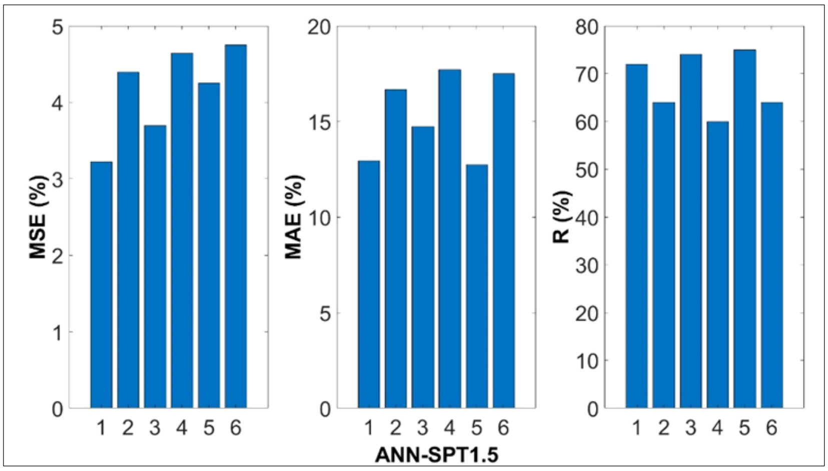


Figure 8. Statistical Indicators of Models at 1.5 m

For subset 2, the MAE values ranged from 7.14 to 10.7, while the coefficient of correlation (R) values from 0.88 to 0.92 and MSE ranged between 1.92 and 2.56. Model 3.0-N5, which has three hidden layers and 16 neurons in each layer, was the best performing model for the 3 m depth database subset. Figures 9 and 10 show the results of the models for subset 2.

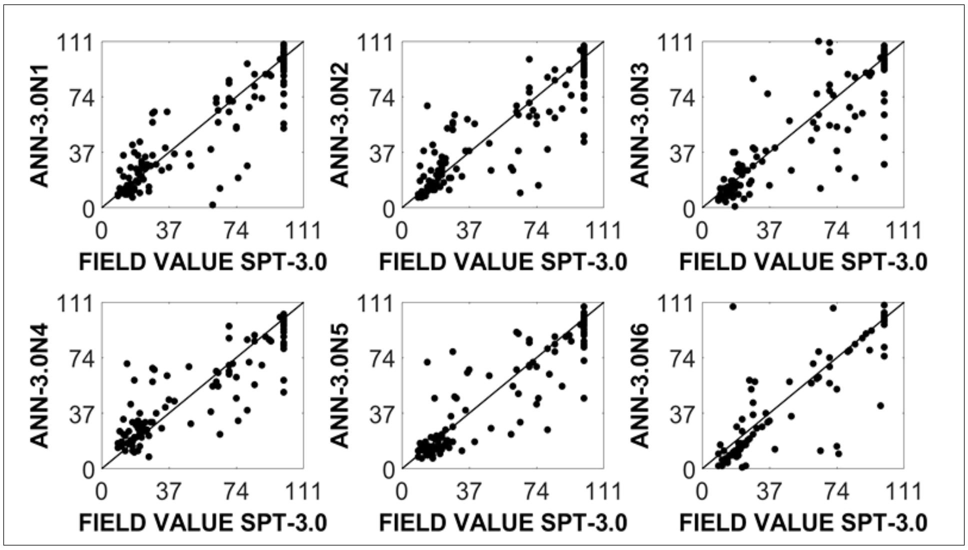


Figure 9. Comparison of Models at 3.0 m

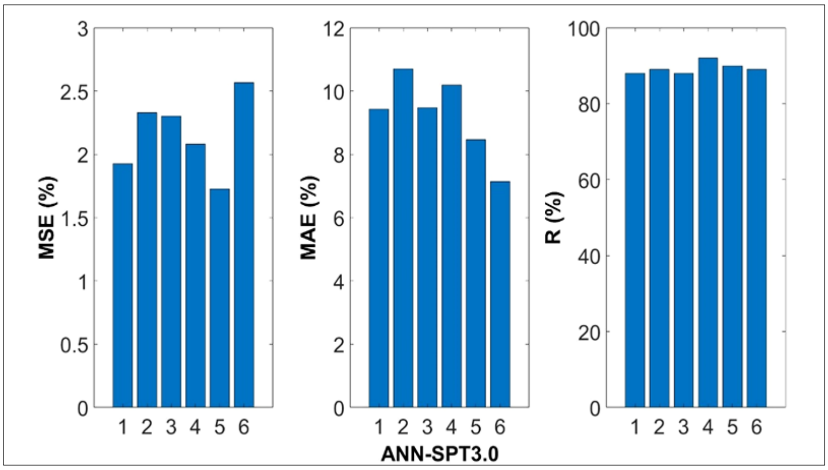


Figure 10. Statistical Indicators of Models at 3.0 m

For subset 3, the MAE values ranged from 6.97 to 10.3, while the coefficient of correlation (R) ranged from 0.89 to 0.94, and the mean square error ranged between 1.01 and 2.7. Model 4.5-N44, which has two (02) hidden layers and 32 neurons in each layer, was the best performing model for the depth of 4.5 m. Figures 11 and 12 show the results of the models for subset 3. These models employed sigmoid as the transfer function between input and hidden layers while hyperbolic function between the hidden and output layer.

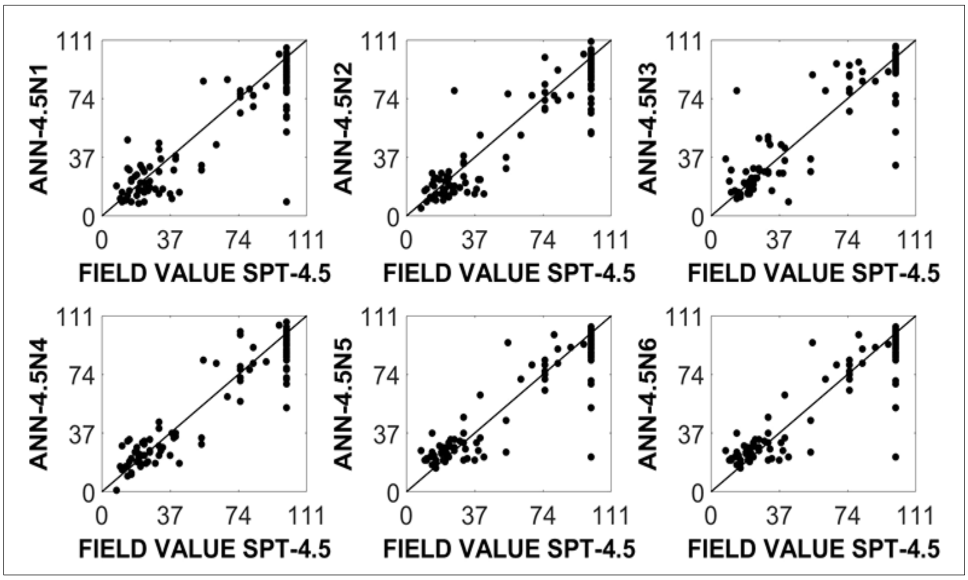


Figure 11. Comparison of Models at 4.5 m

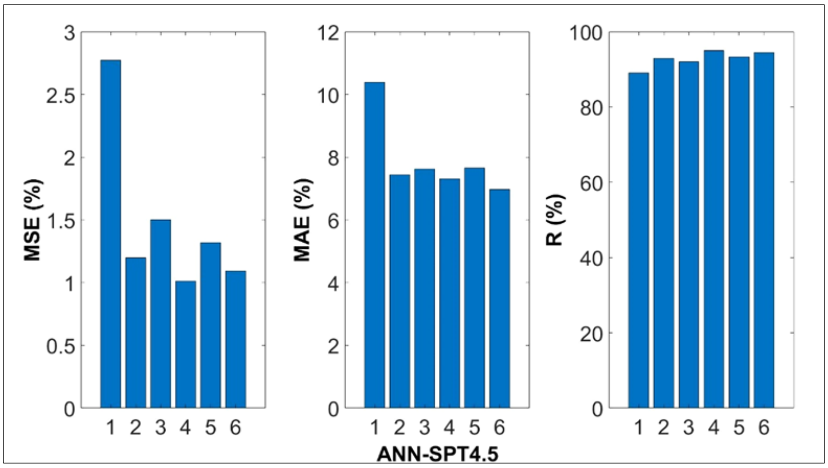


Figure 12. Statistical Indicators of Models at 4.5 m

Among the eighteen models, the optimized models were then tested using test results of randomly selected additional data stations. Finally, the additional 30 tests were performed for validation of the optimized ANN model. The outcome of the validation results is presented in Figure 13.

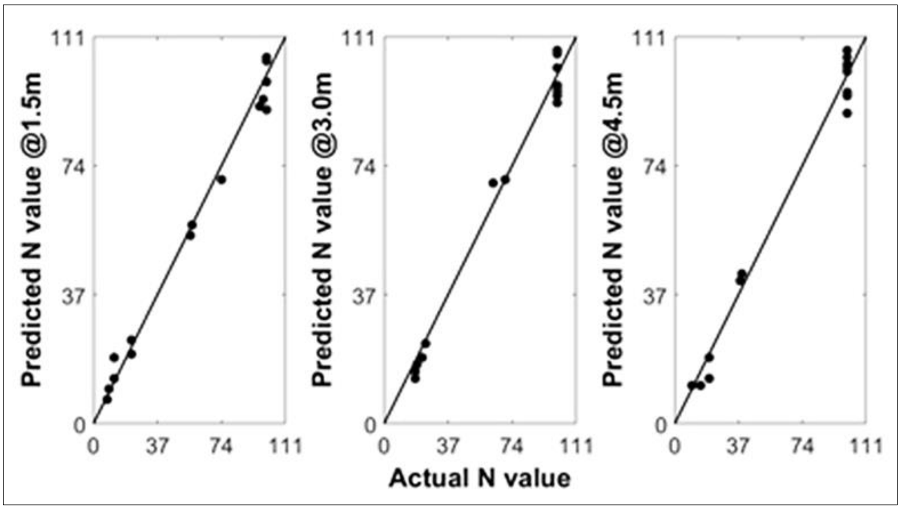


Figure 1. Validation of Optimized ANN Models

It shows the graphical presentations of the validated models. The optimized models predicted the N values well harmonized with field values. Prediction of 1.5-N5 ranged from 88-111%. The predicted N values are greater than 100%, meaning the model predicted value is higher than the actual value of N, as measured in the field. Prediction of 3.0-N5 ranges from 72 to 110%. While the prediction range of 4.5-N4 remains 65 to 110%. A user-friendly Matlab code for the developed AAN model is also being presented as a supplementary tool.

5. Conclusion

The paper presents the use of ANNs to predict N using gradation and Atterberg's limits of the soil. Among the eighteen trial ANN models having different architecture, the Model 1.5N5, 3.0N5, and 4.5N4 were the best performing models for the samples' 1st, 2nd, and 3rd data sets. The study demonstrates the adequate accuracy (R =0.75 to 0.94, MAE = 6.97 to 12.73 MSE=1.01 to 3.22) of the back propagation neural networks to predict the N. For the further verification of optimized models; additional 30 soil samples were extracted and tested. The results were compared with the prediction of optimized ANN models. Predicted N values are well harmonized with field values. It is concluded that ANN modeling is a good technique to predict N from the selected basic soil properties with acceptable accuracy. It will cut down the time and cost required for the preliminary investigation of large-scale projects and serve as ready-to-use databases for single or double-story residential units and select suitable routes for highways. It will be very useful for a site where the mobilization of SPT equipment is not possible due to the difficult terrain during the feasibility phase of projects. The study's outcome will ease out the screening process of available sites for a particular project without requiring much financial implications.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available in the article.

6.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

6.3. Conflicts of Interest

The authors declare no conflict of interest.

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