Prediction of Durability, Resilient Modulus and Resistance Value of Cement Kiln Dust-Stabilized Expansive Clay for Flexible Pavement Application Using Artificial Neural Networks

Anigilaje B. Salahudeen, Mehdi Jalili, Danial R. Eidgahee, Kennedy C. Onyelowe, and Mohsen K. Kabiri

Abstract Artificial neural networks (ANNs) can be used in soil stabilization aspect of geotechnical engineering. As such, this study aimed at applying the ANNs as a soft computing approach to predict the durability, resistance value and resilient modulus of Nigerian expansive clay also called black cotton soil. A soft computing approach using multilayer perceptrons (MLPs) artificial neural networks (ANNs) that are trained with the feed forward backpropagation algorithm was used in this study for the simulation of some strength properties of cement kiln dust-stabilized expansive clay. For each of the three ANN model development, eight input for one output data set were used. The mean squared error (MSE) and *R*-value were used as yardstick and criterions for acceptability of performance. In the neural network development, NN 8-17-1, NN 8-24-1 and NN 8-18-1, respectively, for durability, resilient modulus and resistance value that gave the lowest MSE value and the highest combined *R*-value were used in the hidden layer of the networks architecture which performed satisfactorily except for resistance value. 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 0.8388, 0.8433 and 0.7572

A. B. Salahudeen (✉)
Department of Civil Engineering, University of Jos, Jos, Nigeria
e-mail: bunyamins@unijos.edu.ng

M. Jalili
Department of Civil Engineering, Islamic Azad University, Semnan Branch, Semnan, Iran
e-mail: m.jalili@semnaniau.ac.ir

D. R. Eidgahee
Department of Civil Engineering, Faculty of Civil Engineering, Semnan University, Semnan, Iran
e-mail: d.rezazade@semnan.ac.ir

K. C. Onyelowe
Department of Civil Engineering, Michael Okpara University of Agriculture, Umudike, Nigeria
e-mail: konyelowe@mouau.edu.ng

M. K. Kabiri
Department of Civil Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
e-mail: mohsen.kabiri@srbiau.ac.ir

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for the durability, resilient modulus and resistance value, respectively. The values by durability and resilient modulus met the minimum criteria of 0.8 conventionally recommended for strong correlation condition. A strong correlation was observed between the experimental values as obtained by laboratory test procedures and the predicted values using ANN.

Keywords Artificial neural networks · Cement kiln dust · Durability · Expansive clay · Flexible pavement · Resilient modulus · Resistance value

1 Introduction

California bearing ratio and unconfined compressive strength tests on soft soils are strength characteristics that are used for the determination of long-term performance and behavior of stabilized soils through loss of strength in moisture environment [1]. Durability, which is the ability to retain stability and integrity over years of exposure to adverse environment is one of the most important aspects of additive-based stabilized soil layers in pavement design [2]. The ability of a pavement layer to maintain desired properties over the life of a pavement is an important consideration. Variations in climatic conditions have been recognized as a major factor affecting pavement performance [3]. Cement kiln dust (CKD) was used in this study to stabilize expansive clay. 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 [4].

The resistance value (resistance to loss in strength under adverse field conditions) is an engineering property used to characterize materials in construction environments, especially in pavement construction. It measures the materials resistance to loss in strength when immersed in water. In most cases, foundation materials subjected to vertical loading suffer lateral deformation and the ability to withstand this form of failure is known as resistance value [5, 6]. The resistance value is determined in this study through the resistance to loss in strength of the soil specimen. Resilient modulus is used to characterize pavement materials under loading conditions that will not result in failure of the pavement system. Resilient modulus is a measure of elastic modulus of a material at a given stress and is expressed as the ratio of applied deviator stress to recoverable strain. AASHTO [7] pavement design guide requires the use of resilient modulus to represent the material strength of pavement layers. Therefore, an accurate measurement of resilient modulus is needed to ensure the efficiency and accuracy of the pavement design.

Artificial neural network (ANN) is an imitation of the human brain. An artificial thinking machine is really beyond the capacity of the most advanced supercomputers [8]. In recent times, artificial neural networks (ANNs) have been applied to many geotechnical engineering applications. Shahin et al. [9] have used back-propagation neural networks to predict the settlement of shallow foundations on cohesionless soils. The results indicated that ANNs are a promising method for predicting settlement of shallow foundations. Kolay et al. [10] made use of ANN in predicting the compressibility characteristics of soft soil settlement in Sarawak, Malaysia. Benali et al. [11] used ANNs for principal component analysis and prediction of the pile capacity based on SPT results. ANNs were used by Salahudeen et al. [12] 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, also known as black cotton soils or 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 [13, 14]. The absence of quartz in the clay mineralogy enhances the formation of fine-grained soil material, which is impermeable and waterlogged. 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 occupy an estimated area of 104×10^3 km^2 in north-east region of Nigeria. Cracks measuring 70 mm wide and over 1 m deep have been observed and may extend up to 3 m or more in case of high deposit [15].

Durability and resistance value are usually determined from unconfined compressive strength (UCS) test. The resilient modulus of soil is typically determined using the repeated load triaxial test. However, these tests require a well-trained personnel and expensive laboratory equipment. In addition, they are considered to be relatively time consuming [16]. Alternatively, these parameters can be predicted accurately using artificial neural networks (ANN) simulations since they are related to several index properties of soil, such as the particle size, Atterberg's limits and compaction characteristics. This study aimed at using index soil properties to develop an optimized neural network for durability, resilient modulus and resistance value (resistance to loss in strength) using artificial neural networks (ANNs).

2 Materials and Methods

2.1 Materials

The expansive clay soil 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.

2.2 Methods

Laboratory Tests. Laboratory tests were performed on the natural soil samples in accordance with BS 1377 [17] and on the cement kiln dust-treated expansive clay in accordance with BS 1924 [18]. The tests conducted include particle size distribution, specific gravity, linear shrinkage, Atterberg's limits, compaction characteristics test to determine the OMC and MDD, California bearing ratio and unconfined compressive strength (UCS) test. 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 with three compactive energies of British Standard Light (BSL), West African Standard (WAS) and the British Standard heavy (BSH) energies. This assisted in generating the huge database needed for the ANN simulation. The three target parameters were obtained from Eq. 1–3.

$$\text{Durability (kPa)} = \text{UCS}(7\,\text{days cured} + 7\text{days soaked}) \tag{1}$$

$$\text{Resilient Modulus (MPa)} = 1500 \times \text{soaked CBR} \tag{2}$$

$$\text{Resistance Value}(\%) = \frac{\text{UCS}(7\,\text{days cured} + 7\text{days soaked})}{\text{UCS}(14\,\text{days cured})} \times 100 \tag{3}$$

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 backpropagation algorithm. 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 use the following transfer or activation function:

$$X = \sum_{i=1}^{n} x_i w_i \quad Y = \begin{cases} +1, & \text{if } X \geq \theta \\ -1, & \text{if } X < \theta \end{cases} \tag{4}$$

The output of one processing element provides the input to the next processing elements. 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 durability, resilient modulus and resistance value (resistance to loss in strength). The multilayer perceptron architecture of networks used for the ANN model development is shown in Fig. 1.

Data Division and Processing in Artificial Neural Network. In developing the ANN model, the available data were randomly divided into three sets: a training set

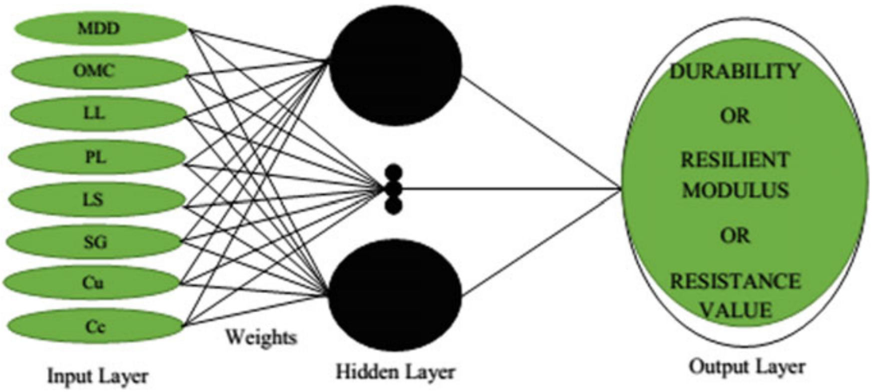


Fig. 1 Multilayer perceptron architecture of ANN network

(70%) for model calibration, a testing set (15%) and an independent validation set (15%) for model verification. Once available data are divided into their subsets, the input and output variables were pre-processed, and 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. 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:

$$R = \frac{\sum_{i=1}^{N}(O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{N}(O_i - \overline{O})^2 \sum_{i=1}^{N}(P_i - \overline{P})^2}} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}} \tag{6}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|O_i - P_i| \tag{7}$$

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 $\overline{O}$ and $\overline{P}$ are the mean of observed and predicted outputs, respectively.

3 Results and Discussions

3.1 Data Processing for ANN

In ANN prediction modeling, 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 Figs. 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12.

Fig. 2 Frequency of SG

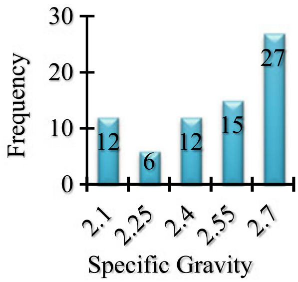


Fig. 3 Frequency of LS

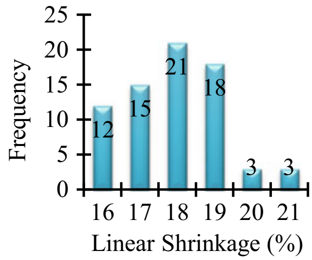


Fig. 4 Frequency of C_u

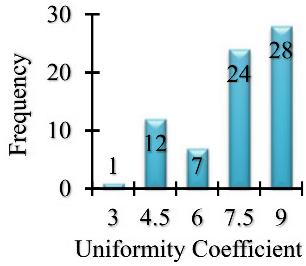


Fig. 5 Frequency of C_c

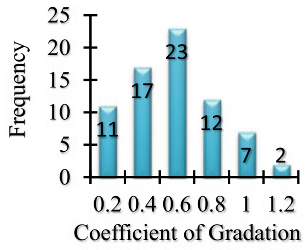


Fig. 6 Frequency of LL

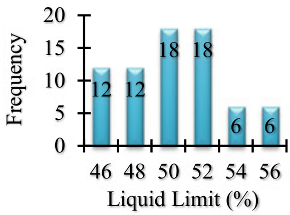


Fig. 7 Frequency of PL

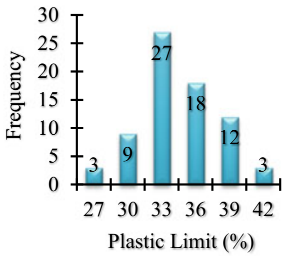
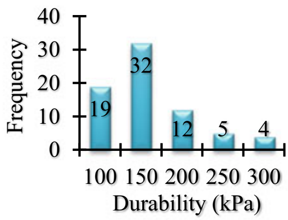


Fig. 8 Frequency of durability



3.2 *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.

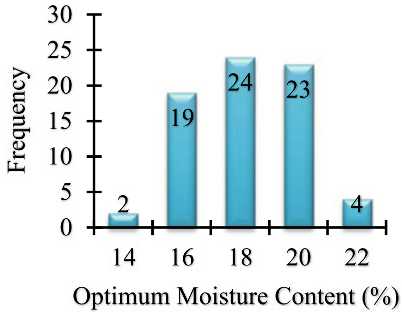


Fig. 9 Frequency of OMC

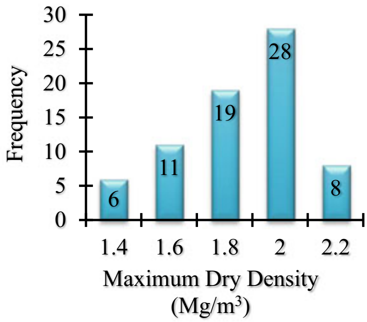


Fig. 10 Frequency of MDD

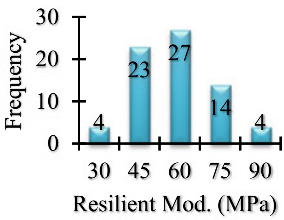


Fig. 11 Frequency of resilient modulus

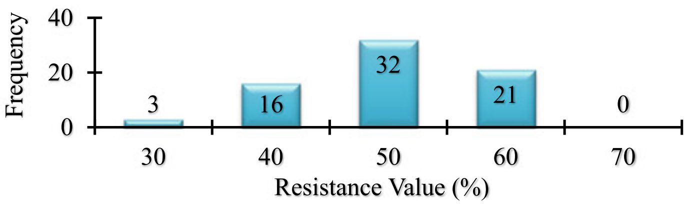


Fig. 12 Frequency of resistance value

These NN 8-n-1 network architectures are shown in Figs. 1, 2 and 3. In this study, 21 different number of hidden nodes (NN 8-5-1 to NN 825-1) 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 5–25 neurons was based on recommendations in the literature [10, 12, 19, 20] in which it was concluded that the use of neuron number below or above certain limit could cause insufficient or saturation of the network which results to lesser quality simulated results due to undesirable feedbacks to the network. Therefore, $n = 17$, $n = 24$ and $n = 18$ neurons, respectively, for durability, resilient modulus and resistance value that yielded low MSE values and the highest *R*-value on the average were used in the hidden layers of the three sets of target predicted. Eidgahee et al. [20] 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. [19] used only MSE values as criterion. It was observed, however, in this study, that the best criteria for reliable choice of the neuron numbers to yield better results is the combined (all) *R*-value that has a reasonably low MSE value and not necessarily the lowest.

3.3 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 1. It is obvious from these statistical results that the models developed in this study performed satisfactorily having high *R*-values and low error values except for that of resistance value which yielded a

Table 1 Parameters and regression values for model performance evaluations

Parameters	Durability	Resilient modulus	Resistance value
Number of neurons	17	24	18
k	0.7013	0.7067	0.404
MSE (ANN)	0.026279	0.011704	0.089317
R-training	0.9908	0.9291	0.954
R-validation	0.8529	0.9032	0.5934
R-testing	0.6359	0.6403	0.2652
R-all data	0.8388	0.8433	0.7572
MAE	0.065	0.081	0.106
MSE (statistical)	0.012583	0.014466	0.023682
RMSE	0.112	0.12	0.154

poor performance. The statistical parameters give acceptable results that confirmed the best generalization of the developed models for durability and resilient modulus.

The variation of experimental and ANN predicted UCS values are shown in Figs. 13, 14 and 15. The performance of the simulated networks for durability and resilient modulus were satisfactory having *k* values of 0.7013 and 0.7067, respectively. *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 Golbraikh and Tropsha [21] and Alavi et al. [22] that the value of *k* should be close to unity as a criterion for excellent performance. The poor performance of the simulated networks for resistance value may be due to the fact that it depends on two different UCS tests—7 days curing and 7 days soaking on one hand and then 14 days curing of a different sample on the other hand. This is not the case in durability and resilient modulus which depend on a single UCS and CBR tests, respectively.

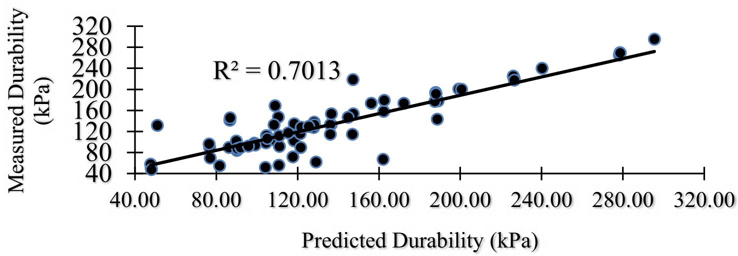


Fig. 13 Variation of experimental and ANN predicted durability

Fig. 14 Variation of experimental and ANN predicted resilient modulus

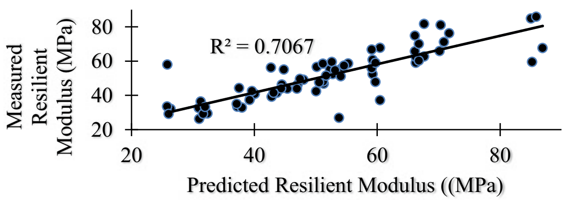
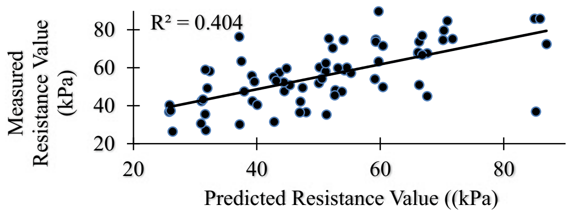


Fig. 15 Variation of experimental and ANN predicted resistance value



3.4 Model Validation

The coefficient of correlation (*R*-value) is a measure used to evaluate the relative correlation and the goodness-of-fit between the predicted and the observed data. Salahudeen et al. [2] suggested that a strong correlation exist between any two set of variables if the *R*-value is greater than 0.8. However, Kolay et al. [10] 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 toward 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, Salahudeen et al. [12] 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 the 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 2. Based on the results of different NN 8-17-1, NN 8-24-1 and NN 8-18-1 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 0–1.

Table 2 Conditions of model validity

Target	Statistical parameter	Condition	Obtained value	Remarks
Durability	*R*	>0.8	0.8388	Satisfactory
	k	Should be close to 1	0.7013	Good
	MSE	Should be close to 0	0.012583	Satisfactory
	MAE	Should be close to 0	0.065	Satisfactory
	RMSE	Should be close to 0	0.112	Good
Resilient modulus	*R*	>0.8	0.8433	Satisfactory
	k	Should be close to 1	0.7067	Good
	MSE	Should be close to 0	0.014466	Satisfactory
	MAE	Should be close to 0	0.081	Satisfactory
	RMSE	Should be close to 0	0.12	Good
Resistance value	*R*	>0.8	0.7572	Poor
	k	Should be close to 1	0.404	Poor
	MSE	Should be close to 0	0.023682	Good
	MAE	Should be close to 0	0.106	Poor
	RMSE	Should be close to 0	0.154	Good

Based on the suggestion of Naderpour et al. [19], argument of Salahudeen et al. [12], conclusions of Shahin [9] and observations in this study, it is obvious from Table 2 that the developed models in this study for durability and resilient modulus 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 values as obtained by laboratory tests and the predicted values using ANN. Eidgahee et al. [20] reported that strong correlation exists between the experimental and predicted values if the *R*-value is greater than 0.8 and the MSE values are at minimum. The results obtained for durability and resilient modulus in this study can therefore be concluded to be satisfactory and yielded good simulation results.

4 Conclusion

Artificial neural networks (ANNs) were used in this study to develop predictive optimized models for durability, resilient modulus and resistance value of cement kiln dust-treated expansive 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 durability and resilient modulus of CKD-treated expansive clay that are trained with the feed forward backpropagation algorithm performed satisfactorily.
2. 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 8-17-1 and NN 8-24-1, respectively, for durability and resilient modulus that gave the low MSE values and the highest *R*-values were used in the hidden layer of the networks architecture which performed satisfactorily.
3. For the normalized data used in training, testing and validating the neural network, the performance of the simulated networks for durability and resilient modulus was very good having *R*-values of 0.8388 and 0.8433 for durability and resilient modulus, respectively. These values met the minimum criteria of 0.8 conventionally recommended for strong correlation condition.
4. The obtained simulation results for durability and resilient modulus are satisfactory and a strong correlation was observed between the experimental values as obtained by laboratory tests and the predicted values using ANN. The simulation results of resistance value performed poorly and yielded unacceptable result generally.

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