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CALIFORNIA BEARING RATIO PREDICTION OF MODIFIED BLACK CLAY USING ARTIFICIAL NEURAL NETWORKS

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Artificial neural networks (ANNs) is yet to be 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 CBR values of Nigerian black clay. A soft computing approach using multilayer perceptrons (MLPs) artificial neural networks (ANNs) that are trained with the feed forward back-propagation algorithm was used in this study for the simulation of soaked and unsoaked California bearing ratio (CBR) of cement kiln dust-modified black clay. Eight input and two output data set were used for the ANN model development. The input data are the 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 output (target) been the soaked and unsoaked CBR. The mean squared error (MSE) and R-value were used as yardstick and criterions for acceptability of performance. In the neural network development, NN 8-8-1 and NN 8-17-1 respectively for soaked and unsoaked CBR that gave the lowest MSE value and the highest R-value were used 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 0.9986 and 0.991 for the soaked and unsoaked CBR 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 soaked and unsoaked CBR values as obtained by laboratory test procedures and the predicted values using ANN.

Keywords: artificial neural networks; California bearing ratio; black clay; soil modification; cement kiln dust

INTRODUCTION

The California bearing ratio (CBR) test is one of the most common strength tests conducted to evaluate subgrade quality of soils and the suitability of soils for sub-base and base courses in flexible pavements. The CBR test was devised in 1929 in an attempt to eliminate some of the deficiencies of field loading tests and to provide a quick method for comparing local base and sub-base materials available

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for reinforcing the subgrade (Franco and Lee, 2012). CBR is the ratio of force per unit area required to penetrate in to a soil mass with a circular plunger of 50mm diameter at the rate of 1.25mm per minute. CBR is an indirect measure of shearing resistance of the soil material under controlled density and moisture conditions. The CBR method of design is purely empirical and has several limitations (Yashas et al., 2016). The CBR test is essentially a laboratory test but in some instances the test is carried out on the soil in-situ.

A traditional method of soil modification for flexible pavements 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 in-situ shear strength and/or CBR of the subgrade (Salahudeen et al., 2014). 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 foundation or pavement by preventing loss of base material into subgrade (Khan et al., 2016). Cement kiln dust (CKD) was used in this study to modify black 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).

In this study, standard laboratory procedures were used to determine the properties of natural and CKD-treated black clay using three compactive energies. The study aimed at using the soil properties to develop an optimized neural network for the soaked and unsoaked CBR of natural and CKD-modified black clay using multi-layer networks variety of learning technique of back-propagation in Artificial Neural Networks (ANNs). Artificial Neural Networks (ANNs), which is a form of artificial intelligence that in its architecture attempts to simulate the biological structure of the human brain and nervous system was used in this study.

Black clay is an expansive soil that is so named because of its colour. Black clays 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 103 km2 in North-east region of Nigeria, show a general pattern of cracks during the dry season of the year. Cracks measuring 70mm wide and over 1m deep have been observed and may extend up to 3m or more in case of high deposit (Adeniji, 1991).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. 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 predicting 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 literatures are source of hope for the beneficial use of ANNs in geotechnical applications.

Artificial neural networks (ANNs) are the most widely used pattern recognition procedures. These black-box models have the ability to operate on large quantities of data and learn complex model functions from examples, i.e., by training on sets of input and corresponding output data. The employed philosophy for model generation is similar to the one used for developing conventional statistical models. However, the greatest advantage of ANNs over traditional modelling techniques is their ability to capture nonlinear and complex interactions between variables of a system without having to assume the form of the relationship between input and output variables. Despite the use of geotechnical data for ANNs predictions, similar data set to those used herein have not been reported in the literatures, most especially in relation to CBR. This is a knowledge gap discussed in this study. Therefore, this study is aimed at applying the ANNs to predict the CBR values of Nigerian black clay modified with CKD using multilayer perceptrons (MLPs) artificial neural networks (ANNs) that are trained with the feed forward back-propagation algorithm based on eight input and two output data set in MATLAB R2014.

MATERIALS AND METHODS

Materials

The black clay samples used for this study was obtained from Dadinkowa, Gombe State, Nigeria. The Cement Kiln Dust (CKD) was obtained from Sokoto Cement Factory, Sokoto, the capital of Sokoto State, Nigeria.

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 black 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 California bearing ratio test. All tests were first carried out on the natural soil then on the CKD-modified soils in steps of 0, 2, 4, 6, 8 and 10% CKD content by dry weight of the soil. Three compactive energies used in this study 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 two outputs were used separately for the ANN model development. The input data are specific gravity (SG), linear shrinkage (LS), uniformity coefficient (Cu) coefficient of gradation (Cc), liquid limit (LL), plastic limit (PL), optimum moisture content (OMC) and maximum dry density (MDD) with the outputs (targets) been the soaked and unsoaked CBR. Multilayer perceptron architecture of networks used for the ANN model development for soaked and unsoaked CBR are shown in Figures 1 and 2 respectively.

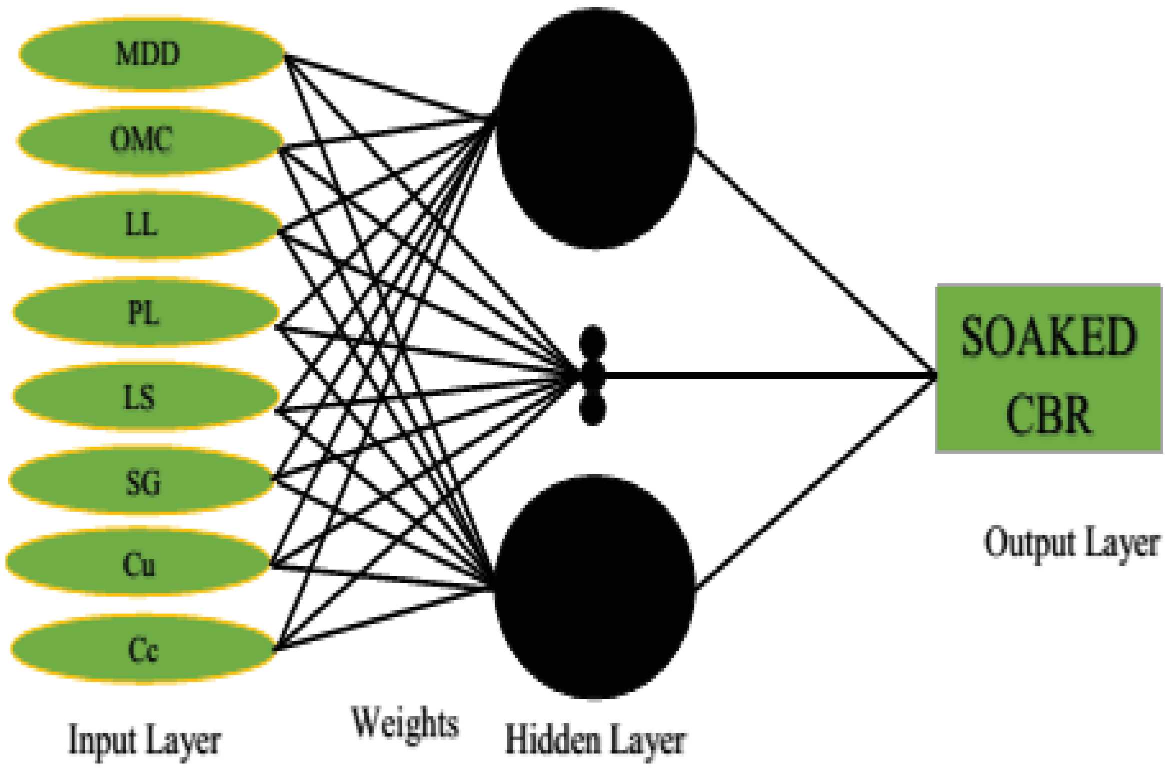

Figure 1: Multilayer perceptron architecture of network used for ANN model development for soaked CBR

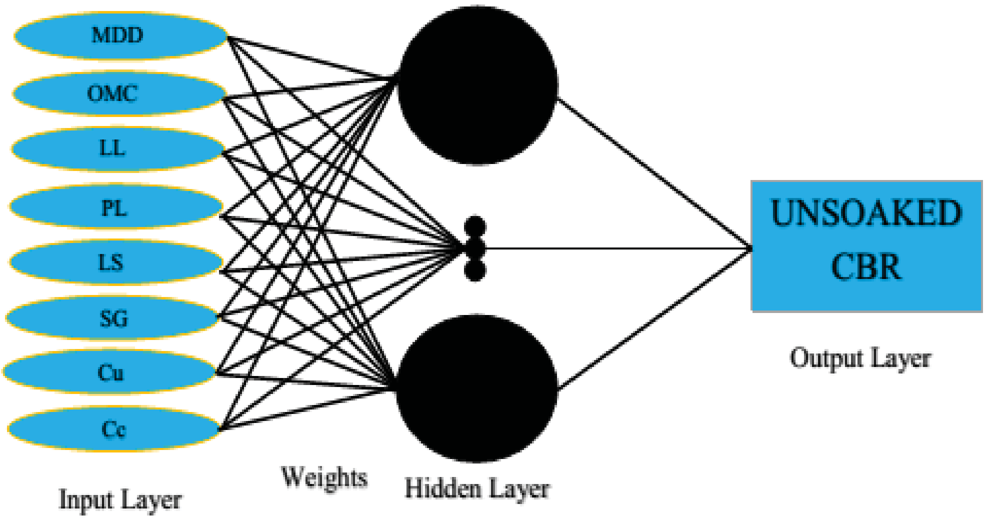

Figure 2: Multilayer perceptron architecture of network used for ANN model development for unsoaked CBR

Data Division and Processing in Artificial Neural Network

In developing the ANN model, the available data (a total of 72 data set) 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 literatures, 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:

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

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

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

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 two 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 3 – 12.

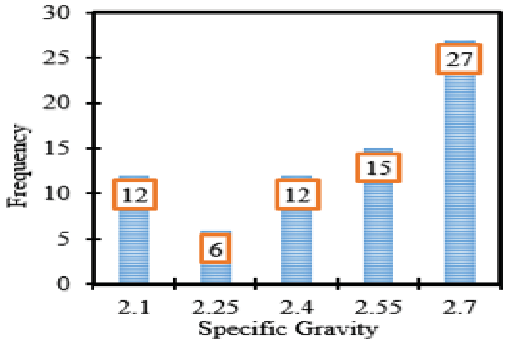

Figure 3: Frequency of SG

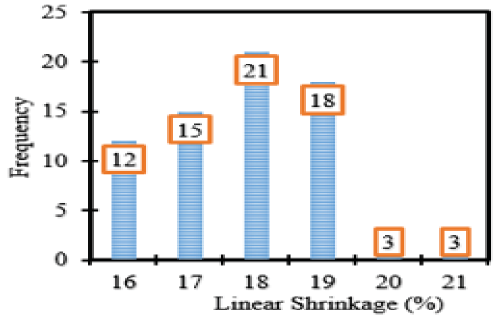

Figure 4: Frequency of LS

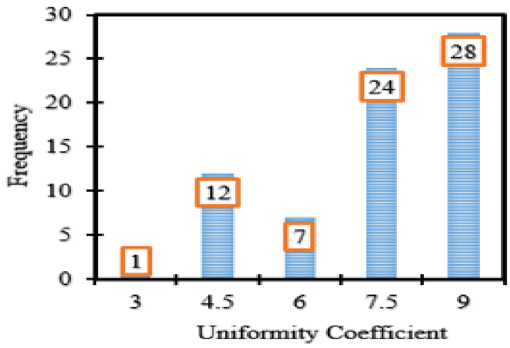

Figure 5: Frequency of C_u

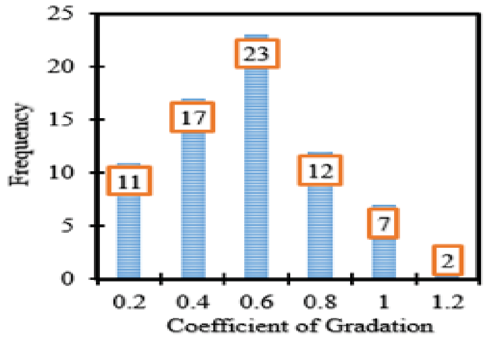

Figure 6: Frequency of C_c

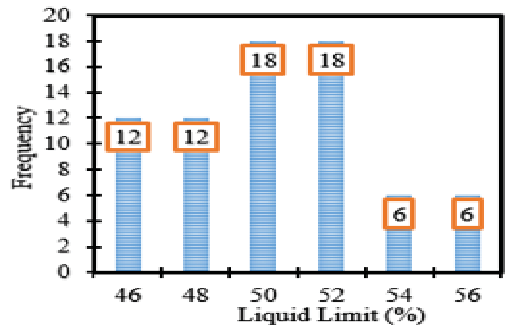

Figure 7: Frequency of LL

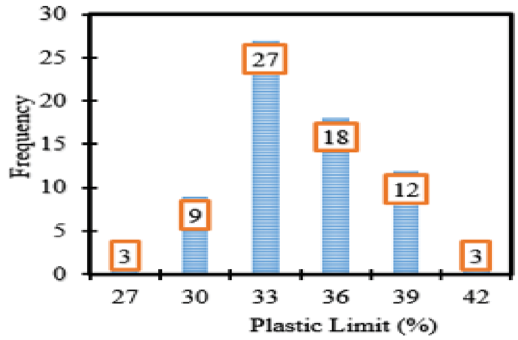

Figure 8: Frequency of PL

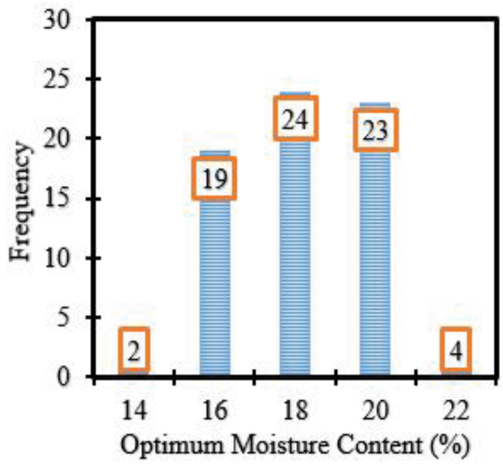

Figure 9: Frequency of OMC

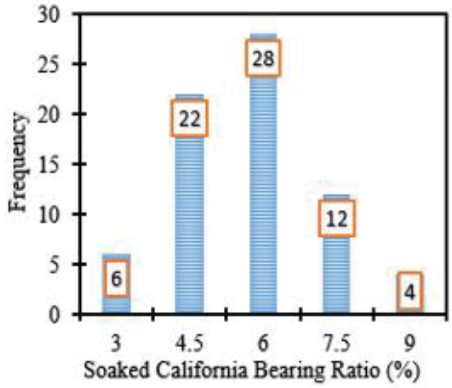

Figure 11: Frequency of soaked CBR

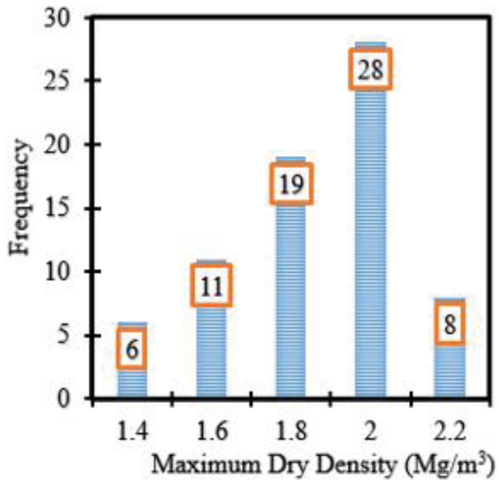

Figure 10: Frequency of MDD

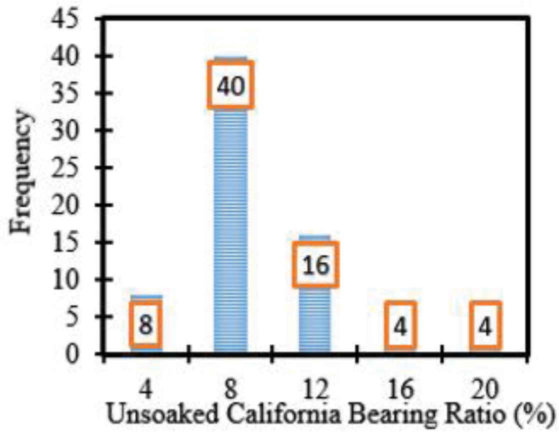

Figure 12: Frequency of unsoaked CBR

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

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
Soaked CBR (%)	2.5	8.4	4.94	1.4642	0.296397
Unsoaked CBR (%)	3.36	19.2	7.71	3.9585	0.513424

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 and 2. In this study, 20 different number of hidden nodes (NN 8-1-1 to NN 8-20-1) 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 – 20 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 up to 20 number of neurons. Therefore, 8 and 17 neurons for soaked and unsoaked CBR respectively that yielded the lowest MSE value and the highest R-value on the average were used in the hidden layers. 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 10-8-1 and NN 10-17-1 networks respectively for the soaked and unsoaked CBR are shown in Figures 13 - 16. 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.

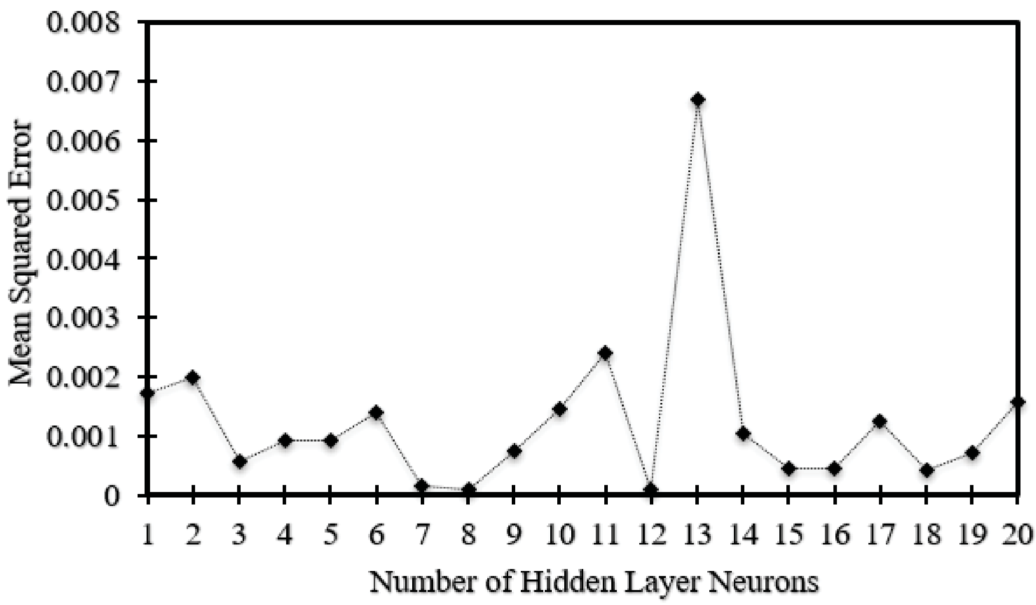

Figure 13: Variation of mean squared error with number of hidden layer neurons for soaked CBR

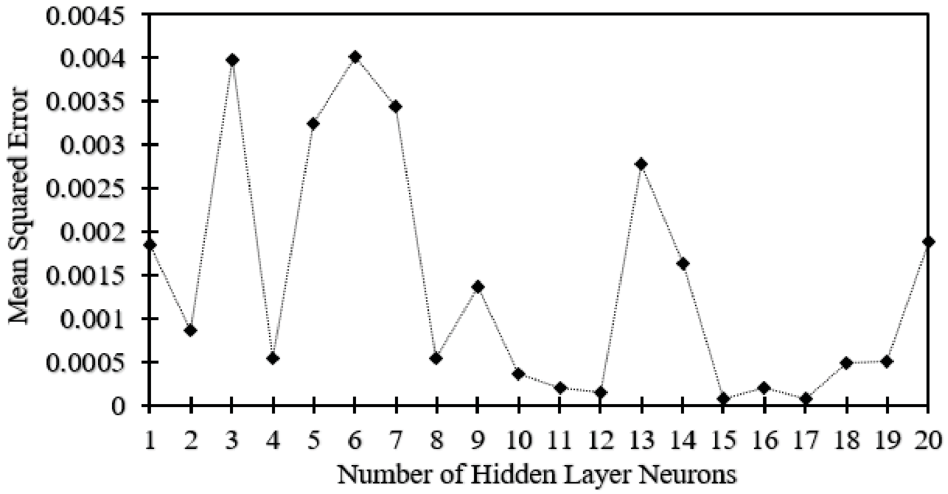

Figure 14: Variation of mean squared error with number of hidden layer neurons for unsoaked CBR

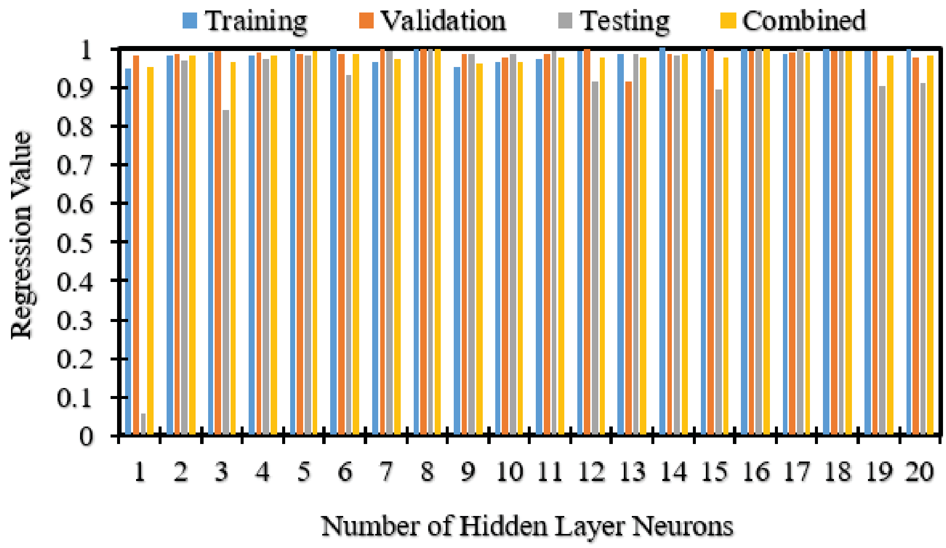

Figure 15: R-values for ANN performance with number of hidden layer neurons for soaked CBR

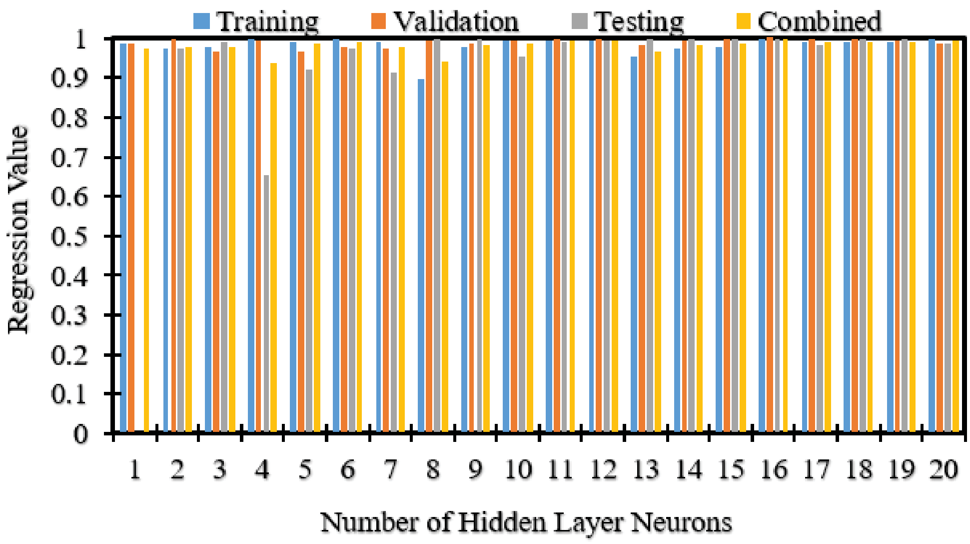

Figure 16: R-values for ANN performance with number of hidden layer neurons for unsoaked CBR

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 gives acceptable results that confirmed the best generalization of the developed models.

The variation of experimental and ANN predicted soaked and unsoaked CBR values together with the error variations are shown in Figures 17 - 20. The performance of the simulated network was very good having k values of 0.9973 for the soaked CBR and 0.9811 for the unsoaked CBR, where 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.

Table 2: Parameters and regression values for model performance evaluations

Parameters	Soaked CBR	Unsoaked CBR
Number of Neurons	8	17
k	0.9973	0.9811
MSE (ANN)	0.0000793	0.0000791
R-Training	0.9988	0.9912
R-Testing	0.9976	0.9806
R-Validation	0.9996	0.9993
R-Combined Data	0.9986	0.991
MAE	0.008	0.012
MSE (Statistical)	0.00013	0.00109
RMSE	0.00013	0.03298

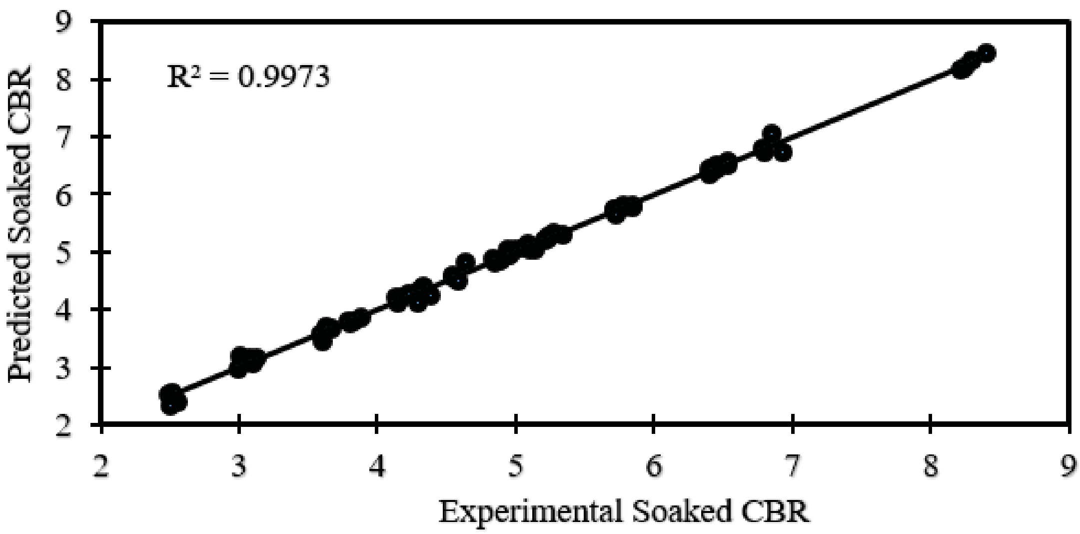

Figure 17: Variation of experimental and ANN predicted soaked CBR values

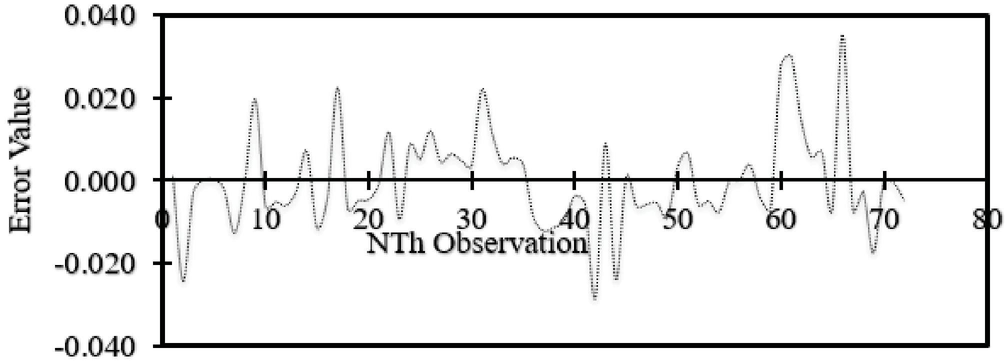

Figure 18: Variation of error values with number of observation for soaked CBR

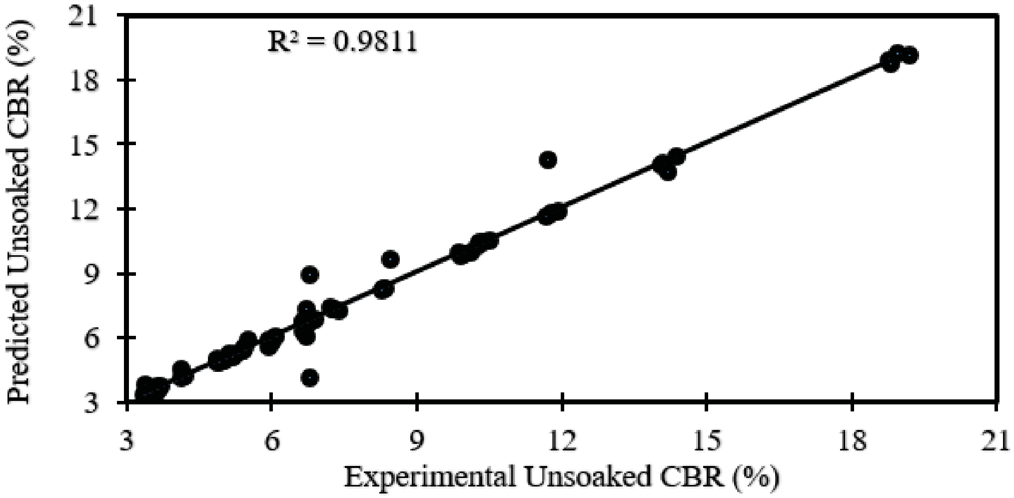

Figure 19: Variation of experimental and ANN predicted unsoaked CBR values

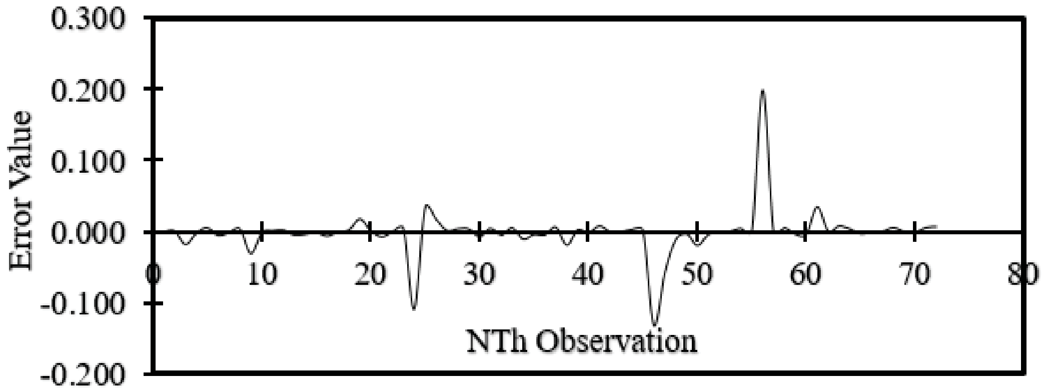

Figure 20: Variation of error values with number of observation for unsoaked CBR

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-n-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
Soaked CBI	R	> 0.8	0.9986	Satisfactory
	k	Should be close to 1	0.9973	Satisfactory
	MAE	Should be close to 0	0.008	Satisfactory
	MSE	Should be close to 0	0.00013	Satisfactory
	RMSE	Should be close to 0	0.00013	Satisfactory
Unsoaked CBR	R	> 0.8	0.991	Satisfactory
	k	Should be close to 1	0.9811	Satisfactory
	MAE	Should be close to 0	0.012	Good
	MSE	Should be close to 0	0.00109	Satisfactory
	RMSE	Should be close to 0	0.03298	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 soaked and unsoaked CBR 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.

CONCLUSION

Artificial neural networks (ANNs) was used in this study to develop a predictive optimized models for soaked and unsoaked CBR of a cement kiln dust-modified black clay. Based on the results of the developed ANN models, the following conclusions were made:

1. The multilayer perceptrons (MLPs) ANN used for the simulation of soaked and unsoaked CBR of CKD-modified black clay performed satisfactorily.
2. The mean absolute error (MAE), root mean square error (RMSE) and R-value were used as yardstick and criterions. In the neural network development, NN 8-7-1 and NN 8-17-1 respectively for soaked and unsoaked CBR that gave the lowest MSE value and the highest R-value were used in the hidden layer of the networks architecture and performed satisfactorily.
3. 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 0.9986 and 0.991 for the soaked and unsoaked CBR respectively. These values met the minimum criteria of 0.8 conventionally recommended for strong correlation condition.
4. All the obtained simulation results are satisfactory and a strong correlation was observed between the experimental soaked and unsoaked CBR values as obtained by laboratory tests and the predicted values using ANN.
5. A similar study is recommended for unconfined compressive strength test for flexible pavement construction.

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