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PREDICTION OF UNCONFINED COMPRESSIVE STRENGTH OF TREATED EXPANSIVE CLAY USING BACK-PROPAGATION ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The multilayer perceptrons (MLPs) artificial neural networks (ANNs) that are trained with feed forward back-propagation algorithm was used in this study for the simulation of unconfined compressive strength (UCS) of cement kiln dust-treated expansive clay. Artificial neural networks (ANNs) are yet to be efficiently extended to soil stabilization aspect of geotechnical engineering. As such, this study aimed at applying the ANNs as a soft computing approach to predict the UCS values of Nigerian expansive clay. For each of the three ANN model development, eight inputs and one output data set were used. The mean squared error (MSE) and R-value were used as yardstick and criteria for acceptability of performance. In the neural network development, NN 8-11-1 that gave the lowest MSE value and the highest R-value were used for all the three outputs in the hidden layer of the networks architecture which performed satisfactorily. For the normalized data set used in training, testing and validating the neural network, the performance of the simulated network was satisfactory having R values of 0.9812, 0.9783 and 0.9942 for the 7, 14 and 28 days cured UCS respectively. These values met the minimum criteria of 0.8 conventionally recommended for strong correlation condition. All the obtained simulation results are satisfactory and a strong correlation was observed between the experimental UCS values as obtained by laboratory test procedures and the predicted values using ANN.

Keywords: *Artificial neural networks, cement kiln dust, expansive clay, multilayer perceptrons, soil treatment, unconfined compressive strength.*

INTRODUCTION

Unconfined compressive strength (UCS) test is used to obtain the shear strength parameters of cohesive (fine grained) soils either in undisturbed or remoulded state. The test is not applicable to cohesionless or coarse grained soils. The results of UCS test provide an estimate of the relative consistency of the soil. UCS is used in all geotechnical engineering designs (e.g. road pavements, foundations, retaining walls, slopes and embankments) to obtain a rough estimate of the soil strength and viable construction techniques (Salahudeen *et al*., 2014). It is also used to determine the undrained shear strength or undrained cohesion of fine grained soils. UCS is strain controlled and when the soil sample is loaded rapidly, the pore pressures undergo changes that do not have enough time to dissipate. Hence, the test is representative of soils in construction sites where the rate of construction is very fast and the pore waters do not have enough time to dissipate.

The conventional method of soil modification for flexible pavements constructed on soft soil consists of providing a stiffer load bearing base over the soft subgrade. The required thickness of the base is determined from the unconfined compressive strength (UCS) and/or CBR of the subgrade. For very soft to soft subgrade like that of black clays used in this study, the required base thickness often becomes high. In such situation the use of chemical modification/stabilization can result in substantial reduction of base thickness. This improves the performance of the geotechnical structure by preventing loss of base material into subgrade (Khan *et al*., 2016). Cement kiln dust (CKD) was used in this study to treat expansive clay. CKD is the fine grained, solid highly alkaline waste removed from cement kiln exhaust gas by air pollution control devices. The physical and chemical properties of CKD can vary from plant-to-plant, depending on the raw materials used and type of collection process in the plant (Rahman *et al.,* 2011).

The study aimed at using the soil properties to develop an optimized neural network for the 7, 14 and 28 days cured UCS of natural and CKD-treated expansive clay using multi-layer networks variety of learning technique of back-propagation in Artificial Neural Networks (ANNs). Artificial Neural Networks (ANNs) is a form of artificial intelligence that in its architecture attempts to simulate the biological structure of the human brain and nervous system. In recent times, Artificial Neural Networks (ANNs) have been applied to many geotechnical engineering applications. Shahin *et al.* (2002) have used back-propagation neural networks to predict the settlement of shallow foundations on cohesionless soils. The predicted settlements found by utilizing ANNs were compared with the values predicted by three commonly used deterministic methods. The results indicated that ANNs are a promising method for predicting settlement of shallow foundations on cohesionless soils, as they perform better than the conventional methods that are empirical based. Kolay *et al*. (2008) made use of ANN programming in predicting the compressibility characteristics of soft soil settlement in Sarawak, Malaysia. Benali *et al*. (2013) used ANNs for principal component analysis and prediction of the pile capacity based on SPT results. ANNs was used by Salahudeen *et al*. (2018) to predict the optimum moisture content and maximum dry density of Nigerian black cotton soil. All these literature are source of hope for the beneficial use of ANNs in geotechnical applications.

Expansive clay is in the group of problem soils encountered by geotechnical engineers. The expansive clays used in this study are also known as black cotton soils or black clays which are confined to the semi-arid regions of tropical and temperate climatic zones and are abundant where the annual evaporation exceeds the precipitation (Warren and Kirby, 2004). Black clays occur in continuous stretches as superficial deposits and are typical of flat terrains with poor drainage. The absence of quartz in the clay mineralogy enhances the formation of fine-grained soil material, which is impermeable and waterlogged (Balogun, 1991). The mineralogy of this soil is dominated by the presence of montimorillonite which is characterized by large volume change from wet to dry seasons and vice versa. Deposits of black clay, which occupy an estimated area of 104 x 10^3 km^2 in North-east region of Nigeria, show a general pattern of cracks during the dry season of the year. Cracks measuring 70 mm wide and over 1m deep have been observed and may extend up to 3m or more in case of high deposit (Salahudeen *et al.*, 2019).

MATERIALS AND METHODS

Materials

The expansive clay samples used for this study were obtained from Dadinkowa, Gombe State, Nigeria. The Cement Kiln Dust (CKD) was obtained from Sokoto Cement Factory, Sokoto, Sokoto State, Nigeria and was added to the soil at 0, 2, 4, 6, 8 and 10% of the dry weight of the soil. The properties of the natural expansive clay soil are summarized in Table 1, while the oxide compositions of the soil and cement kiln dust used in the study are given in Table 2.

Table 1: Properties of the natural expansive clay soil

Property	Quantity
Percent passing BS No 200 sieve, %	73.6
Natural moisture content, %	210
Liquid limit, %	48.2
Plastic limit, %	27.2
Plasticity index, %	21.0
Linear shrinkage, %	16.9
Free swell, %	80.0
Specific gravity	2.33
AASHTO classification	A-7-6 (16)
USCS	CL
NBRRI classification	High swell potential
Maximum dry density, Mg/m^3	1.63
Optimum moisture content, %	18.0
Colour	Greyish black
Dominant clay mineral	Montmorillonite

Table 2: Oxide composition of natural expansive clay soil and cement kiln dust

Oxide (%)	Soil	CKD
CaO	3.58	44.28
SiO_2	49.00	7.23
Al_2O_3	15.10	1.90
Fe_2O_3	14.23	4.47
MgO	-	0.82
MnO	0.23	0.11
BaO	-	0.10
Ag_2O	2.17	-
SO_3	-	0.13
TiO_2	2.09	0.23
ZnO	-	0.01
LOI (1000^oC)	11.10	39.28

METHODS

Laboratory Tests

Laboratory tests were performed on the natural soil samples in accordance with BS 1377 (1990) and on the cement kiln dust treated expansive clay in accordance with BS 1924 (1990). The tests conducted include, particle size distribution, specific gravity, linear shrinkage, Atterberg limits, compaction characteristics test to determine the OMC and MDD and unconfined compressive strength (UCS) test cured for 7, 14 and 28 days. All tests were first carried out on the natural soil then on the CKD-treated soils in steps of 0, 2, 4, 6, 8 and 10% CKD content by dry weight of the soil. Standard laboratory procedures were used in this study to determine the properties of natural and CKD-treated expansive clay using three compactive energies. The three compactive energies used are the British Standard light (BSL), West African Standard (WAS) and the British Standard heavy (BSH) energies.

Artificial neural networks model development

The types of neural networks used in this study are multilayer perceptrons (MLPs) that are trained with the feed forward back-propagation algorithm. The typical MLP consists of a number of processing elements (neurons) that are arranged in layers: an input layer, an output layer, and two hidden layers. Each processing element in the specific layer is joined to the processing element of other layers via weighted connections. The input from each processing element in the previous layer is multiplied by an adjustable connection weight. This combined input then passes through a nonlinear transfer function (TANSIG function for layer one and PURELIN function for layer two) to produce the output of the processing element. The neurons uses the following transfer or activation function:

$$X = \sum_{i=1}^{n} x_i w_i \qquad Y = \begin{cases} +1, if\ X \geq \theta \\ -1, if\ X < \theta \end{cases} \tag{1}$$

The output of one processing element provides the input to the next processing elements. In this work, the ANN model was developed with flexible and useful software for this type of application; the MATLAB R2014. In this study, eight input and three outputs were used separately for the ANN model development. The input data are specific gravity (SG), linear shrinkage (LS), uniformity coefficient (C_u) coefficient of gradation (C_c), liquid limit (LL), plastic limit (PL), optimum moisture content (OMC) and maximum dry density (MDD). The outputs (targets) data are the 7, 14 and 28 days cured unconfined compressive strength (UCS) values. The multilayer perceptron architecture of networks used for the ANN model development for the 7, 14 and 28 days cured unconfined compressive strength (UCS) are shown in Figures 1 - 3 respectively.

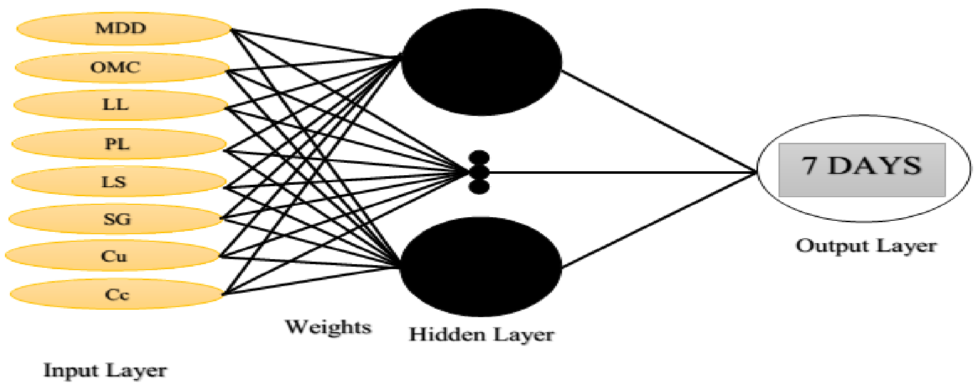


Figure 1: Multilayer perceptron architecture of ANN network for 7 days cured UCS

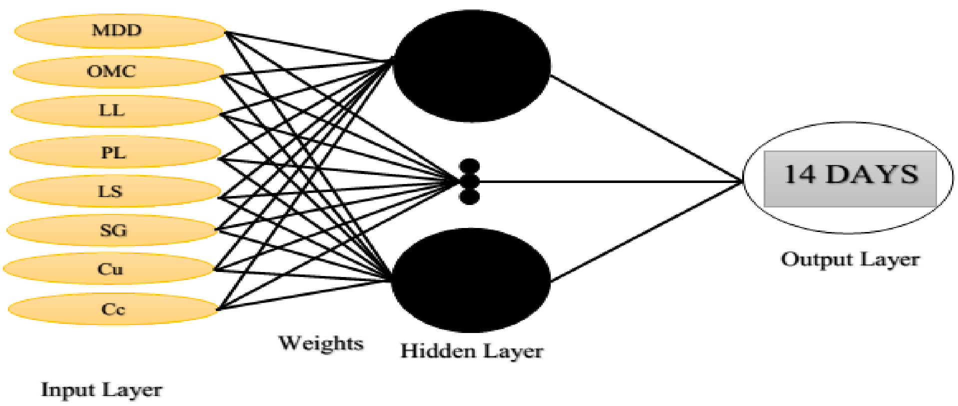


Figure 2: Multilayer perceptron architecture of ANN network for 14 days cured UCS

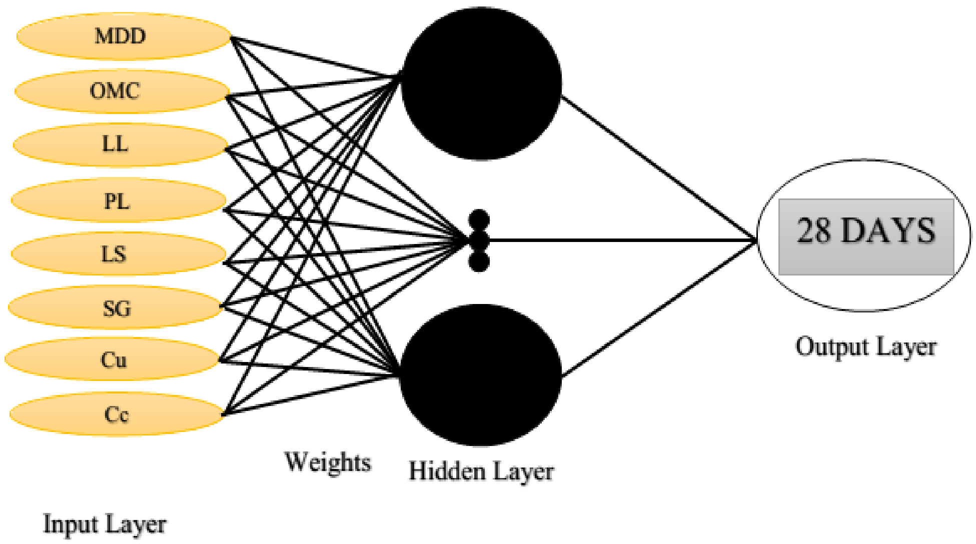


Figure 3: Multilayer perceptron architecture of ANN network for 28 days cured UCS

Data division and processing in artificial neural network

In developing the ANN model, the available data were divided into their subsets. In this work, the data were randomly divided into three sets: a training set for model calibration, a testing set and an independent validation set for model verification. In total, 70% of the total data set were used for model training, 15% were used for model testing and the remaining 15% were used for model validation. Once available data are divided into their subsets, the input and output variables were pre-processed, in this step the variables were normalized between -1.0 and 1.0.

Model performance evaluation

The performance of the developed ANNs model was evaluated to ensure that the model has the ability to generalize its performance within the limits set by the training data rather than been peculiar to the input - output relationships contained in the training data. The conventional approach is to test the model performance on an independent validation set of data that was not used in the training process. In the literature, the common measures often used are statistical measures which include the correlation coefficient (R), the mean absolute error (MAE) and the root mean square error (RMSE). The formulas used for these measures are:

$$R = \frac{\sum_{i=1}^{N}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2 \sum_{i=1}^{N}(P_i - \bar{P})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}} \quad (3)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - P_i| \quad (4)$$

where, N is the number of data points used for the model development; O_i and P_i are the observed and predicted outputs, respectively and $\bar{O}$ and $\bar{P}$ are the mean of observed and predicted outputs, respectively.

RESULTS AND DISCUSSIONS

Data Processing for ANN

In ANN prediction modelling, the efficiency of input data and their ability to accurately predict the output (target) is largely dependent on the relationship between the input and the output. In this study, eight input geotechnical soil parameters that have direct effects on the outputs were considered. In order to give a detailed insight of the general data used for the study, a frequency bar chart was used to present the research data of a total of 72 set as shown in Figures 4 - 14.

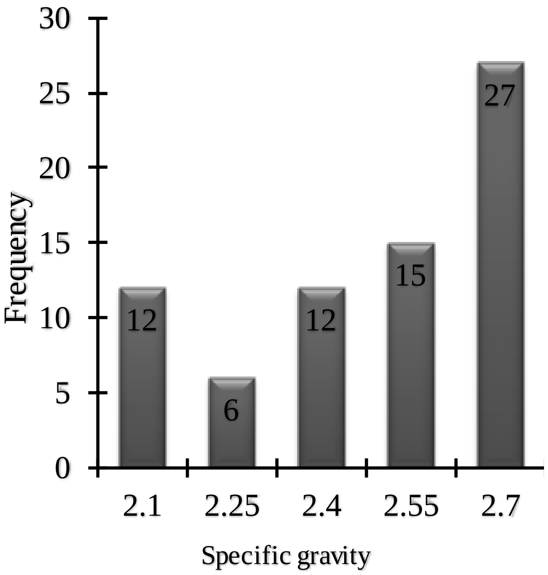


Figure 4: Frequency of SG

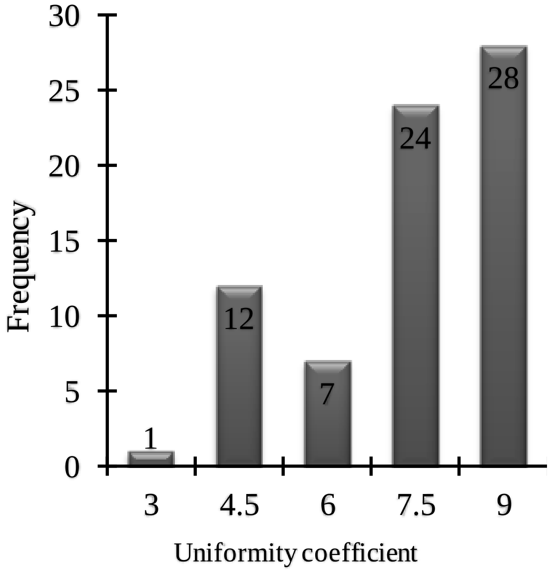


Figure 6: Frequency of C_u

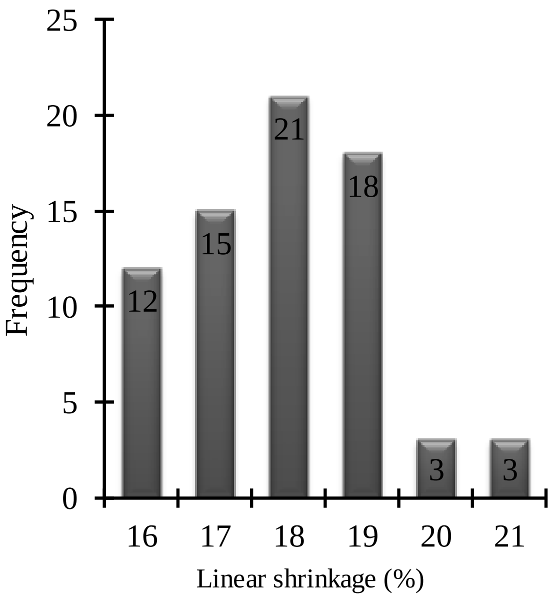


Figure 5: Frequency of LS

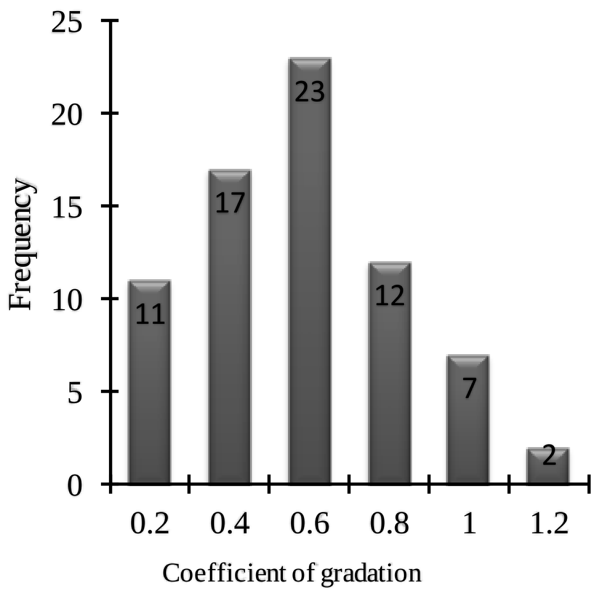


Figure 7: Frequency of C_c

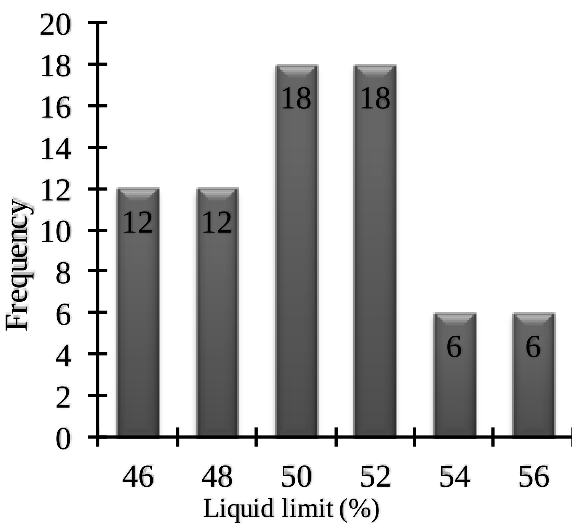


Figure 8: Frequency of LL

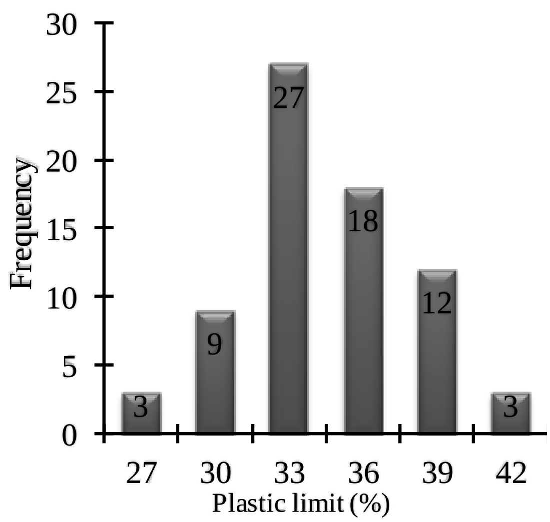


Figure 9: Frequency of PL

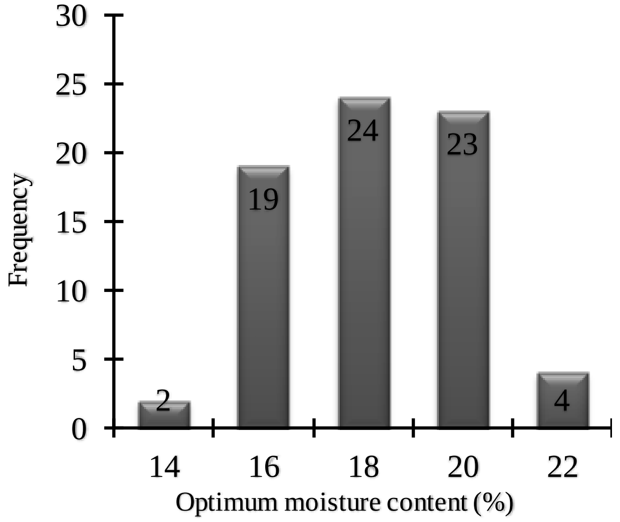


Figure 10: Frequency of OMC

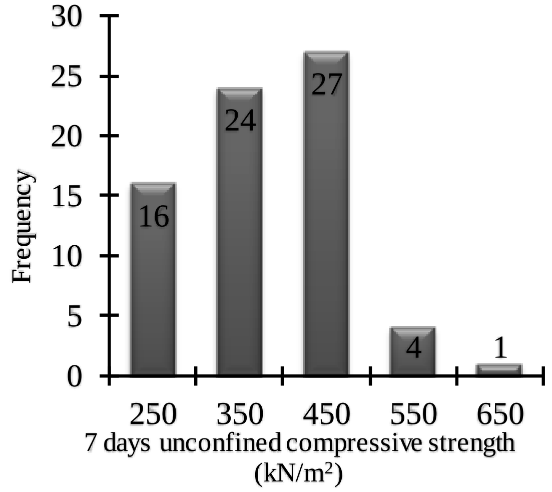


Figure 12: Frequency of 7 days UCS

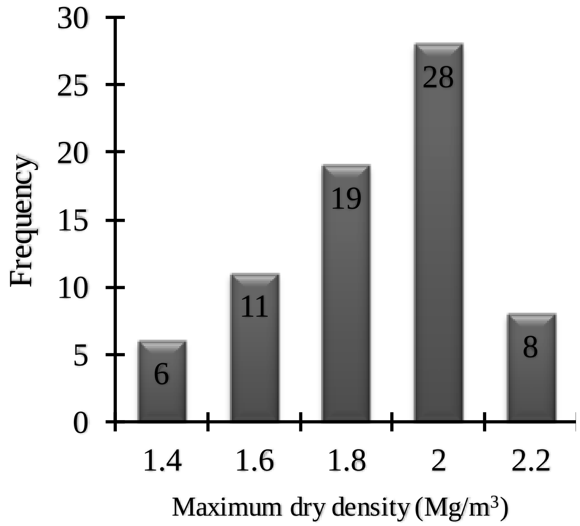


Figure 11: Frequency of MDD

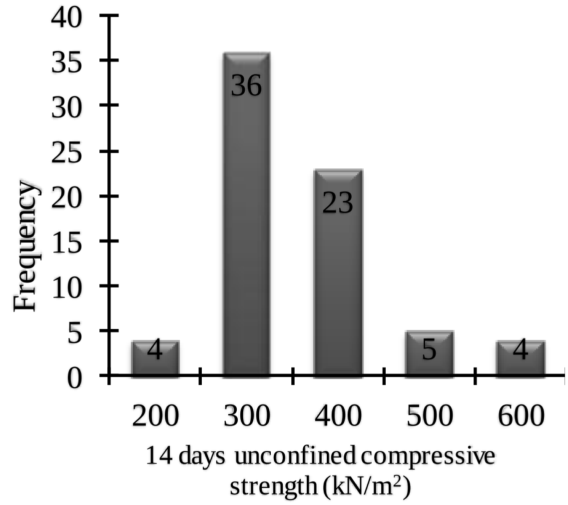


Figure 13: Frequency of 14 days UCS

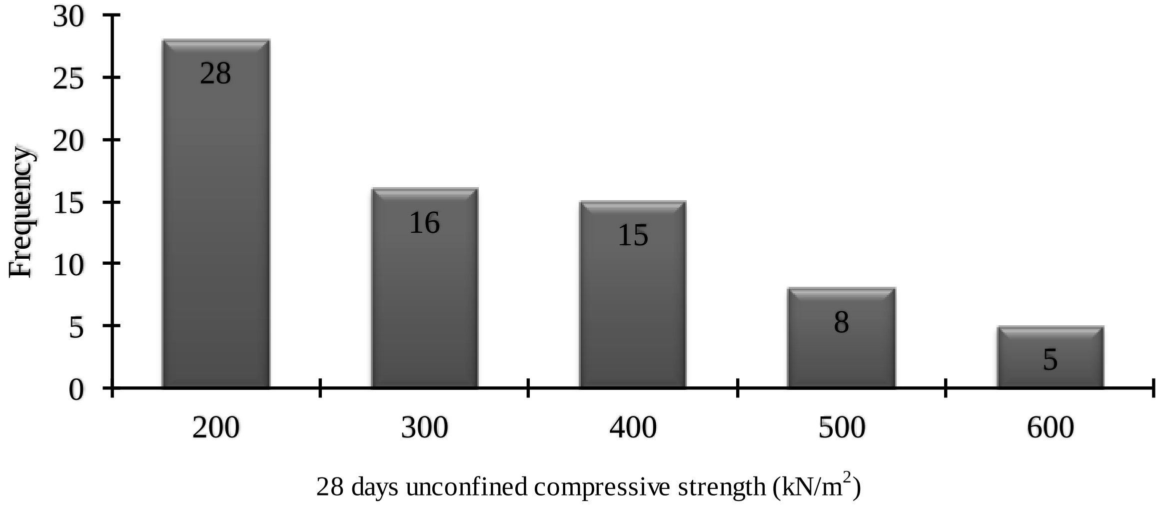


Figure 14: Frequency of 28 days UCS

Table 1: Descriptive statistics of experimental data used for ANN model development

Soil parameter	Minimum	Maximum	Mean	Standard deviation	Coefficient of variation
SG	2.03	2.63	2.403	0.207	0.086142
LS (%)	15.26	20.19	17.4	1.2612	0.072483
C_u	2.83	8.96	6.61	1.6201	0.245098
C_c	0.02	1.04	0.48	0.2489	0.518542
LL (%)	45.5	55.94	49.43	2.8494	0.057645
PL (%)	26.9	39.74	33.41	3.32	0.099371
OMC (%)	13.7	21.3	17.3	1.9195	0.110954
MDD (Mg/m^3)	1.325	2.111	1.75	0.214	0.122286
7 Days UCS (kN/m^2)	210.52	571.13	333.48	86.6079	0.259709
14 Days UCS (kN/m^2)	163.49	562.64	305.41	86.0751	0.281835
28 Days UCS (kN/m^2)	160.29	567.4	281	116.4093	0.414268

The descriptive statistics of the experimental data as obtained from various laboratory tests used for the ANN model development are presented in Table 1.

The optimized network

In this study, NN 8-n-1 network architecture was used for the network optimization. The first digit of the component is the number of input nodes, n is the number of hidden nodes (number of neurons) and the third digit is the number of output nodes. These NN 8-n-1 network architectures are shown in Figures 1 - 3. In this study, 15 different numbers of hidden nodes (NN 8-1-1 to NN 8-15-1) were tried in order to determine the best performing n-number. The mean squared error (MSE) and R-value were used as yardstick and criterions in this regard. The choice of 1 - 15 neurons was based on the study of Kolay *et al.* (2008) on tropical soft soil using ANN in which it was concluded that the use of neuron number above 10 could cause saturation of the network which results to lesser quality simulated results due to undesirable feedbacks to the network. This phenomenon may lead to network confusion that could result to lower accuracy in the simulated results. However, several other researches in the literature considered more than 10 numbers of neurons. Therefore, n=11 neurons that yielded the lowest MSE value and the highest R-value on the average were used in the hidden layers of the three sets of UCS prediction. Shahin *et al.* (2001), Shahin (2013) and Eidgahee *et al.* (2018) stated that the best measure for the performance of the ANN developed models should be based on the lowest MSE values and the highest R-values. However, other researchers like Naderpour *et al.* (2010) used only MSE values as criterion. The MSE and the R-values that led to the choice of NN 8-11-1 networks for all the 7, 14 and 28 days curing period UCS are shown in Figures 15 - 20. It should be noted that in situations whereby it is difficult to make a reliable choice of the neuron numbers based on the R-values, the MSE values takes preference to yield better results.

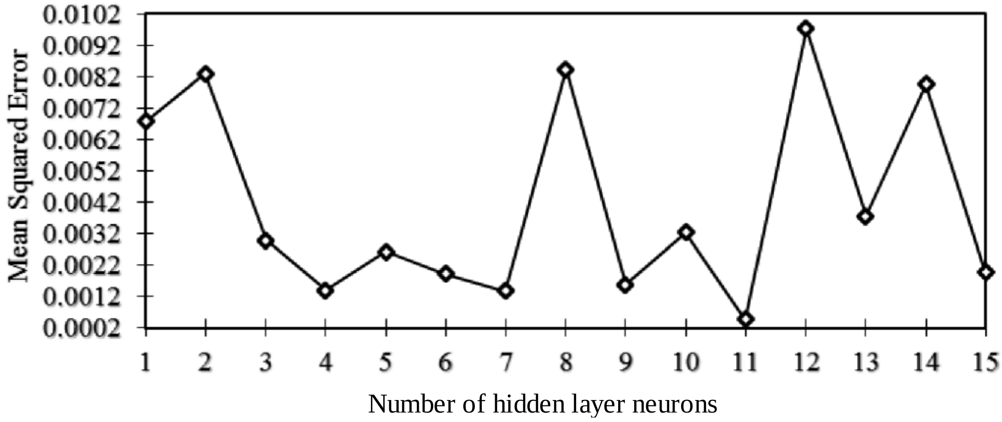


Figure 15: Variation of mean squared error with number of hidden layer neurons for 7 days cured UCS

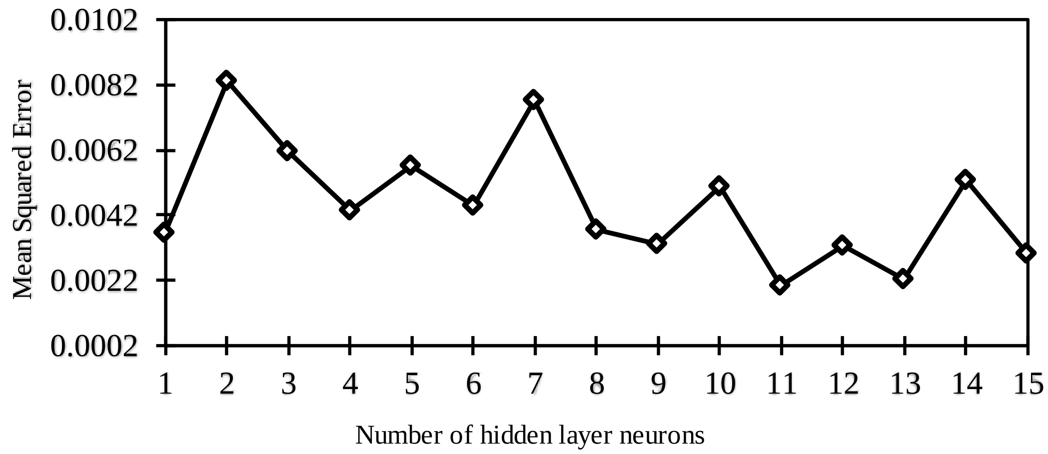


Figure 16: Variation of mean squared error with number of hidden layer neurons for 14 days cured UCS

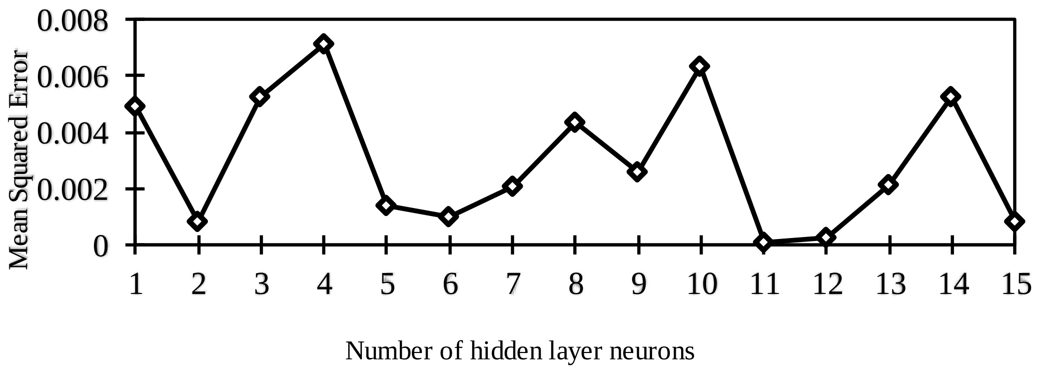


Figure 17: Variation of mean squared error with number of hidden layer neurons for 28 days cured UCS

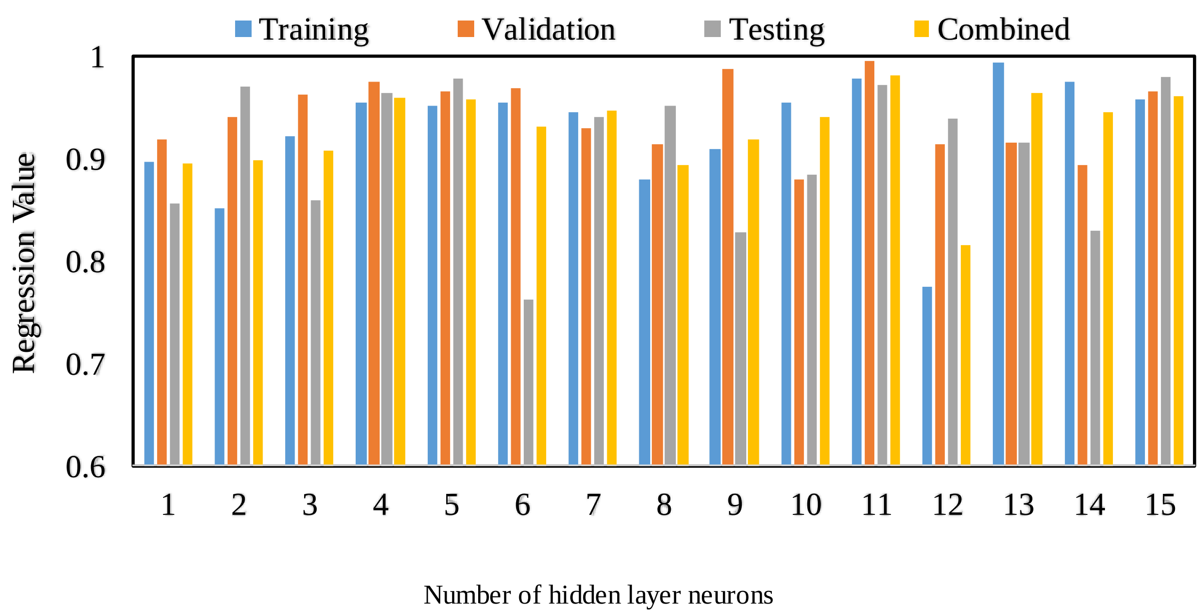


Figure 18: R-values for ANN performance with number of hidden layer neurons for 7 days cured UCS

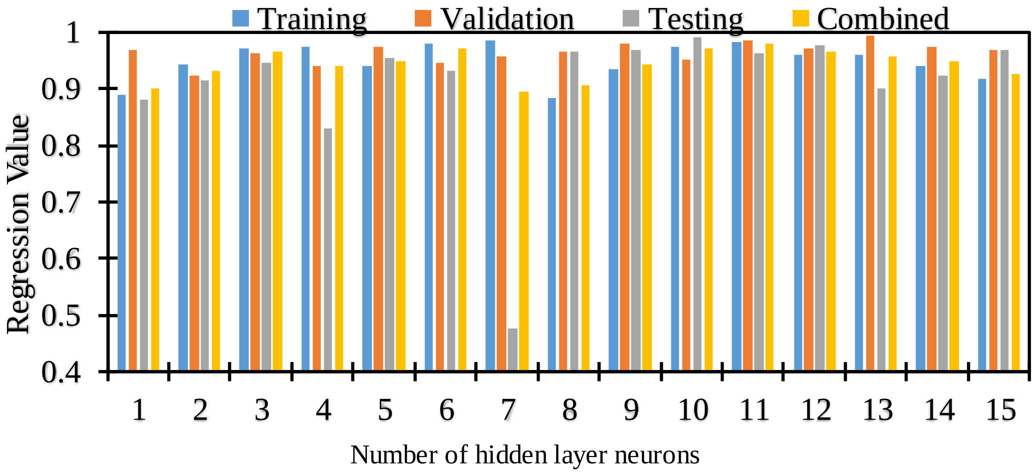


Figure 19: R-values for ANN performance with number of hidden layer neurons for 14 days cured UCS

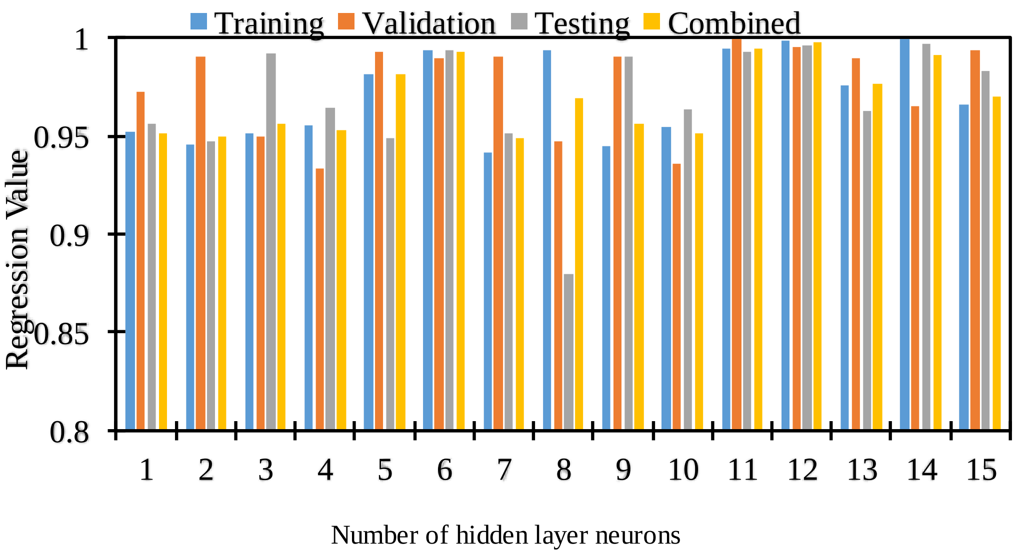


Figure 20: R-values for ANN performance with number of hidden layer neurons for 28 days cured UCS

ANN model development results

The regression values for model performance evaluation showing the k (slope), R-values, mean absolute error (MAE), mean squared error (MSE) and the root mean squared error (RMSE) are presented in Table 2. It is obvious from these statistical results that the models developed in this study performed satisfactorily having high R-values and low error values. The statistical parameters give acceptable results that confirmed the best generalization of the developed models.

Table 2: Parameters and regression values for model performance evaluations

Parameters	7 days UCS	14 days UCS	28 days UCS
Number of neurons	11	11	11
k	0.9629	0.9572	0.98
MSE (ANN)	0.000473	0.002056	0.000105
R-Training	0.9782	0.9824	0.9946
R-Validation	0.996	0.9843	0.9992
R-Testing	0.9711	0.9615	0.9929
R-All Data	0.9812	0.9783	0.9942
MAE	0.02	0.039	0.018
MSE (Statistical)	0.001797	0.002815	0.001686
RMSE	0.042	0.05306	0.04106

The variation of experimental and ANN predicted UCS values together with the error variations are shown in Figures 21 - 26. The performance of the simulated network was very good having k values of 0.9629, 0.9572 and 0.98 respectively for the 7, 14 and 28 days cured UCS. k is the slope of the regression line through the origin in the plot of the experimental values to the predicted values. It was reported by Alavi *et al.* (2011) and Golbraikh and Tropsha (2002) that the value of k should be close to unity as a criteria for excellent performance.

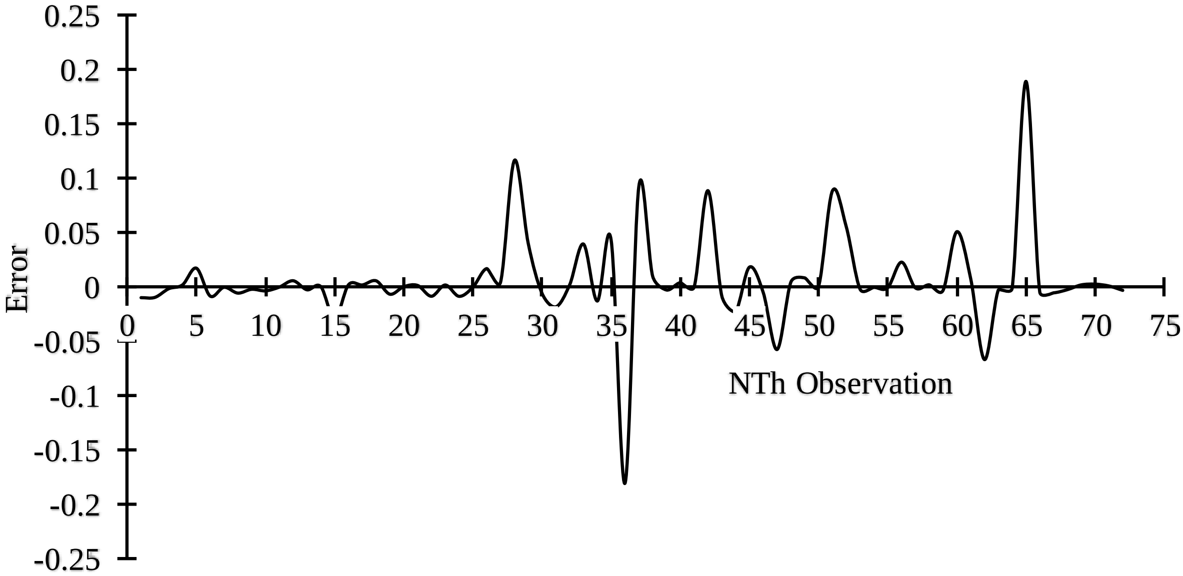
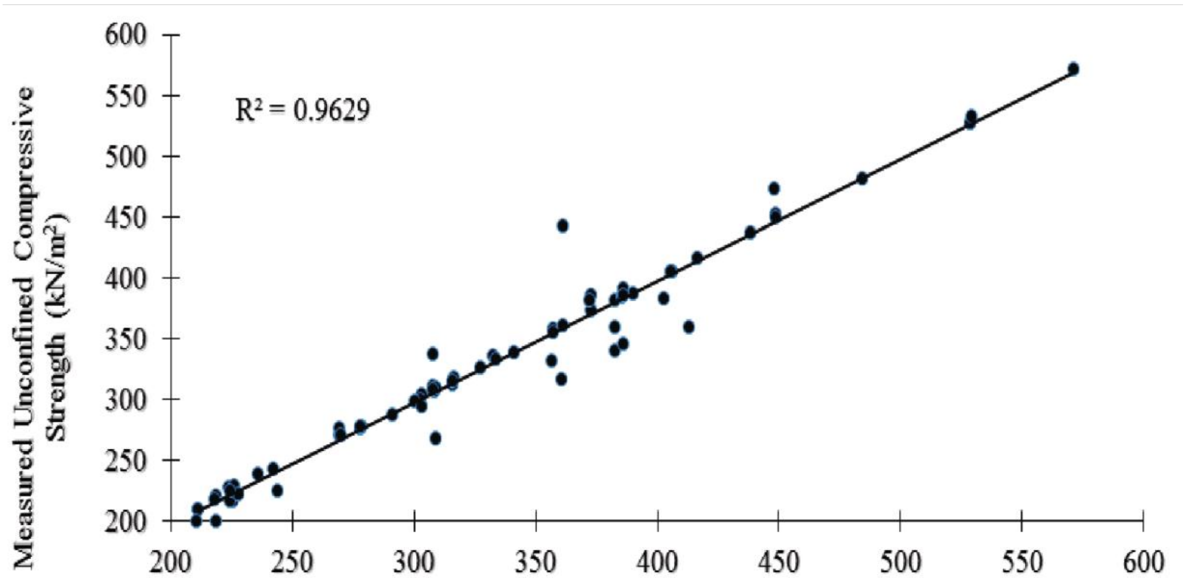


Figure 21: Variation of error values with data set for 7 days cured UCS



Predicted unconfined compressive strength (kN/m^2)

Figure 22: Variation of experimental and ANN predicted UCS values (7 days curing)

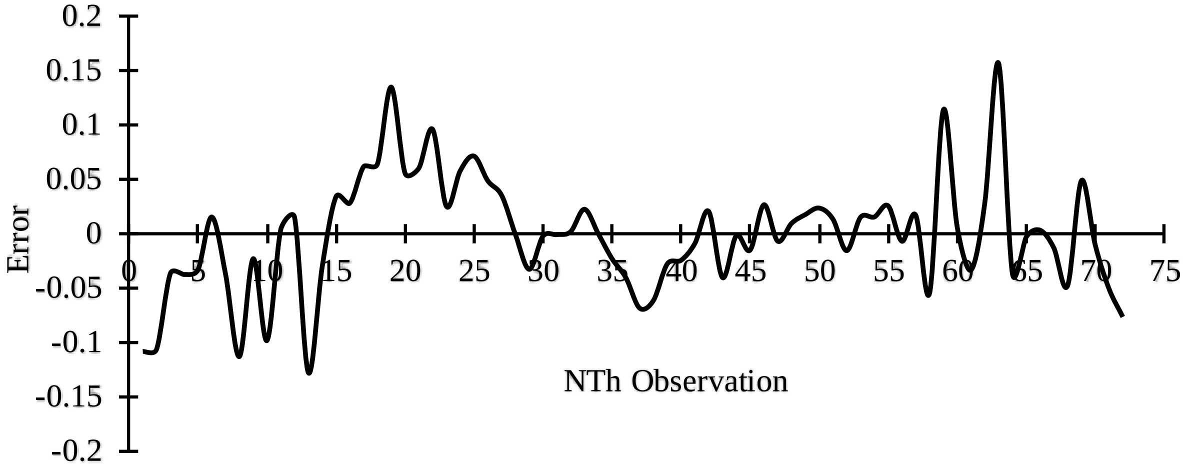


Figure 23: Variation of error values with data set for 14 days cured UCS

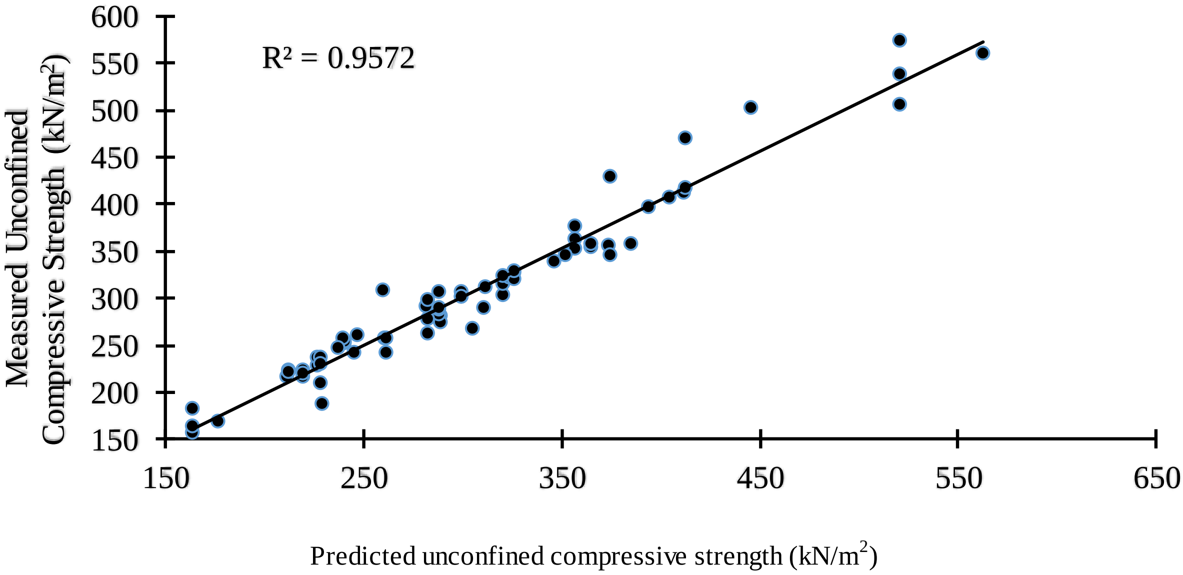


Figure 24: Variation of experimental and ANN predicted UCS values (14 days curing)

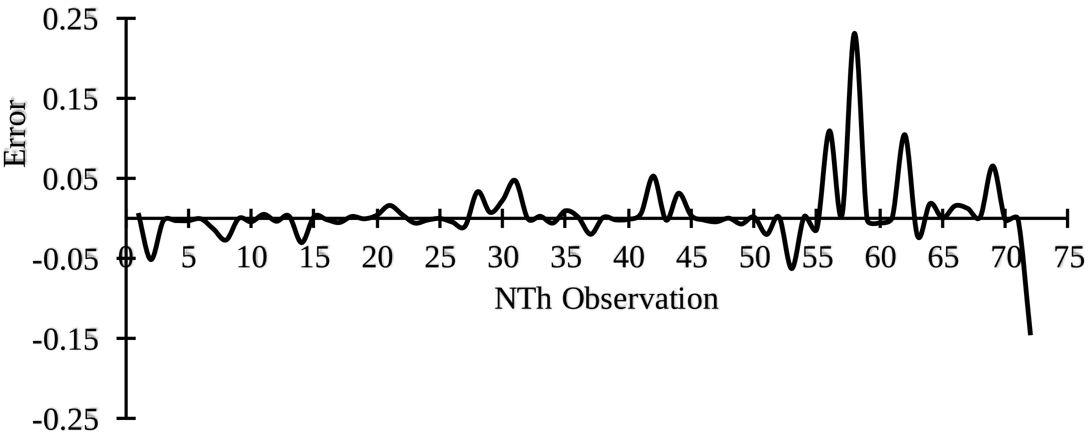


Figure 25: Variation of error values with data set for 28 days cured UCS

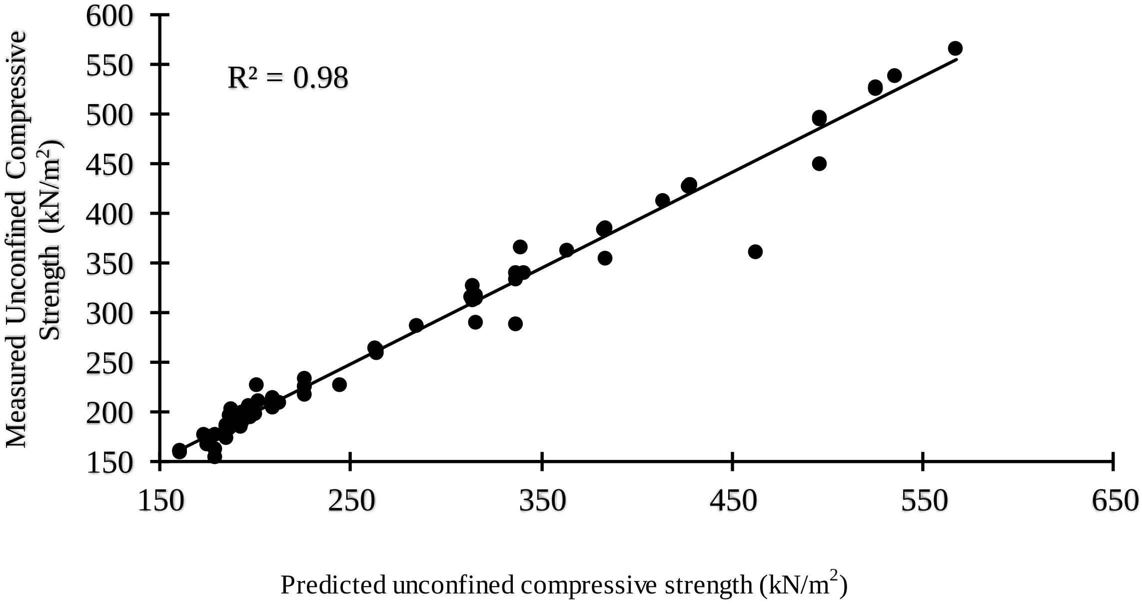


Figure 26: Variation of experimental and ANN predicted UCS values (28 days curing)

Model validation

The coefficient of correlation (R) is a measure used to evaluate the relative correlation and the goodness-of-fit between the predicted and the observed data. Smith (1986) suggested that a strong correlation exist between any two set of variables if the R value is greater than 0.8. However, Das and Sivakugan (2010) are of the opinion that the use of R value alone can be misleading arguing that higher values of R may not necessarily indicate better model performance due to the tendency of the model to deviate towards higher or lower values in a wide range data set.

The RMSE on the other hand is another measure of error in which large errors are given greater concern than smaller errors. However, Shahin (2013) argued that in contrast to the RMSE, MAE eliminates the emphasis given to larger errors and that both RMSE and MAE are desirable when the evaluated output data are continuous. Consequently, the combined use of R, RMSE and MAE in this study was found to yield a sufficient assessment of ANN model performance and allows comparison of the accuracy of generalization of the predicted ANN model performance. This combination is also sufficient to reveal any significant differences among the predicted and experimental data sets.

The conditions of model validity in this study are stated in Table 3. Based on the results of different NN 8-11-1 networks used in this study, it was observed that the errors are at their best performance when they are less than 0.01 but still yield good and acceptable performance when greater than 0.1 in a value range of 0 to 1.

Table 3: Conditions of model validity

Target	Statistical parameter	Condition	Obtained value	Remarks
7 days curing UCS	R	> 0.8	0.9812	Satisfactory
	k	Should be close to 1	0.9629	Satisfactory
	MAE	Should be close to 0	0.02	Good
	MSE	Should be close to 0	0.001797	Satisfactory
	RMSE	Should be close to 0	0.042	Good
14 days curing UCS	R	> 0.8	0.9783	Satisfactory
	k	Should be close to 1	0.9572	Satisfactory
	MAE	Should be close to 0	0.039	Good
	MSE	Should be close to 0	0.002815	Satisfactory
	RMSE	Should be close to 0	0.05306	Good
28 days curing UCS	R	> 0.8	0.9942	Satisfactory
	k	Should be close to 1	0.98	Satisfactory
	MAE	Should be close to 0	0.018	Good
	MSE	Should be close to 0	0.001686	Satisfactory
	RMSE	Should be close to 0	0.04106	Good

Based on the suggestion of Smith (1986), argument of Das and Sivakugan (2010), conclusions of Shahin (2013) and observations in this study, it is obvious from Table 3 that the developed models in this study performed satisfactorily and have good generalization potential. The achieved high R values and low values of errors are highly desirable in ANN simulation as they indicate acceptable results. A strong correlation was observed between the experimental UCS values as obtained by laboratory tests and the predicted values using ANN. Ahmadi *et al*. (2014) and Eidgahee *et al*. (2018) reported that strong correlation exist between the experimental and predicted values if the R-value is greater than 0.8 and the MSE values are at minimum. In a related study by Naderpour *et al*. (2010), R-values of 0.9346, 0.9686, 0.9442 and 0.944 were reported for training, testing validation and their combination which were concluded to be satisfactory and yielded good simulation results.

CONCLUSIONS

Artificial Neural Networks (ANNs) was used in this study to develop a predictive optimized models for Unconfined Compressive Strength (UCS) of a cement kiln dust-treated expansive clay. Based on the results of the developed ANN models, the following conclusions were made:

i. The multilayer perceptrons (MLPs) ANN used for the simulation of UCS of CKD-treated expansive clay that are trained with the feed forward back-propagation algorithm performed satisfactorily.

ii. The mean absolute error (MAE), root mean square error (RMSE) and R-value were used as yardstick and criteria. In the neural network development, NN 8-11-1 that gave the lowest MSE value and the highest R-value were used in the hidden layer of the networks architecture which performed satisfactorily.

iii. For the normalized data used in training, testing and validating the neural network, the performance of the simulated network was very good having R values of 0.9812, 0.9783 and 0.9942 for the 7, 14 and 28 days cured UCS respectively. These values met the minimum criteria of 0.8 conventionally recommended for strong correlation condition.

iv. All the obtained simulation results are satisfactory and a strong correlation was observed between the experimental UCS values as obtained by laboratory tests and the predicted values using ANN.

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