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Improvement of Correlation using Artificial Neural Networks Technique for the Prediction of Resistivity against Soil Strength Properties

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Abstract

Objectives: To investigate the relationship of laboratory electrical resistivity with soil shear strength properties at a controlled moisture content (30%). However, this research was carried out to collect the forty (40) samples from different locations of Perak state, Malaysia under different atmospheric conditions incorporating characterization of soil tests, laboratory 1D resistivity method using fabricated sand box. **Methods/Statistical Analysis:** This work was carried out through direct shear test by using DS7 software to evaluate cohesion and angle of friction, the values ranges from 21.22kPa to 87.25kPa and 5.17° to 42.85° respectively. **Findings:** The obtained correlation models were compared to the co-efficient of R2 predicted from artificial neural network system. Lavenberg-Marquardt learning rule was utilized up to 20 hidden neurons which showedthe higher accuracy in all soil samples. Relationship developed between laboratory electrical resistivity with cohesion and angle of friction were found out to be more significant with co-efficient of regression values for cohesion enhanced from 0.54 to 0.70 (all soils), 0.265 to 0.515 (silty-sand soils) and 0.027 to 0.540 (clay soils). Similarly, for angle of friction the R2 improved from 0.56 to 0.66 (all soils), 0.57 to 0.763 (silty-sand) and 0.21 to 0.447 (clay soils) respectively. Therefore, the findings reported in this study has been improved which could be helpful because ANNproduces promising results and its advantages can be utilized by developing or using new algorithms in future studies which can produce more precise evaluations. **Applications/ Improvements:** Artificial Neural Networks (ANN) are the algorithms that can be used to perform non-linear statistical modeling and able to provide a new alternative regression values. Therefore, in the current this technique is applied on the same data extracted from least-square regression analysis in order to achieve better and improved correlation models.

Keywords: Artificial Neural Network, Laboratory Resistivity, Soil Shear Strength Properties, Wenner Probe Method

1. Introduction

A natural and excavated slopes are the fundamental aspect of geotechnical engineering and plays a vital role when designing building, roads, tunnels and other engineering structures. Precise determination of engineering properties of soil is important for designing the proper engineering structure[1]. The thought of investigating for metals by method for electrical resistivity was presented in mid-1800, yet its fruitful application did not take after until almost a century later. The progressions created on soil by escalated horticultural generation are variable in space and time. As an outcome, a constant and exact spatially and fleeting follow-up of the soil physical and chemical properties are needed. Geophysical strategies have been connected to soil sciences for an impressive period. The general standard of geophysical investigation is to non-rudely gather information on the medium under scrutiny[2]. Among such systems, those in view of the electric properties appear to be especially encouraging in light of the fact that soil materials and properties are emphatically corresponded and can be

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evaluated through the geoelectrical properties. A soil investigation venture is imperative to offer information to diagram and improvement besides organic evaluation. The guideline outline is to engage adequate and mild layout of the proposed undertaking. The extent of soil examination relies on upon the sort, size and variability of the structure[3]. Gue mentioned that among the critical element in slope stability which is the need of checking of slopes especially in hill side development, which could be done among others by checking the FOS. For a regular checking and calculation of FOS in a certain stretch of slopes for the purpose of identification of risk/danger for example, bore hole sampling would not be practical due to the above mentioned reasons. This is because many bore holes are required to check the factor of safety at different locations on the slopes in order to determine the risk/hazard. Hence an alternate quick and less expensive method of assessing FOS is essential so as to enable rapid and extensive measurements and calculation for the factor safety and bearing capacity of soil[4].

So far, there had been many extensive studies carried out on the electrical resistivity survey. Electrical resistivity process is a vital and long established study technique. Borehole electrical resistivity logging has been generally utilized with extra ordinary accomplishment as a part of the hydrocarbon industry for decades. Lately, the first advancement of the marine Controlled Source ElectroMagnetic(CSEM) study techniques was used. The measure of water present in the soil is a standout amongst the most essential parameters which geotechnical design necessities to know. It can be characterized on the premise of volume or weight. On the off chance that moisture content is measured by weight then it is called as gravimetric water content. In weight premise, the proportion of measure of water present in the void to the measure of solids is known as water content. The measure of water in soils incredibly influences its resistivity. In coarse-grain soils, pore-water encourages momentum conduction as particles can free moves in liquid medium, therefore creates electrolytic conduction. Clayey soils by and large have lower resistivity values as the present conduction happens through electrolytic and also electronic conduction. A few past inquiries about demonstrated that dampness substance is key element that controls electrical resistivity in soil. Non-direct relationship in the middle of resistivity and water content has been seen in all distributed writing[5].

The use of artificial neural networks in the field of geotechnical engineering has been practiced over the last many years which produced a reasonable success. Previous suggested that it has been employing in evaluating the pile capacity prediction, modelling of soil behaviors, slope stability calculations, hydraulic conductivity and so on[6]. The soil engineering properties exhibits the wide variety of uncertainty due to heterogeneity behavior associated with it. To know the complex behavior traditional forms of relationships model will not be able to justified properly Thus, Artificial neural network could be the better option in establishing the reliable relationships model with non-linear data points[7]. In the recent times, different studies have been done on correlating the soil engineering properties with the geotechnical and geophysical parameters incorporating the neural networks. In the following section some of the previous work has been reviewed.

Siddiqui conducted experimental procedure on 10 different bore holes with 79 samples. His finding was based on the correlation between electrical resistivity and geotechnical parameters of soil which incorporated both laboratory and field resistivity. The relationship developed showed some how good correlation model between moisture content and electrical resistivity values as the trend line was increasing with the increase in electrical resistivity. Whereas, the other relationships were developed amongst cohesion and angle of friction which did not found to be significant as the co-efficient of regression R^2= 0.138 and 0.287[8].

Several other attempts have also been made by many researchers to create relationships between electrical resistivity and various soil properties such as, water content, thermal resistivity, hydraulic conductivity and ground water distribution in order to understand the phenomenon of resistivity in soil[9]. The utilization of electrical resistivity by geotechnical engineers has been expanding overall. However, there are exceptionally restricted studies have been directed to get geotechnical parameters utilizing electrical resistivity tool. Acquiring geotechnical properties has turn into a vital issue in geotechnical building with a specific end goal to look at the progressions of frictional point and attachment with the varieties of soil sorts, porosity, immersion degree, dampness content, pH, compaction energy and molecule size appropriation of soil[10]. These are most extreme important parameters in predicating the establishments of earth structures, element of security, bearing capacity and so forth. The relationships of diverse geotechnical properties with electrical resistivity will close the gap. Geophysical and geotechnical testing will have the capacity to interpret the geophysical information and use the data for their framework[11]. Therefore an option and brisk and less costly strategy for evaluating soil properties, (for example, water content, porosity, immersion degree, friction angle, unit weight and so forth.). whereas, borehole examining is extravagant and time-consuming.

A few endeavors have been made by numerous scientists to relate electrical resistivity with different soil parameters. In the present study, the fundamental concern is the designing properties of soil, a study has demonstrated that there were relationship of the electrical resistivity in compacted clay soil with hydraulic conductivity and a percentage of the electrical resistivity along with the index properties under the laboratory conditions[12]. Pozdynakov has made an exhaustive study on the impacts of electrical resistivity in various sorts of soil with differing physical and chemical properties, for example, water content, saltiness, humus content, soil mineralogy and Cation Exchange Capacity (CEC)[13]. In addition to this, electrical resistivity is likewise identified with the liquefaction[14] and the identification of geomembrane failures an instrument known as; Electrical Resistivity Cone Test (ERCP) for the estimation of electrical resistivity of delicate seashore soil and the void proportion is assessed utilizing the relationship between the electrical resistivity imaging and void ratio[15]. One of the researcher have utilized 2D resistivity imaging system to guide thick delicate soil deposits in four recovery destinations, and afterward utilized Pusan clay tests to associate with other geotechnical parameters, for example, saltiness, moisture content, organic content, atterberg's limit, unit weight and examining the depth of 50 number of samples in a laboratory. but their study did not demonstrated any significant relationship with geotechnical parameters of soil[16].

ANNs are artificial frameworks that are governed by the working principal of the human brain. These are the kind of system that can be adjusted by their inner structure in connection to the objective of a function. They are specially designed for solving the issues of non-linear variables. The Processing Elements (PE) of the neural networks are termed as 'nodes' which is the basic element of this technique. This system is consisting upon their own input and output nodes which communicates with other nodes or the environment provided by the network[17,26]. Thus, every node has its own functions (f) which transform the input in to the output shown in Figure 1. The simplest form of regression is the linear regression which can be utilized in a possible way

but the neural networks technique can be much helpful in finding out the strong relationships for the complex variables under non-linear conditions[18].

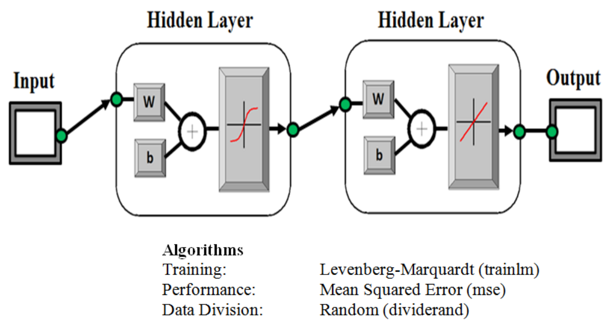

Figure 1. Diagram showing single processing element containing a neuron to calculate an output from input17.

It must be kept in mind that the term 'neural network' emphasizes more on the network rather than on neural. This means that how the artificial neurons are connected to each other is utmost important than the way how these neurons performing in a system for which they are designed. ANNs are the self-adaptive technique compared to the traditional models based methods that are feasible for the non-linear data. For a modelling this approach is the most powerful tool for finding the relationship of unknown data. ANNs can easily correlate the values of input data sets and the targeted values. This can be considered as a decision making process which can easily predict the outcome of an input data sets provided to the system[19].

The use of artificial neural networks in the field of geotechnical engineering has been practicing over the last many years which produced a reasonable success. Previous suggested that it has been employing in evaluating the pile capacity prediction, modelling of soil behaviors, slope stability calculations, hydraulic conductivity and so on[6]. The soil engineering properties exhibits the wide variety of uncertainty due to heterogeneity behavior associated with it. to know the complex behavior traditional forms of relationships model will not be able to justified properly Thus, Artificial neural network could be the better option in establishing the reliable relationships model with non-linear data points[7,20]_ENREF_8. In the recent times, a different study has been done on correlating the soil engineering properties with the geotechnical and geophysical parameters incorporating the neural networks. In the following section some of the previous work has been reviewed. The development of possible correlations model of various soil engineering properties is always being an issue. Goh[21] established a correlation model between relative density and cone resistance from cone penetration test (CPT) incorporating both consolidated and over-consolidated sand and the neural network model was found to be more significant with the regression co-efficient $R^2 = 0.91$.

Two researchers[22] investigated the relationship on residual frictional angle and index properties of clayey soil. The number of samples involved in their study was around 54 which according to the neural network technique were separated as; 39 samples for training the data and 15 goes for testing the data. The ANN model gives the best prediction value for the residual friction angle from the input parameters such as, atterberg's limit and clay fraction.

Similar sort of study was conducted in Gorgan, Iran on 125 soil samples gathered from 32 different soil profile. The study was focused on the prediction of cation exchange capacity (CEC), field capacity and permanent wilting point from the parameters inserted as input was clay (%), silt (%), sand (%), organic content and bulk density. The all three parameters were predicted the solid models with 10, 2 and 6 neurons respectively[23].

Prediction of shear strength parameters of soils using artificial neural networks were discussed by [24]. Cohesion and internal angle of friction are considered as one of the main parameters of soil in designing of engineering structures. Therefore, artificial neural technique and Multivariate Regression technique (MR) were applied to soil shear strength parameters and the obtained results shows that ANN models still the best in the performance than the multivariate regression techniques[25].

2. Experimental Procedure

2.1 Materials

This paper introduces to a research methodology that has been adopted to investigate relationship between electrical resistivity values and soil shear strength parameters in order to understand the phenomena under laboratory conditions.The research methodology consists of laboratory investigations. The study area has covered the Perak state, Malaysia. Laboratory investigations has followed the Wenner electrode resistivity approach and soil characterization test on insitu soil samples obtained from the surface at a depth of 0.3- 0.5 meters. The soil samples were collected from ten (40) different sites of Perak.

The Wenner electrode method was applied to evaluate the forty different samples under laboratory conditions in a fabricated soil box, using simple equipment and accessories in acquiring the electrical resistivity value e.g. handheld multimeter, D.C power source, insulated wires, measuring tapes, stainless steel electrodes. The electrical resistivity of soil is controlled by the equation (1). The experimental setup for progressing the research for calculating laboratory resistivity is appeared in Figure 2.

$P = 2\pi RL$ (1)

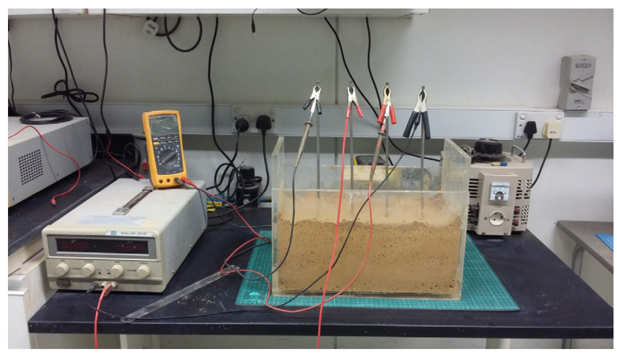

Figure 2 Wenner probes method ina fabricated sand box.

Shear strength parameters, such as, cohesion and angle of friction were determined by direct shear test in relation with BS 1377: Part 7: 1990, clause 6. ELE direct shear testing device with computerized digital logger and DS 7 data recording software was utilized can be seen in Figure 3. The shearing device was set to advance at a rate of 0.20mm/min. recording of the readings of the force, the horizontal displacement, the vertical deformation and elapsed time was done at a regular intervals of the horizontal displacement and such that at least 20 readings were taken up to the maximum load (peak shear strength).

Figure 3 Laboratory scale shear box setup.

For the current resaerch, the most significant simulation and data modelling technique used is Artificial Neural Network (ANN). ANN models are self-learning, self-versatile having adaptable models which yield more precise expectations. The neural system tool compartment of MATLAB 7.0, GUI, graphical user interface utility, was used for preparing and testing of ANN models. Multilayer Feed Forward (MLFF) systems have been utilized as a part of building neural system models. It comprises of more than one layer (i.e. include, covered up and yield layers), all the data are moved in the forward course just, i.e. from information neurons to yield neurons through the hidden layer. It is frequently known as Multilayer Perceptrons (MLP).

3. Results and Discussion

3.1 Soil Investigations Result

The obtained samples from different locations of Perak state, Malaysia were then brought to the geotechnical laboratory of universiti teknologi petronas for the further soil investigations where numerous soil tests were performed (e.g. moisture content, cohesion and angle of friction) incorporating laboratory resistivity test (Wenner array).

Insitu moisture content ranges from 17.75% to 31%. Direct shear test was conducted by using the DS-7 software to calculate the strength parameters of soil (i.e. cohesion and angle of friction). The friction angle more or less shows the similar shear strength which ranges from 5.17 to 43.25 deg, but the lowest degree was observed for one of the clay sample 5.17°. Cohesion varies from 20.45kpa to 75.24kpa. The resistivity of all soil samples were calculated at controlled moisture content (30%) using 1500ml water for every single layer in a sand box to understand the phenomenon of heterogeneous soil under laboratory conditions. All forty (40) samples showed the different resistivity values at same amount of water content which was in between 61.9285 ohm-m and 1592.1065 ohm-m.

3.2 Correlation of Laboratory Electrical Resistivity against Soil shear Strength Paramaters

The outcome from electrical resistivity tests (laboratory) and soil characterization tests were investigated collectively to comprehend the interrelation between electrical resistivity and various soil properties, for instance, cohesion and angle of friction. Laboratory resistivity values were correlated with numerous soil parameters. The relationships between electrical resistivity and different properties of soil tests were assessed by utilizing simple regression analysis method. polynomial curve fitting approximations were applied and the best estimate comparison with higher relationship coefficient was chosen.

Figure 4 shows the obtained results of cohesion with electrical resistivity for all types of soil. The relationship between cohesion and resistivity has shown the significant trend based on the previous studies where polynomial curve had been plotted and cohesion seems to be increasing and decreasing at regular intervals with the increasing of resistivity values and co-efficient of regression $R^2 = 0.13$[1]. But for current work, Polynomial curve fitting was incorporated to obtain the best possible trend. The cohesion values ranges from 20.45 KPa to 75.24 KPa. According to the trend represented in graph, cohesion increases with the increasing in electrical resistivity with the co-efficient of regression $R^2 = 0.54$. This can be considered as a good regression value in contrast to previous findings.

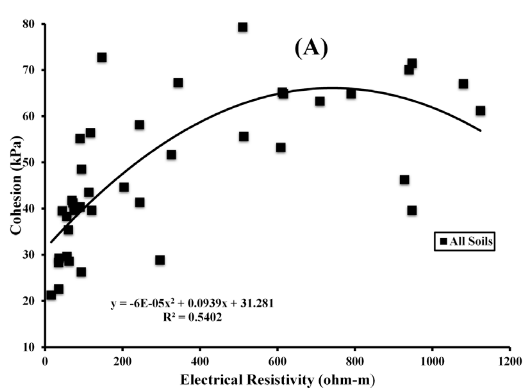

Figure 4 Correlation of laboratory resistivity against cohesion.

So far, only few studies have been conducted to correlate the cohesion with electrical resistivity of the soil. One of them was the outcome of Fikri[23] which demonstrate the linear relationship on clay soil samples with laboratory resistivity which is compared with the current study shown in Figure 5. Similar kind of relationship was also put forwarded by [3]. Figure 4 narrow down the comparison of relationship of previous work between cohesion and electrical resistivity of the soil with the current research work.

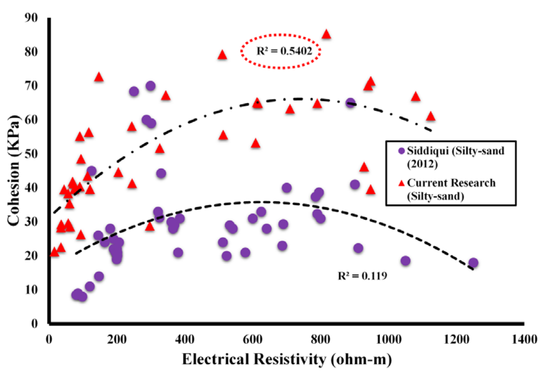

Figure 5 Comparison of cohesion-resistivity model obtained by current research with Siddiqui8.

Similarly, the relationship was also established between laboratory resistivity and angle of friction. The relationship between friction angle and resistivity demonstrates increasing pattern with R^2=0.58 for all soil specimens as appeared in Figure 6. The acquired result is very justifiable because of the way that shear strength of soil declines with increasing water content [24]. Increment in water content, reduces electrical resistivity of soil. Thus, at higher resistivity values, higher frictional point will be watched. Another conceivable purpose behind this expanding pattern may be the porosity of the soil. Porosity will influence the pore size and volume of air voids which is turn increment or less

ening the level of saturation. About immersed pores structure spans in the middle of particles and more prominent molecule contact[9, 25]. In this way, lower and higher electrical resistivity connected with grinding point are the results of diminishing or expanding electrical conductivity in pores and along the strong surface. From the figure it can be concluded that friction angle has a better relationship with laboratory electrical resistivity at a controlled moisture content. Although it varies with the increase in water percentage present inside the pores of soil. It is also found that clay soils has increasing relationship of resistivity and friction angle which does not give any sense and the co-efficient of $R^2 = 0.21$. Whereas, silty-sand soils showed the quantitative relationship between angle of friction and electrical resistivity with $R^2 = 0.57$.

From the Figure 7, the only related work done on friction angle and electrical resistivity of soil conducted by [1,23] which shows the obtained relationships between current research. The observed relationship from current research also analyzed by applying logrithmatic curve fittings which shows the highest amount of deflection from the past work. The co-efficient of regression $R^2 = 0.28$ was obtained from previous research whereas, the current study follows the more significant $R^2 = 0.55$ compared to previous ones.

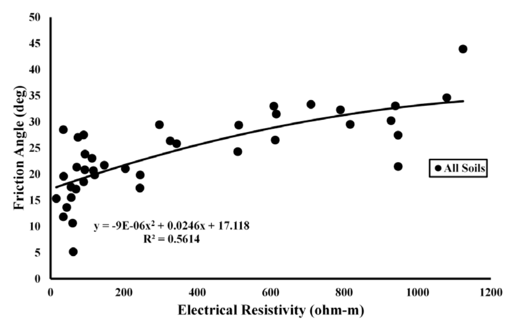

Figure 6 Correlation between friction angle and electrical resistivity for all soils.

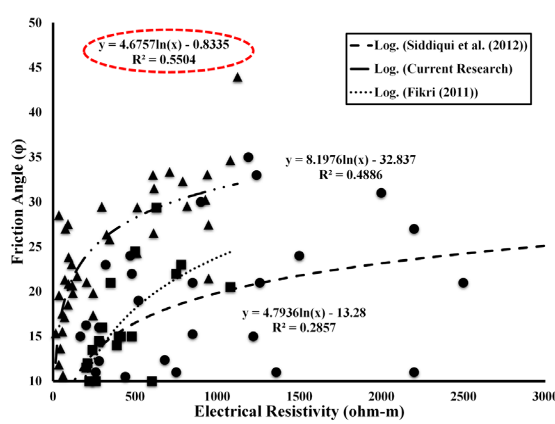

Figure 7 Comparison between current and previous study on the relationship of friction angle-resistivity of soil1, 23.

3.3 Predicted Results of Regression and Artificial Neural Network Models

An artificial neural network model allows the precise relationship between the variables. The data utilized for the modeling was the same as used in regression analysis. ANN models are considered as one of the most self-learning, self-adaptive and flexible for predicating the values with good accuracy. The neural network toolbox of MATLAB R2014a, GUI, graphical user interface utility was incorporated for the training and testing of data which yield the ANN models. Single input parameter (electrical resistivity) was used for training the neural network models along with unidirectional output (i.e. cohesion, angle of friction, plasticity index, bulk unit weight, porosity and degree of saturation of a soil).

There were twenty (20) Multilayer Feed Forward (MLFF) networks were prepared using Lavenberg-Marquardt (LM) algorithm. Total number of neurons in a hidden layer was selected as twenty from 1 to 20. Therefore, the possible best network with optimum root mean square error (RMSE) was selected for the evaluation of predicted different soil engineering properties. Table 1 presents the minimum and maximum values for all the models obtained using the in-situ soil (all soil samples, silty-sand soil and clayey soil samples). Since the optimum and peak values based on the normalization and denormalization for all values being incorporated in ANN models. According to the predicted values generated from the neural network model, both regression analysis and neural network were compared to obtain the best possible outcome from the regression values.

3.3.1 Cohesion

The obtained root mean square error RMSE (KPa) for all soil sample during testing the data was obtained through ANN. The results shown that neural network with Lavenberg-Marquardt (LM) have lowest root mean square error for all soils (0.0658KPa) at neuron 17. For silty-sand and clay soil were also incorporated with LM algorithms in order to obtain the less amount of errors in the predicted models of ANN. The suggested root mean square error was found out to be 0.0128KPa for silty-sand and 0.0447KPa for clay soils in prediction of cohesion at neuron 9 and 11 respectively.

Comparative analysis of predicted cohesion values is obtained through ANN models for all soil samples, silty-sand and clay soil using equations from regression analysis. The accuracy shown by predicted ANN models showed precise correlation with the co-efficient of R^2 increased from 0.540 to 0.70 in all soils (shown inFigure 8). Similarly, the silty-sand soil samples predicted ANN values as 0.515 and for clay it was again the best value predicted from regression analysis with the co-efficient of R^2 jumps from 0.027 to 0.540 is shown in Figures 9 and 10. The obtained graph can clearly indicate that the ANN predicted data points are tend to be closer towards the experimental line in comparison with the regression predicted values.

Table 1. Input and Output ANN models showing optimum and peak values for all soils, silty-sand and clay soils

Sample Description	Data Type	Soil Parameters	Optimum Value	Peak Value
All Soils	Input	Electrical Resistivity (Ω-m)	34.96	1124.19
		Cohesion	21.34	85.33
		Angle of friction	5.19	43.96
Silty-sand soils	Input	Electrical Resistivity (Ω-m)	113.04	1124.19
		Cohesion	26.32	85.33
		Angle of friction	17.36	43.96
Clay soils	Input	Electrical Resistivity (Ω-m)	34.96	93.40
		Cohesion	22.58	48.54
		Angle of friction	5.19	28.52

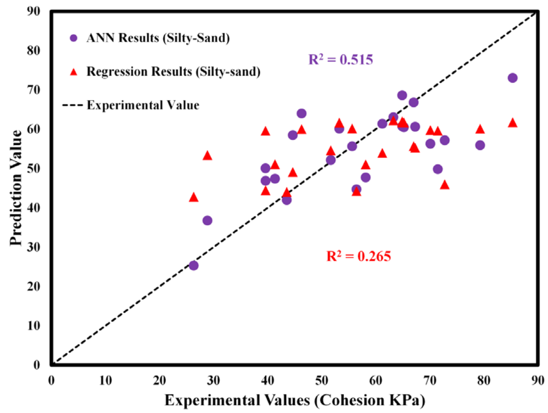

Figure 9 Comparison of ANN and Regression predicted models of cohesion for silty-sand using resistivity as an input parameter.

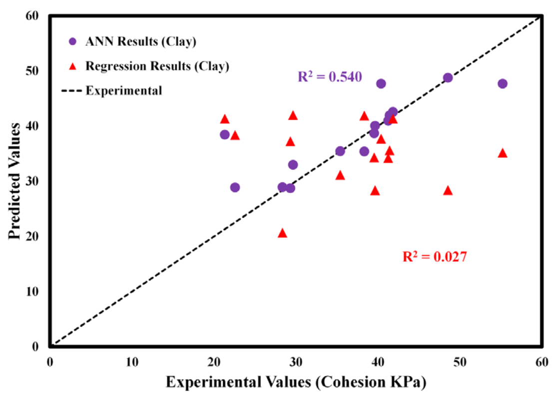

Figure 10 Comparison of ANN and regression predicted models of cohesion for silty-sand using resistivity as an input parameter.

3.3.2 Angle of Friction

Root mean square error RMSE values obtained by different neural networks with learning algorithm rule and number of neurons in hidden layers for estimation of friction angle for all soils, silty-sand and clay soil samples respectively. Lavenberg-Marquardt learning algorithm yield lowest RMSE (0.0517°) at 07 neuron in a hidden layer for all soils. In silty-sand the RMSE (0.0399°) obtained at neuron 05 in a hidden layer. Clay soil using Lavenberg-Marquardt learning rule in a neural network also gives the lowest RMSE (0.1293°) at the number of neuron 18 in a hidden layer.

Based on their combined analysis the predicted values of friction angle (φ) developed in regression and artificial neural network methods are shown in Figures 11, 12 and 13 for all soils, silty-sand and clay soils which showed stronger correlation models in all three cases. The co-efficient of R^2 for all predicted values used from regression were calculated through equations obtained from regression analysis. The value generated from ANN model is 0.665 which is still higher than the predicted regression value (0.561) for all the soils. In the same way silty-sand and clay composition soil has generated good predicted ANN values in contrast to regression analysis, for silty-sand and clay the outcome of the predicted values enhanced from 0.572 to 0.763 and 0.211 to 0.477 respectively.

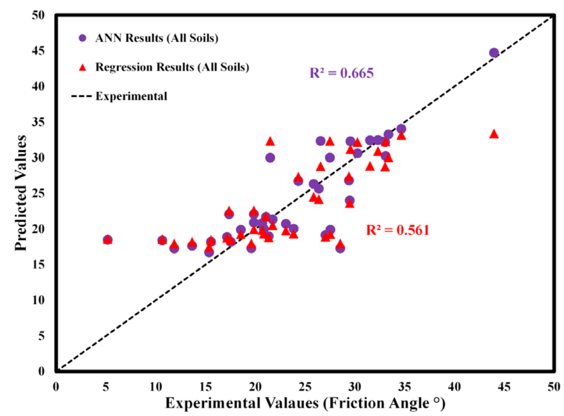

Figure 11 Comparison of ANN and regression predicted models of friction angle for silty-sand using resistivity as an input parameter.

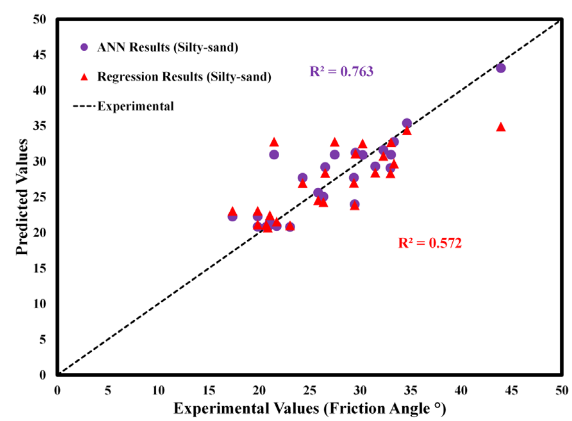

Figure 12 Comparison of ANN and regression predicted models of friction angle for silty-sand using resistivity as an input parameter.

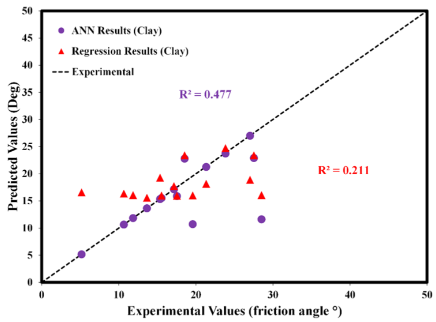

Figure 13 Comparison of ANN and regression predicted models of friction angle for silty-sand using resistivity as an input parameter.

Based on the improved predicted regression analysis, the obtained values of hidden neurons and co-efficient of R^2 are summarized in Tables 2 and 3.

4. Conclusion

Soil investigation is the key factor in identifying the failures associated with the engineered structure. Precise determination can be able to solve the problems in an appropriate manner based on the information provided from the subsurface properties. The advanced form of simulation technique artificial neural network system was applied on the same data extracted from simple regression analysis in order to achieve more precise relationship. All neural network models were trained using single input (electrical resistivity) and single output (i.e. cohesion and angle of friction). Lavenberg-Marquardt (LM) learning algorithm with 20 hidden neurons were prepared in the neural network system. The best neuron with the lowest value representing the root mean square error was selected in the prediction of various soil properties. The ANN predicted model can be useful in generating the significant relationships between the geotechnical parameters which will be further verified by the existing equations. This can be considered as a decision making process which can easily predict the outcome of an input data sets provided to the system.

Table 2. Summary of regression and ANN models for cohesion

Sample description	Regression analysis		Artificial Neural Network	
	Equations	R^2	No of neurons	R^2
All soils	$C = -6E - 05\rho^2 + 0.0939\rho + 31.281$	0.540	17	0.701
Silty-sand	$C = -5E - 05\rho^2 + 0.0717\rho + 36.559$	0.265	09	0.515
Clay	$C = -0.0007x^2 + 0.443x + 13.51$	0.027	11	0.540

Table 3. Summary of regression and ANN models for angle of friction

Sample description	**Regression analysis**		**Artificial Neural Network**	
	Equations	R^2	No of neu-rons	R^2
All soils	$\Phi = -9E - 06\rho^2 + 0.0246\rho + 17.118$	0.56	07	0.665
Silty-sand	$\Phi = -2E - 06\rho^2 + 0.0162\rho + 19.247$	0.57	05	0.763
Clay	$\Phi = -0.0004\rho^2 + 0.3689\rho + 24.088$	0.21	18	0.477

5. Acknowledgement

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