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PREDICTION OF BEARING CAPACITY FOR SOILS IN BASRAH CITY USING ARTIFICIAL NEURAL NETWORK (ANN) AND MULTI-LINEAR REGRESSION (MLR) MODELS

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ABSTRACT

The bearing capacity of soil is considerably very important for geotechnics and engineering geology, since it is a significant parameter for the foundation's design. In the present paper, application of Artificial Neural Network (ANN) as a method for bearing capacity forecasting of spread foundations in some of Basrah's soils was highlighted. This research reports the final results of laboratory tests for 87 soil sample at 3 m depth in different cohesionless soils in Basrah province. For the aim of creating ANN models, training and testing steps were done, making use of available experimental's results were obtained from the soil investigation reports. The applied data in this ANN models are arranged in component of 9 input parameters which cover liguid limit (L.L.), plasticity index (P.L.), Sand percentage, Fines percentage, optimum moisture content percentage (O.M.C.%), Sulfur trioxide (SO_3), Total suspended solids (TSS), Chlorine (Cl^-), and gypsum percentage. Relating to these input parameters, in the ANN models is forecasted the ultimate bearing capacity (q_u). The last parameter been set as the required target (i.e. Output) in the ANN model. The results of the training as well as testing processes in the ANN models have indicated that the neural networks have powerful prospective for forecasting the ultimate bearing capacity. The overall performance of ANN model was put in comparison to that of Multi-Linear Regression (MLR) model. It really is exposed that the overall performance of ultimate bearing capacities of suggested NN model is fairly satisfactory. Findings show that the recommended ANN model is an appropriate tool for forecasting the bearing capacity in the spread-foundations. Coefficient of determination (R^2) equals to 0.9860 for training and equal to 0.9915 for testing, strongly implies that the ANN model shows a high level of reliability in forecasting the bearing capacity of spread foundation.

Keyword: Bearing capacity, spread foundations, artificial neural network, sensitivity analysis, multi-linear regression analysis.

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1. INTRODUCTION

The column-load of low or moderate rise structures is transmitted to the underlying soils by using spread or shallow foundations. That is why the shallow-foundation is a load holding structure in which transfers loads exclusively to the soil that is underlying. Sallow foundation is simply alluding to the foundation with embedded depth-to-width ratio which is equal to or less than 4, as reported [1].

Two important criteria which can be necessary to be controlled when the geotechnical designing of spread-foundations: ultimate bearing capacity and foundation's settlement under structural loads. Thus, these two criteria show that there are different approaches in both laboratory and in-situ reports to investigate the ultimate bearing capacity. In Geotechnical engineering, bearing capacity of soils need to be identified because of its significance in foundation design. The resistance of foundations when the maximum pressure is enforced through the foundation to the underlying soil before the failure due to the shearing is described as the bearing capacity of soil.

Numerous scientists have formulated many solutions which are semi-empirical for the bearing capacity of spread foundations [2-4]. Initially, a semi-empirical equation formed by Terzaghi (1943) [5] for the objective of calculating the ultimate bearing capacity for foundations. Afterwards, a general equation for bearing capacity is proposed by Meyerhof (1963) [6], which is a similar equation to that of Terzaghi, but Meyerhof's equation involved different depth and shape factors. It is note to know that in soil, the shear-strength above underneath level of footing is included in Meyerhof's equation. Thenceforth, the Meyerhof's equation was modified by Hansen (1968) [7]. Then, Vesic (1973) [8] applied an equation much like that advised by Hansen (1968). Finally, many researchers obtained alternative methods to forecast bearing capacity due to the fact that the traditional computing approaches not to give an accurate result [9-10].

One of the more preferred prediction methods is the Artificial Neural Network (ANN) which imitates the structure of the biological neural network as well as its learning system. The ANN has basic calculating elements named neurons. This permits the analysis of non-linear interactions between any parameters of the soil and foundation. The ANN provides faster and much better results in comparison to earlier traditional computing methods. Presently, ANN system which is the sub field of Artificial Intelligence (AI), are applied for solving a broad range of problems and applications in civil engineering [10-13]. The majority significant property of application of ANN in civil engineering problems is that ANN can be learn directly from experiments. One other essential properties of ANN tend to be proper or nearly proper response to the incomplete-tasks, it produce a general results from the unique cases, and it can extract the information from poor or noisy data. The pointed out capabilities of ANN application make it a powerful tool in solving of many problems in civil engineering, where information can be complex or perhaps in a quantity that is insufficient [14]. ANNs have already been practiced in geotechnical engineering with different problems and applications [15-19]. For shallow foundations, the ultimate bearing capacity forecasting in the cohesionless-soils was studied by application of ANN [17-18].

In the current past, the ANNs, have now been used successfully for dealing with the problems of bearing capacity in both shallow and deep foundations [20-21]. In the study of

Shahin et al [22] that shown the predicting-possibility of spread-foundation's settlement using ANN techniques. In their study, they gathered 189 individual cases (database) for ANN's construction. They concluded that the proposed ANN method operates fairly well in the predicting of the settlement in spread foundation. Another study introduced by Soleimanbegi and Hataf [23] employed the feedforward BP-ANN in shallow foundation for the forecasting of the bearing capacity. They obtained compiled of 351 records (database) from the field measurement and laboratory of bearing capacity in spread foundations with reinforced cohesionless-soils. They concluded that predictive model using ANN system outperforms the conventional forecasting methods of bearing capacity. An additional study prepared by Adrash et al. [24] reviewed the soft computation techniques and its application in forecasting of the bearing capacity in cohesionless soils. They outlined in their research that the application of ANN for the estimation of bearing capacity, in the cohesionless, soils is in good-agreement with the experimental outcomes.

Another study of bearing capacity estimating, in circular footing on soft clay stabilized with granular soil, introduced by Ornek et al. [25], which is performed several field-tests on various footings with different diameters in multilayer granular soil at different thicknesses. They suggest in their conclusion that ANN models is reliable and simple tools in the estimation of the bearing capacity for foundations.

Generally, there are two procedures for neural systems training and testing. Training process of an ANN often demands a large training sample set. Anyhow, after the training process, it may be utilized immediately for the replacement of complex-system dynamics. The use of ANN as a fast, valid and viable tool in solving problems regarding the estimation of bearing capacity happens to be outlined in literature lately [26]. The primary objectives with this research are to suggest a predictive model basedon ANN for bearing capacity and to construct a different model with various ANN-architectures.

For the aim of these ANN-model's constructing, 87 database were applied in the training and testing for the ANN-model's that were collected from soil investigation reports for some soils in Basrah province. In ANN-models, the training and testing processes founded with different architectures, the L.L., P.L., Sand%, Fines%, MC%, SO_3, TSS, Cl^-, and gypsum%, that were entered as input; whereas the values of the ultimate bearing capacity were considered as output. This study also utilized the Multi-Linear Regression (MLR) model as a statistical model for the estimation of ultimate bearing capacity depending on the all of the 87 database for the model's building. An evaluation of the comparative study between the proposed ANN models and the MLR model was discussed in this research.

2. ARTIFICIAL NEURAL NETWORK (ANN)

Synthetic neural systems tend to be computer system designs that simulate the biological system in which is stressed. A neural network may be explained a massively synchronous allocated processor that includes a natural predisposition for keeping the experiential-knowledge and rendering it designed for usage [27]. The primary element of this model is the framework of its information handling unit. The typical biological neuron model is demonstrated in Fig. 1. This biological neuron is the base of artificial neuron model.

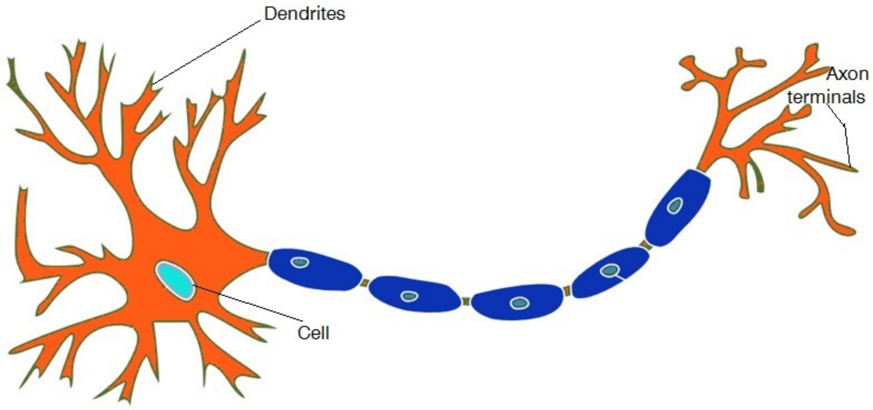

Figure 1 biological neuron

A biological neuron consists of four main components: dendrites, cell-body, synapses, and axon. The signal from other neurons is received by the dendrites. The axon of any single neuron, acts to form synaptic-connections with the other neurons. The aim of cell-body in neuron is the summation of incoming signals via dendrites. In the case of the input signals that tend to be adequate to activate the neuron to its threshold-level, an impulse is sent to its axon. Having said that, in the event that if inputs try not to achieve the desired level, no impulse will take place certainly.

The analogy regarding a neuron that is biological and an artificial neuron model is demonstrated in Fig. 2.

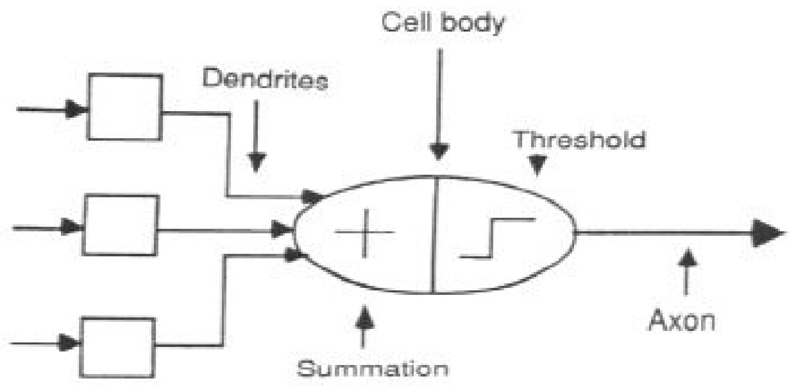

Figure 2 Neuron model

The concept that is fundamental of neural networks, is the construction associated with the information handling system [28]. Typically, an ANN are constructed of input layer, often named as processing units or nodes, one hidden layer or multi-hidden layers, additionally one output layer. The layers which are neighboring completely interconnected by weight. The fundamental element of a neural network is the artificial neuron which clearly indicated in Fig. 3 that is made of three main elements, particularly called bias, weights, along with the activation-function. The input layer receives the information coming from the exterior environment, and then transfers them to the hidden layer without carrying out any calculation [29-30]. Layers amongst the input and output layers are referred to as a hidden layer that can comprise a big number of processing units which is hidden [31]. All issues, which may be solved by a perceptron is resolved with just one hidden layer, however it is occasionally better to utilize two or three hidden layers. Subsequently, the output layer creates the network estimations to the external world [29-30]. Every single neuron of a layer aside from input-layer, estimates firstly a linear-combination of the outputs in the network from a previous layer, as well as a bias. The coefficients of linear-combinations and biases, are definitely named as weights. Then, the neurons in the hidden layer, calculate a nonlinear-function of their particular input. Usually, the sigmoid-function is used as nonlinear-function [28]. Activation-functions work to propose a non-linearity in the direction of neural networks which develops the powerful for the neural networks.

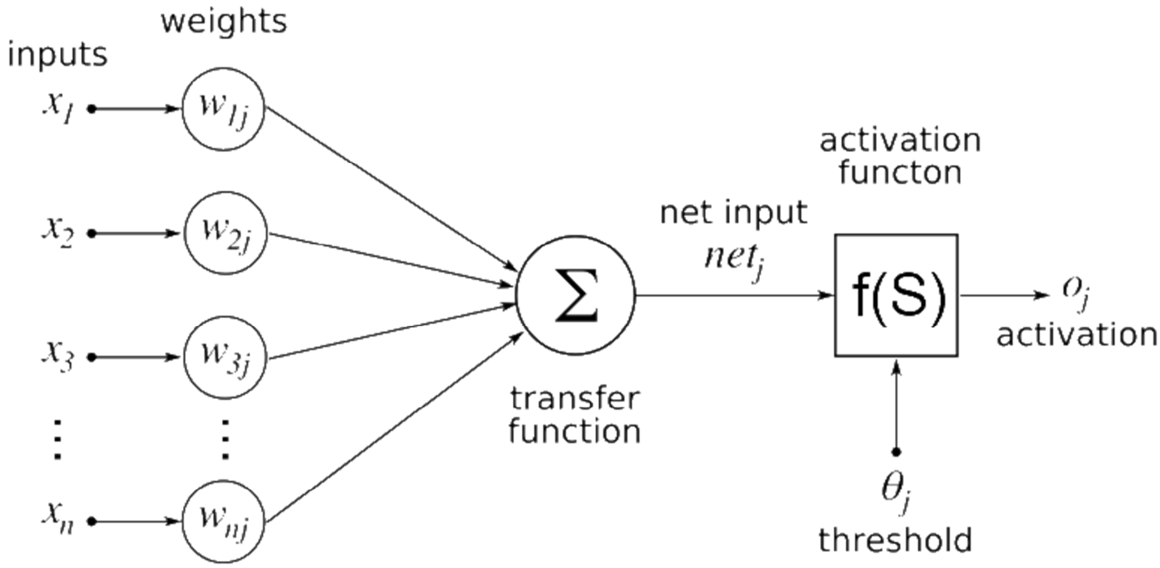

Figure 3 Fundamental component of neural network

Usually, the designer of the network chooses the activation-functions and the learning stage commonly establishes the weights and biases allocated to the connection of the network. Back-propagation algorithm is the most frequent learning method in the ANN. Back-propagation algorithm the most trusted supervised training methods used to train the multilayer neural networks because of its applicability and simple ness. It is a training algorithms for the multilayer perceptron which is the most well-known because it is a gradient-descent method used for minimizing the error in a particular training structure for which it changes the weights at a time with a small amount [12-13]. It is also dependent on the generalized delta rule, which had been made popular by Rumelhart et al. [32]. Since the algorithm is supervised learning, there is certainly inputs and related output. Furthermore, the algorithm is definitely according to the weight correction process. It contains two passes: a backward-pass in addition to a forward-pass.

The essential strategy of the artificial neural network usually contains a training process with the network testing stages. The data set, entered to the network throughout the training stage, is introduced to train the network and the outputs tend to be compared to related target values. The average error seems to indicate the trained network's efficiency.

3. THE DATABASE USED IN ANN

The samples of soils used for the study presented here came from the soil investigation reports and all the location of the sites from these reports were indicated in Fig. 4. Soil samples were taken from 3 m beneath the surface of natural soil using a geologist's machine adapted for this purpose. All soil samples were transported to the laboratory for tests.

The database of 87 recorded cases from the bearing capacity reports for design a spread foundations was compiled from literature. The recorded database consist of the L.L., P.L., Sand%, Fines%, MC%, SO_3, TSS, Cl^-, and gypsum% and the ultimate bearing capacity (qu). Away from the last parameter, the other parameters had been selected as inputs for the ANN model as a result of understood proven fact that they are effective parameters in designing of the spread foundations [22,33]. The field tests were executed in different type of cohesionless soils which range from fine sand to coarse gravel. The data used in this research is statistically tabulated as shown in Table 1. More detail regarding the database is documented in the soil investigation reports for different places in Basrah province. The location map for distribution of 87 sampling areas (database) is shown in Fig.4.

Table 1 Statistically values of parameters (inputs and output) used in the study

Variable	Symbol	Unit	Minimum	Maximum	Average
	L.L.	(%)	18.3	34	27.88
	P.L.	(%)	11.2	31.1	18.15
	Sand	(%)	0.05	68	4.68
	Fines	(%)	32	99.95	95.31
	O.M.C.	(%)	0.02	2.27	0.73
Input	SO_3	(mg/L)	0.019	4	0.63
	TSS	(%)	0.3	5.8	1.64
	Cl^-	(mg/L)	0.05	3.62	1.27
	Gypsum	(%)	0.04	8.6	1.32
Ouput	Qa	(Ton/m^2)	2.93	32.1	5.33

Figure 4 locations map of the sampling areas (database)

4. NEURAL NETWORK ARCHITECTURE

The design of network architecture is dependent on the training algorithm along with the node's number in each of network layers (input, hidden, and output). Despite the reality that numerous scholars have actually identified the structural design of the ANNs [34-35], there is absolutely no confident method to select optimum architecture for network. It's determined through a trial-and-error method. Hence, many networks using different architectures are tried. As a result, the network that works very best is chosen as an optimum network. Therefore, the collected database requires to turned out to be randomly divided for two subsets: which are training and testing. In this research, 80 percent of the data was selected for training objective and the rest (20 percent) was used for testing of ANN model.

5. ACCURACY OF A NEURAL NETWORK

One of the greatest difficult activities in neural netwrods research is to choose the optimal network structure that is centered on dedication of numbers of the neurons and the optimal layers in the selection of the hidden layers which is usually choosing by method of trial and error. Initial weights and other associated parameters, could also impact the overall performance of neural netwrods. Nevertheless there is no really defined rule or procedure to possess the optimal network structure and the parameter-settings in which the trial and error way still remains applicable. This method is extremely time intensive. For the overcoming this problem, a small program was created in Matlab which manages the trial and error strategy conveniently. The program makes various attempts for selecting the layers and the selecting of the neurons in the hidden layers in each of the first and for second hidden layers for a constant-epoch in several times and determines the best structure of the neural netwrods that satisfy the minimum RMSE (root mean squared error) or MAPE (mean absolute percent error) for the testing-set, as training of testing-set is much more crucial.

6. MULTI-LINEAR REGRESSION ANALYSIS

The objective of using the Multi-Linear Regression (MLR) is to establish a relationship amongst variables. The established relationship is between one Dependent Variable (DV) and more than one Independent Variables (IV). In the current research, for better comprehension of prediction efficiency of ANN model, MLR analysis was applied by using of the statistical software SPSS ver. 21. The input layer nodes of the ANN had been selected as an independent variables in MLR analysis, whereas the ultimate bearing capacity was fixed to become the dependent variable.

7. RESULT AND DISCUSSION

This study practiced a multi-layer feed-forward back-propagation neural network. The initial-weights and biases linking neurons for input, hidden and output layers are normally designated in a random way. The proposed network was trained by a training function, which updates its weight and bias values based on the Levenberg–Marquardt (LM) adaptive optimization technique [36]. The training data along with the testing data set which is statistically summarized in Table 1 were provided from previous soil investigation reports. The database includes results of soil test in different places of Basrah province (location map shown in Fig.4) and it was consists of 87 data sets. The input and output data sets had been normalized using the min-max method, which means that all the input and output data ranged between zeros to one. The MATLAB computer- helped software toolbox (2013) was applied for the process of neural network.

The input layer consisted of nine neurons, presenting the L.L., P.L., Sand%, Fines%, MC%, SO_3, TSS, Cl^-, and gypsum%..

Table 2 indicates the architecture and efficiency of different ANN models utilized in trial-and-error strategy. The coefficients of determination (R^2) values for the training, testing, and the overall data were employed to find out the efficiency of the network in the selected stage.

The optimal number of hidden-layers and neurons was decided by trial through the increasing of the number of neurons and checking the network performance. Number of nodes in the hidden-layer in each model, are determined after trying numerous network structures. It was unneeded to stop the process earlier and the total number of epochs was 5000, as there was clearly no significant decrease in the error's measured below this point. For each epoch, if the network's efficiency is decrease in the direction of the goal, subsequently the learning rate is enlarged through the factor-learning increment. But, if network's efficiency is increase, then the learning rate is modified by the factor-learning decrement. Thus, the ANN networks training are stopped after 5000 epochs. The tangent-hyperbolic functions were utilized in both hidden and output layers. The input and output data, were ranged between 0 and 1.0 prior to training. The coefficients of learning and momentum for the LM algorithm were 0.9 and 0.1, respectively.

The mean absolute errors (MAE), root mean square errors (RMSE), and correlation coefficient (R) statistics were used to assess the ANN model statistically. It was found that the first model which includes only one hidden layer carries out as the best model (see Table 2). As shown in Figs.5-7, the R^2 values of the first model recommend that the prediction efficiency of this model is better than the other two models. Therefore, the first model was selected as an optimum network for the ANN.

Table 2 the architecture and efficiency of ANN models

Model	Hidden Layers	Training phase			Testing phase		
		MMSE	MAE	R^2	MMSE	MAE	R^2
M1	1	**0.0007**	0.0206	**0.9860**	**0.0013**	0.0264	**0.9915**
M2	2	0.0014	0.0254	0.9728	0.0021	0.0340	0.9839
M3	3	0.0011	0.0258	0.9774	0.0032	0.0396	0.9688

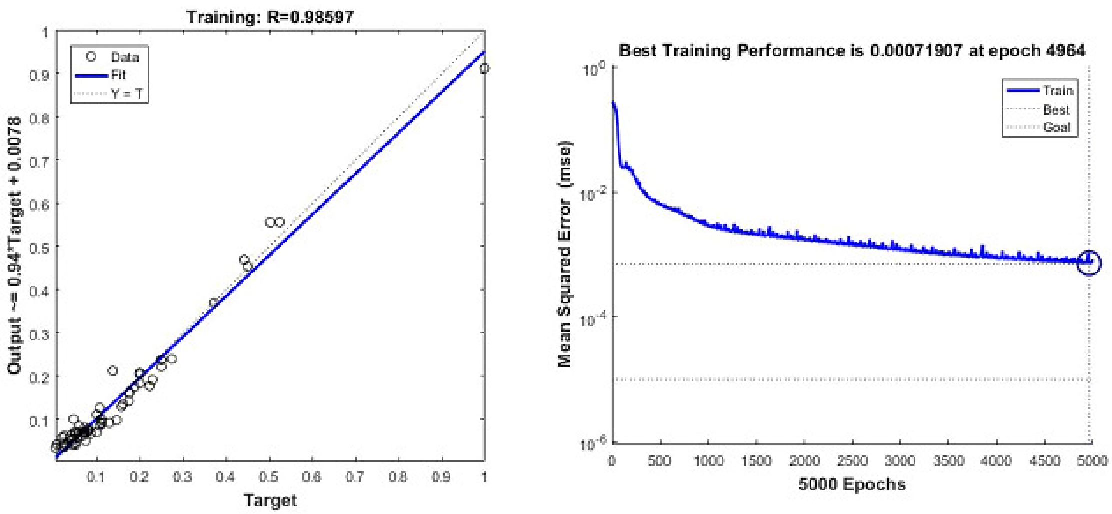

Figure 5 predicted versus measured bearing capacity, in training of M1 model

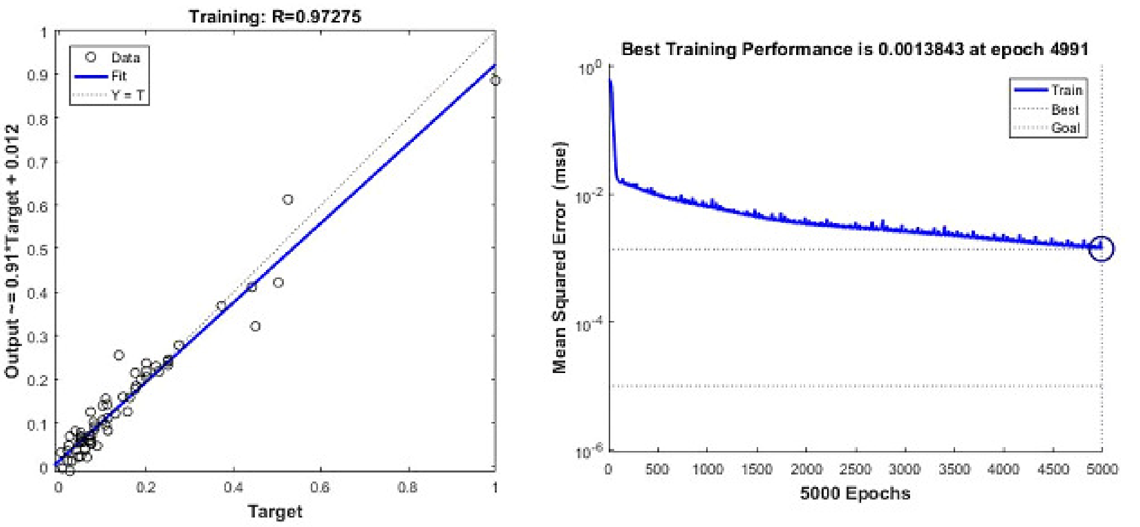

Figure 6 predicted versus measured bearing capacity, in training M2 model

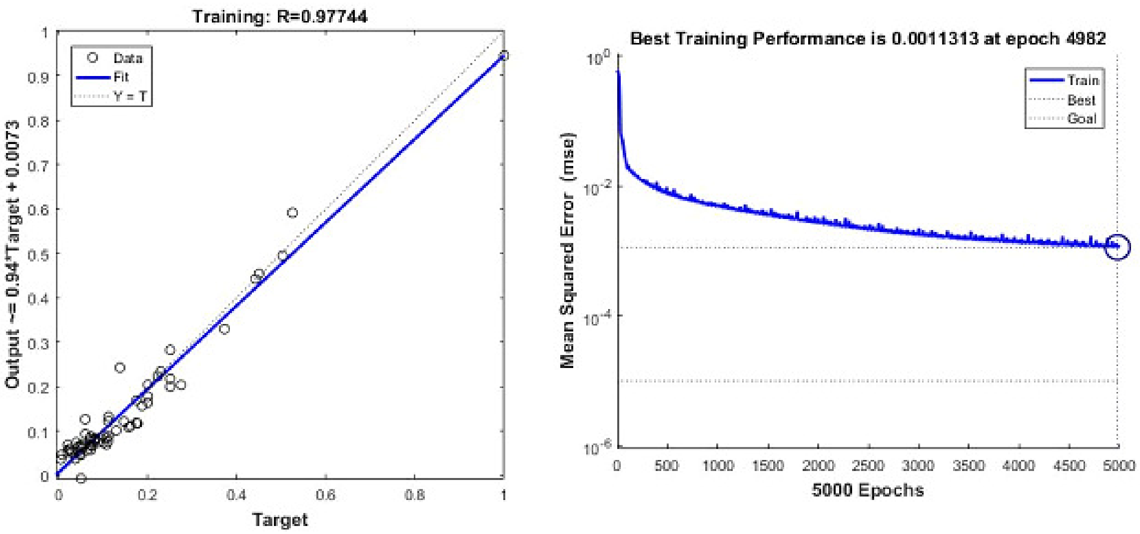

Figure 7 predicted versus measured bearing capacity, in training of M3 model

The prediction efficiency of the proposed ANN model with respect to smaller error is also displayed in Figs.5-7. The coefficient of determination (R^2) value for the first model (M1) was equaled to 0.9915 (in testing) and 0.9860 (in training), shows a strong regression and robust-relationship amongst the predicted and measured bearing capacity. It is shown in Table 2 (bold font). According to these results, the NN model produces useful predictions for bearing capacity.

However, it is found that the following multivariate correlation suggests the best fitting statistical measure for the database given in Table 1. Details of the statistical information of the conducted MLR analysis are given in Table 3. The general equation which is calculated from MLR model is shown below with the coefficient of determination (R^2) is equal to 0.147. The analysis of variance details is shown in Table 4.

Table 3 Details of the statistical information of the MLR predictive model

Independent variables	Coefficient	Standard Error	T Sat	P-value
Constant	467.3	717.0	0.65	0.516
C1: L.L.	0.1886	0.1168	1.62	0.110
C2: P.L.	-0.0032	0.1173	-0.03	0.979
C3: Sand (%)	-4.690	7.169	-0.65	0.515
C4: Fines (%)	-4.670	7.171	-0.65	0.517
C5: O.M.C. (%)	-2.1066	0.8250	-2.55	0.013
C6: SO_3 (%)	-0.898	5.446	-0.16	0.869
C7: TSS (%)	0.2496	0.4053	0.62	0.540
C8: Cl^{-1} (mg/L)	0.7525	0.3605	2.09	0.040
C9: Gypsum (%)	0.449	2.506	0.18	0.858

Bearing capacity = 467 + 0.189 C1 - 0.003 C2 - 4.69 C3 - 4.67 C4 - 2.11 C5 - 0.90 C6 + 0.250 C7 + 0.753 C8 + 0.45 C9

Table 4 Analysis of variance of the MLR predictive model

Source	DF	SS	MS	F-value	P-value
Regression	9	128.237	14.249	1.47	0.175
Residual Error	77	746.716	9.698		
Total	86	874.953			

To own a significantly better comprehension towards the prediction-force of the ANN model, the ANN performance is compared with the MLR analysis model. It can be noticed from the comparison that the MLR model works poorly in the predicting the bearing capacity. Finally, an assessment comparison shows the superiority of the ANN model that proposed in forecasting of the bearing capacity.

8. CONCLUSION

In the existing study, a neural network using the Levenberg–Marquardt training method was applied to forecast the bearing capacity in some cohesionless soils. The database utilized to create the ANN-based predictive model, was predicated on 87 recorded cases gathered from soil investigation reports. Various architecture for network had been trained and tested to find the best network-architecture.

It is noticed that in this study, three ANN model were proposed for the purpose of bearing capacity production. The first model (M1) was very close to experimental results. The network that proposed with only one hidden layer works better than the other models; thus, the first proposed model was chosen as the optimum ANN model. The coefficient of determination (R^2) was used as an evaluated-tool for the prediction-performance of the network. The coefficient of determination (R^2) for the first model (M1) is equals to 0.9915 implies that the predicted bearing capacity by M1 model is in close agreement with the calculated bearing capacity. Comparison involving the prediction performance of ANN models and MLR model shows the superiority of ANN model in solving the problems of the bearing capacity.

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