PREDICTING THE CALIFORNIA BEARING RATIO OF CEMENT-TREATED LATERITES SOIL STABILIZED WITH RICE HUSK ASH USING ARTIFICIAL NEURAL NETWORK MODELS

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ABSTRACT

With increase in human population, waste generation has also increased. Effective disposal of these wastes has been a problem, it is in this light that economic use of these waste such as rice husk has been in the fore-burner. Combustion of rice husk produces rice husk ash (RHA), a pozollanic material, which can be effectively used in partial replacement of the expensive cement in soil stabilization. Also, since carrying out of fundamental tests such as California bearing ratio (CBR) in road construction is time consuming, thus, resulting to reduced efficiency, developing of credible models such as the Artificial neural network (ANN) becomes imperative. In going about this, the soil sample was subjected to preliminary tests, such as; particle size distribution, atterbergs limits and specific gravity tests for purpose of classification. Thereafter, cement at varying proportions of 0-12% at 2% intervals was mixed with RHA in proportions of 0-16% at 2% intervals. The mixes at each stage was subjected to compaction, atterberg limits and CBR tests. The laboratory results served as inputs in developing the ANN model, which predicted both soaked and the unsoaked CBR results. The feed forward neural network with Levenberg-Marquardt back propagation ANN model of MATLAB training was employed to determine the best model. It can therefore be concluded that the ANN models developed can adequately predict the CBR values of cement-treated A-7-5 soil stabilized Rice husk ash (RHA).

Keywords: Artificial neural network, california bearing ratio, ordinary Portland cement, laterites, rice husk ash

1. Introduction

Lateritic soils are commonly used for road construction in Nigeria. Lateritic soil in its natural state sometimes have low bearing capacity and low strength due to high content of clay. When lateritic soil contains a huge amount of clay materials, its strength and stability cannot be guaranteed under load in presence of moisture [1]. Also, when a weak soil is encountered on a site and sourcing for alternative soil proves economically unviable, improving the soil by way of stabilization to meet the desired objective becomes the viable option [2, 3, 4]. Popular industrial stabilizers are cement, lime, flyash and bitumen. Furthermore, the high cost of cement being used as binder, has led to the search for natural materials as either alternative or complement. Research on alternative or complement to cement has so far centered on the partial replacement of cement with different materials [5]. The improvement in the strength and durability of lateritic soil in recent times has become imperative, this has geared researchers towards using stabilizing materials that can be sourced locally at a very low cost [1]. These local materials can be grouped as either agricultural or industrial wastes [6]. In light of this, cheap agricultural waste such as rice husk ash is being studied as replacements for the more expensive cement.

Rice is one of the most cultivated and consumed cereal in the world. In rice producing countries, a traditional waste material known as 'rice husk' is obtained as a by-product in bulk amount from Rice mills. Globally, approximate 600 million tonnes of rice paddies are produced each year. On the average, 20% of the paddy is husk, giving an annual total production of 120 million tonnes. [7,8]. Rice husk is a by-product from agriculture produce when it is harvested, the outermost part of the paddy is the rice husk, also called the rice hull. It is separated from the brown rice in rice milling. Complete burning of rice husk results to rice husk ash (RHA), so for every 1000 kg of paddy milled, about 220 kg (22%) of husk is produced and when the husk is burnt in boilers, about 55 kg (25%) of RHA is generated, if the burning is incomplete, the carbonized rice husk (CRH) is obtained [9]. In line with the Federal Government's drive for Nigeria to be self-sufficient in rice production and to save hundreds of billions of naira annually on rice importation, local rice production has reached 15 million metric tonnes [10], this, in turn has resulted to increased generation of rice husk as waste. Stabilization enhances the desired qualities of a soil [11], chiefly among these, is the California bearing ratio (CBR), a standard for measuring the strength of a given soil in road construction. The design of flexible pavement is much dependent on the CBR of subgrade. CBR values can be measured in the laboratory test in accordance with BS 1377 [12 13,14]. The CBR test performed in the laboratory is time-consuming, a laboratory test generally takes four or more days to measure the soaked CBR value for each soil sample. The result of the tests is actually an indirect measure, which represents comparison of the strength of subgrade material to the strength of standard crushed rock referred in percentage values. Instead, it can be predicted from properties of soils determined in the laboratories. Several studies have been conducted to estimate CBR from Liquid limit, Plasticity Index, standard proctor parameters, the use of artificial neural network has so far held high promises in achieving this [15, 16]. In light of this, developing credible predictive models has been in the fore-burner, the use of artificial neural network (ANN) is fast gaining ground especially in the field of geotechnical engineering [17, 18, 19,20].

[15]. ANN is a massively parallel –distributed information processing system that has certain performance characteristics resembling biological neural networks of human brain [21]. ANNs have been developed as a generalization of mathematical models of human cognition or neural biology. The key element of ANN is the novel structure of its information processing system. An ANN is composed of a large number of highly interconnected processing elements called neurons working in unison to solve specific problems. Neurons having similar characteristics in an ANN are arranged in groups called layers. A way of classifying neural networks is by the number of layers as single, bilayer and multilayer. ANNs can also be categorized based on direction of information flow and processing The main benefits of the ANN according to Khademikia *et al.,* [22] in comparison to other modeling programs are the nonlinearity, adaptively, fault tolerance, uniformity and design.

In recent times, the increase in population has led to the generation of more wastes such as the rice husk, thereby necessitating the need for proper management of these wastes. It is however worthy of note that there is yet to be adequate awareness on the usefulness of these aforementioned wastes in Nigeria, in other words, little or no importance is attached to them. The practice of incinerating them to ash and adopting them as admixtures in stabilized soils due to their pozzolanic values has enhanced their economic value [23]. Also, for greater efficiency in management of time and manpower, the need for developing models in predicting California bearing ratio (CBR) an important parameter in road construction has become imperative. This is expected to address the problems of unnecessary delays at the laboratories and human errors, which can negatively impact on the project.

2. Materials and Methods

Materials The materials used were: rice husk ash, soil samples, ordinary Portland cement and water.

Rice Husk Ash (RHA): The rice husk ash was burnt in open atmosphere and the black ashes obtained were heated in an air tight furnace for 6 hours at 1000^0C to obtain a white coloured ash.

Soil Sample: Soil Sample was collected along Oye-Ekiti – Isan-Ekiti Road, Nigeria at a depth not less than 1.2m below the ground level at 5 different points of about 3m apart using the disturbed sampling technique. It was brought to the soil laboratory and marked indicating the soil description, sampling depth and date of sampling. The soil sample was air-dried for two weeks to allow for partial elimination of natural water content which may affect the analysis, then sieved with sieve no 4 (4.75mm opening) to obtain the final soil sample for the tests. After the drying period of two weeks, lumps in the sample were pulverized under minimal pressure.

Ordinary Portland Cement: This was obtained from a cement store.

Water: The water used was obtained from the running taps in the laboratory, the source was borehole. Distilled water was not used so as to obtain results that would reflect in-situ conditions.

Methods

Determination of the chemical composition of the rice husk ash and soil sample were determined by means of gravimetric method.

The soil sample was subjected to preliminary tests, such as the particle size distribution, specific gravity and Atterberg limits. The natural soil samples were also subjected to compaction tests and the California bearing ratio (CBR).

The soil samples were later treated with cement at values of 0, 2, 4, 6, 8, 10 and 12% which were separately mixed with rice husk ash (RHA) at varying proportions of 2, 4, 6, 8, 10, 12, 14 and 16%. These samples were each subjected to Atterberg limits, compaction and California bearing ratio. The entire tests were carried out according to BS 1377 [12] for natural soil samples and British Standard 1924 [24] for stabilized samples.

Results from the laboratory tests especially that of the liquid limit, plasticity index, maximum dry density, optimum moisture content, the percentages of cement and rice husk ash served as inputs which were employed in developing the Artificial neural network (ANN) model for predicting soaked and unsoaked CBR values of the stabilized soils.

The Artificial Neural Network Design Procedure

The design and deployment of the Artificial Neural Network (ANN) for this research work was divided into six (6) major stages, namely: data acquisition stage; feature selection and data normalization stage, ANN architecture optimization stage, the ANN algorithm optimization stage, ANN initialization and training stage, testing, validation and deployment stage. Feed Forward neural network with Levenberg-Marquardt back propagation ANN model of MATLAB training was used for the computation of data and to determine the best model. The neural network tool box of MATLAB was used for necessary computation required for the development of the models. The Coefficient of Correlation (R) and the Root Mean Square Error (RMSE), were employed to determine the degree of correlation between the target of the soft computing models and their eventual outputs. The six input variables were cement (%), Rice Husk Ash (RHA) (%), Liquid Limit (LL) (%), Plasticity Index (PI) (%), Maximum Dry Density (MDD) (Kg/m^3) , and OMC (%), while CBR Unsoaked (%) and CBR Soaked (%) were the output variables. From the experimental results, 322 set of soil data were obtained, the data were subdivided into 70% for training, 15% for testing and 15% for validation. Table 1 shows details of the components of the ANN model.

Table 1: Details of components of the ANN model.

Number of inputs	6
Number of outputs	2
Number of hidden layer neurons	10
Number of output layer neurons	2
Number of epochs	21

Data division

The randomized data was grouped into training, testing and validation datasets. Training dataset was used to arrive at potentially predictive relations. It is a set of examples employed for learning, that is, to fit the parameters (that is, weights) of the classifier. A test dataset was used to evaluate the strength and utility of a predictive relationship, it is a set of examples used only to measure the performance (generalization) of a fully-specified classifier. So as to avoid overfitting, it was imperative to have a validation set in addition to training and testing sets.

Data normalization

The data normalization operation was carried out in order to eliminate the chance of input weight bias. This enables the network to assign equal importance to several values of input regardless of their magnitude.

Statistical performance indices

This is for the purpose of precision and accuracy. It involves the using the coefficient of determination (R^2) and Root Mean Square Error (RMSE).

The ANN training algorithm

The algorithm employed was the Levenberg-Marquardt (LM). Levenberg-Marquardt (LM) Algorithm is a second order algorithm that trains a network by repeated update of network weights and biases by an optimization technique. The algorithm (which is essentially a trust region type of the Gauss-Newton method) is fast, efficient and often the most recommended choice in supervised training.

Results and Discussions

Table 2 shows the chemical composition of the soil sample, RHA and the ordinary Portland cement by percentage weight composition. According to Ola [16], if silica (SiO_2) to sesquioxide (Fe_2O_3 + Al_2O_3) ratio of a given soil sample is less than 1.33, the soil sample can be said to laterites, if it is between 1.33 and 2.0, it can be said to be lateritic soil, and if it is above 2.0, it is non-lateritic soil. The silica to sesquioxide ratio of the soil sample is 1.28. It therefore means that the soil sample is laterite soil.

Furthermore, RHA passes for pozzolanic materials. According to ASTM C618 [25], a material can pass for a pozzolan if the sum by addition of weight percentages of Fe_2O_3, Al_2O_3 and SiO_2 equal at least 70%. Table 2, under RHA, the sum of SiO_2, Al_2O_3 and Fe_2O_3, equals 86.88. This additive (RHA) is a pozzolan. Also, Table 2 shows the elemental oxides in the ordinary Portland cement used for this study. The constituents clearly shows that the cement meets the stipulated standards as spelt out in the Nigerian Standards NIS 367 [26] and NIS 368-2 [27].

Table 2: Chemical Composition of Soil sample, RHA and Cement

Elemental Oxide	Soil sample	RHA (%)	Cement (%)
SiO_2	54.1	80.30	21.60
Al_2O_3	42.10	2.68	5.90
Fe_2O_3	0.011	3.90	2.70
CaO	0.004	3.00	64.32
MgO	-	1.68	1.72
LOI	-	12.74	1.17

Table 3 shows that the liquid limit value for the soil sample is 62.8%, while its plasticity index is 28.7%. For soil sample to be classified into the A-7-5 subgroup; plasticity index$\leq LL - 30; 28.7 \leq 62.8 - 30 = (32.8)$. The soil sample therefore falls into the A-7-5 subgroup, also, based on the plasticity chart, A-7-5 soil sample is of high clay content (CH), soils with liquid limit values of more than 50% are of high clay content [28].

Table 3: Summary preliminary results of Soil sample B

Properties	Results
Natural Moisture Content (%)	10.42
Liquid Limit (%)	62.8
Plastic Limit (%)	34.1
Plasticity Index (%)	28.7
Specific gravity	2.65
Percentage passing No. 200 Sieve	36.5
AASHTO Classification	A-7-5
USCS Classification	CL
Maximum Dry Density (Kg/m^3)	1452
Optimum Moisture Content (%)	15.2
California Bearing Ratio (Soaked) (%)	4.0
California Bearing Ratio (Unsoaked) (%)	7.4
Colour	Reddish-Brown

Artificial Neural Network (ANN) Results

Figures 1 to 14 show the testing results of the observed (laboratory tests results) and ANN predicted values of unsoaked and soaked CBR of natural soils (A-7-5) and cement-treated soils separately stabilized with Rice husk ash. These values clearly signify the high precision and accuracy of the ANN models [15].

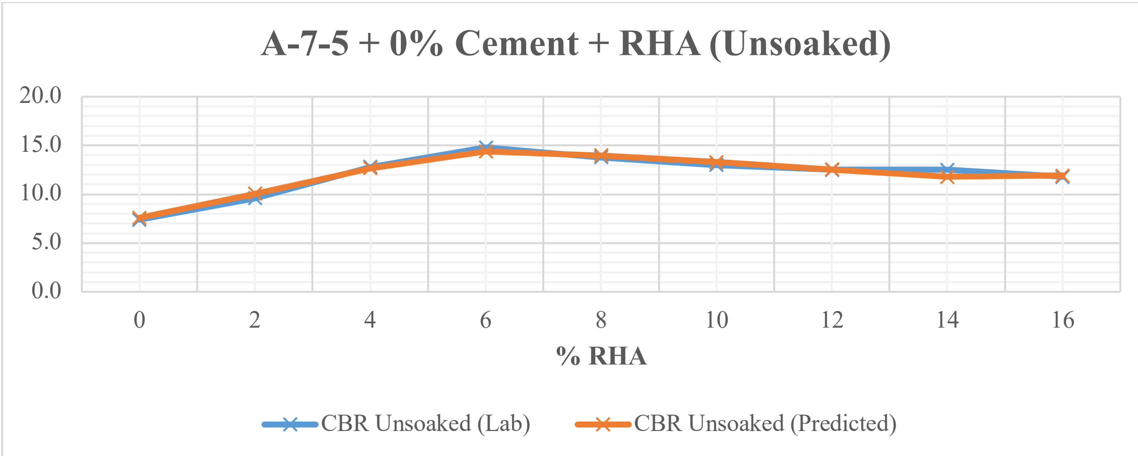

Figure 1. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA +0% cement

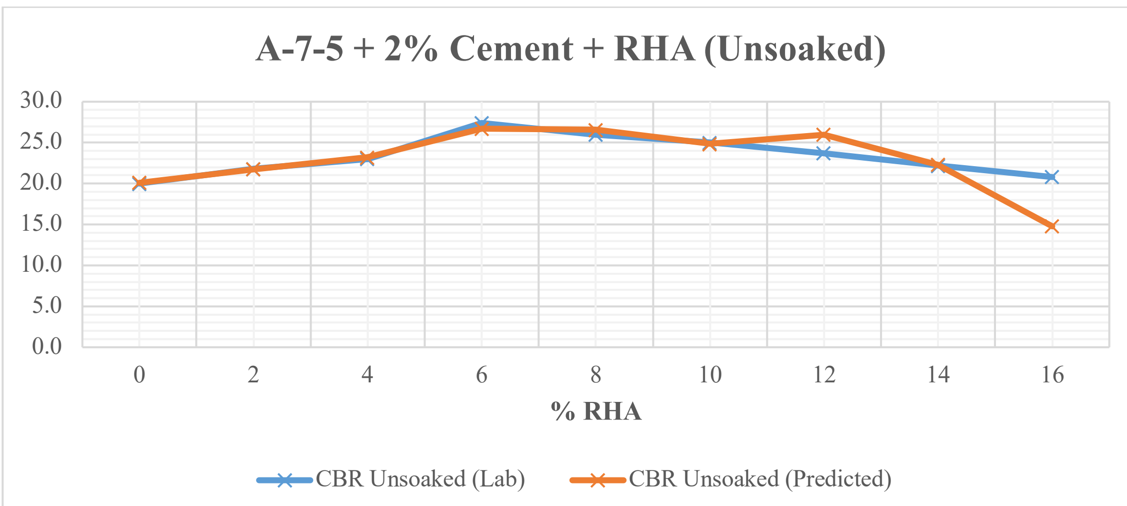

Figure 2. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA + 2% cement

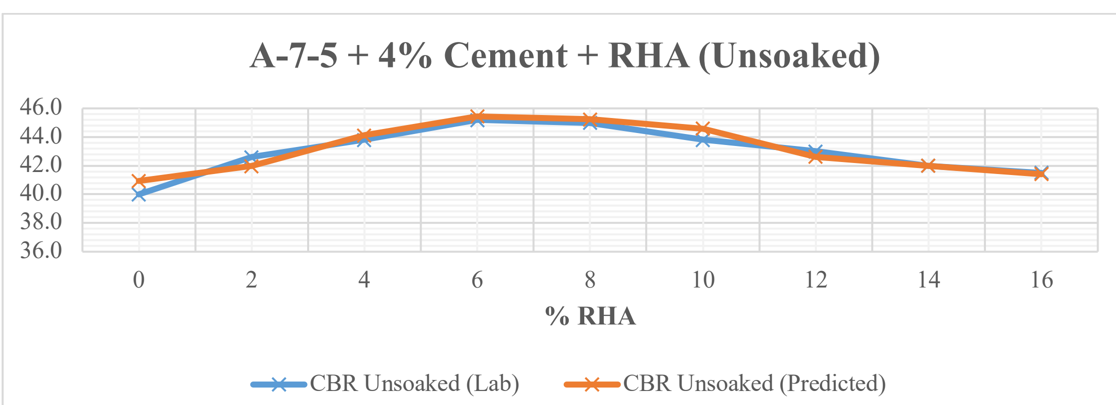

Figure 3. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA +4% cement

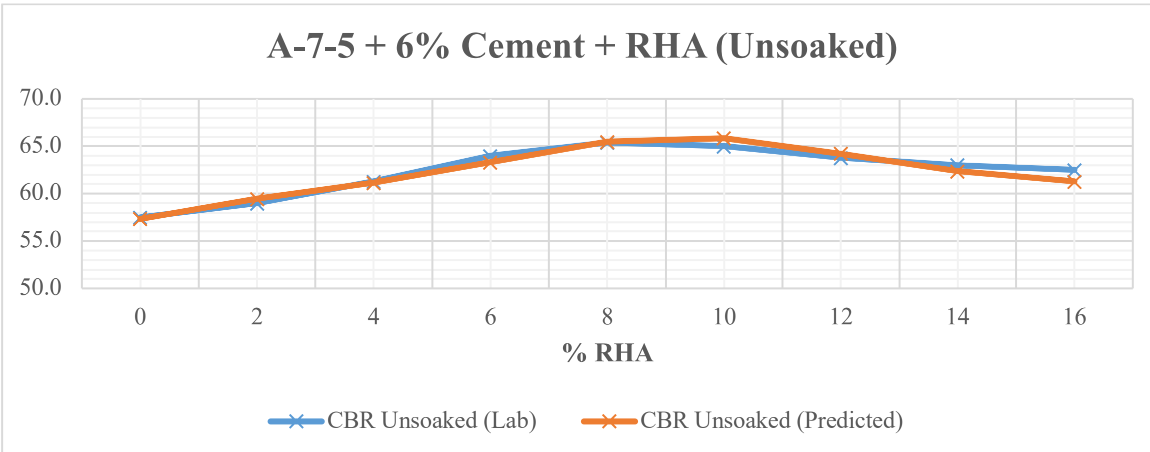

Figure 4. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA +6% cement

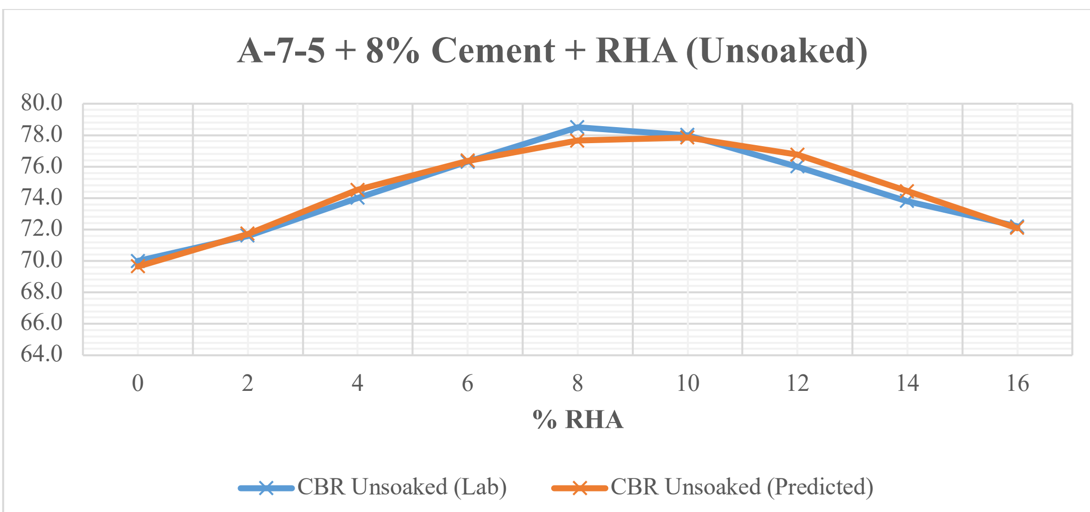

Figure 5. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA +8% cement

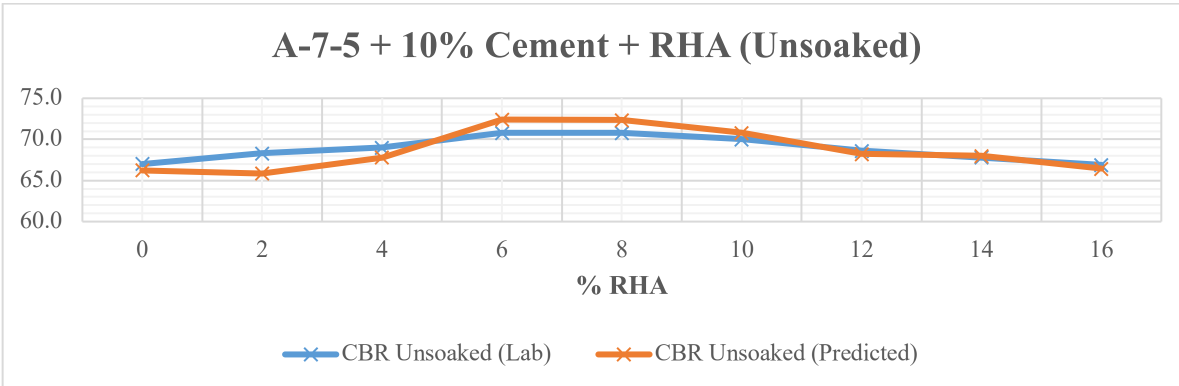

Figure 6. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA + 10% cement

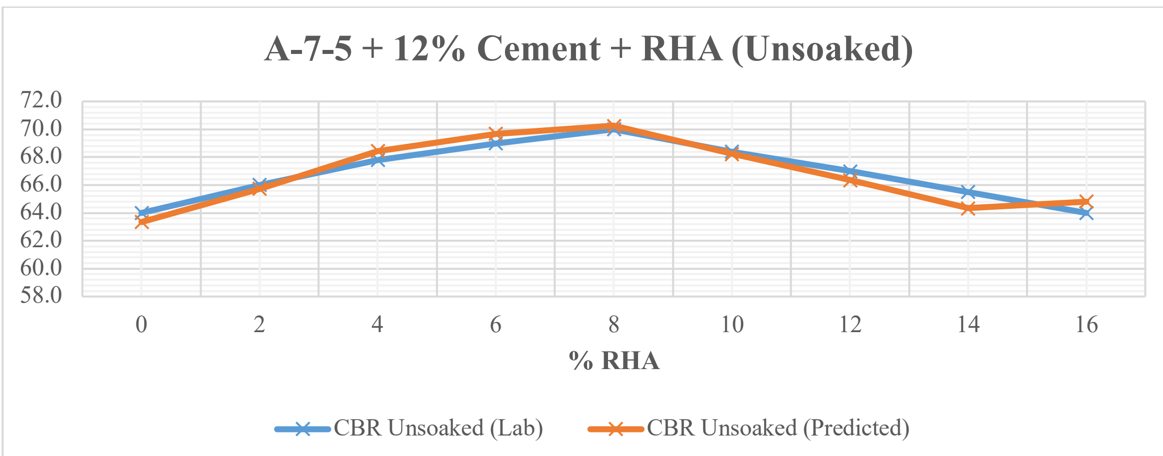

Figure 7. Comparison between observed (lab) and predicted unsoaked CBR values of A-7-5 + RHA + 12% cement

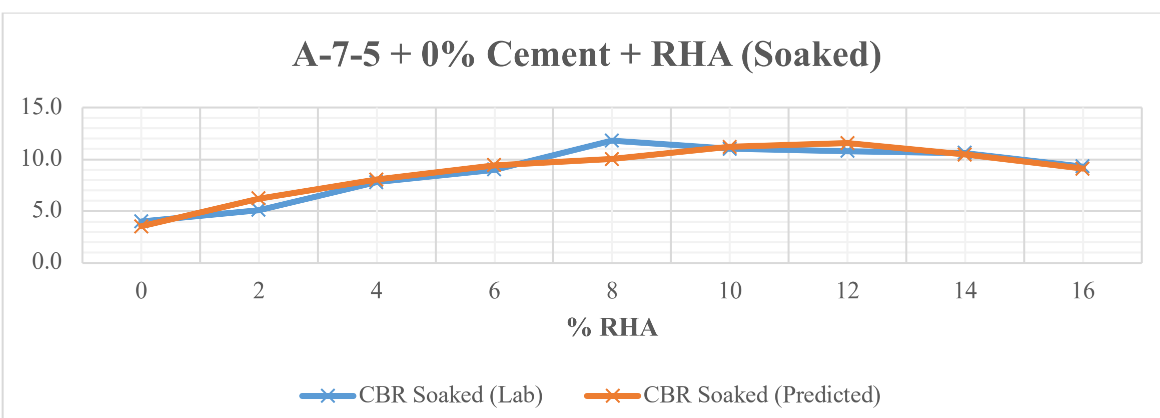

Figure 8. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 0% cement

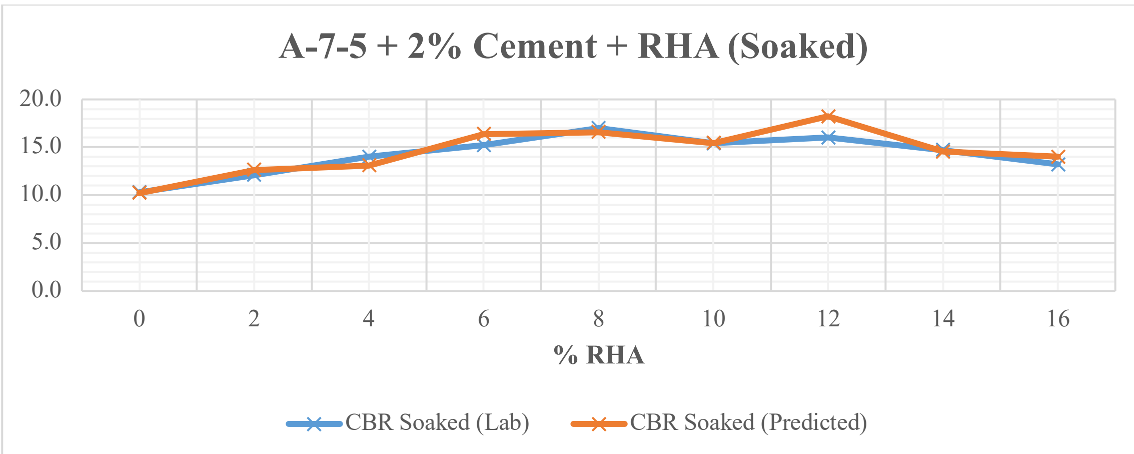

Figure 9. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 2% cement

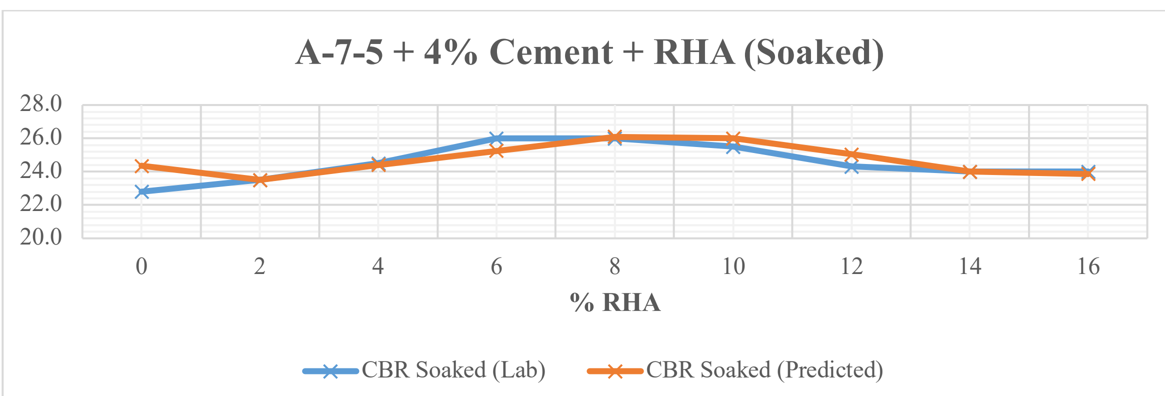

Figure 10. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 4% cement

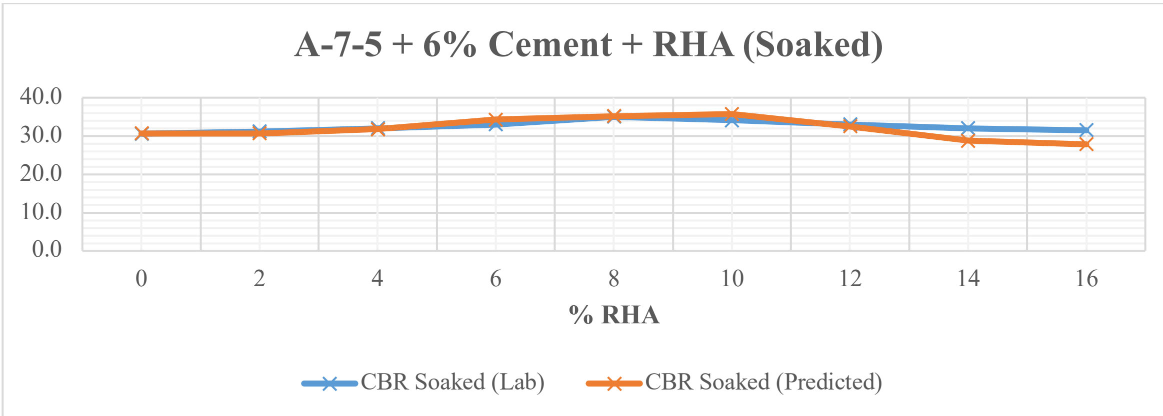

Figure 11. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 6% cement

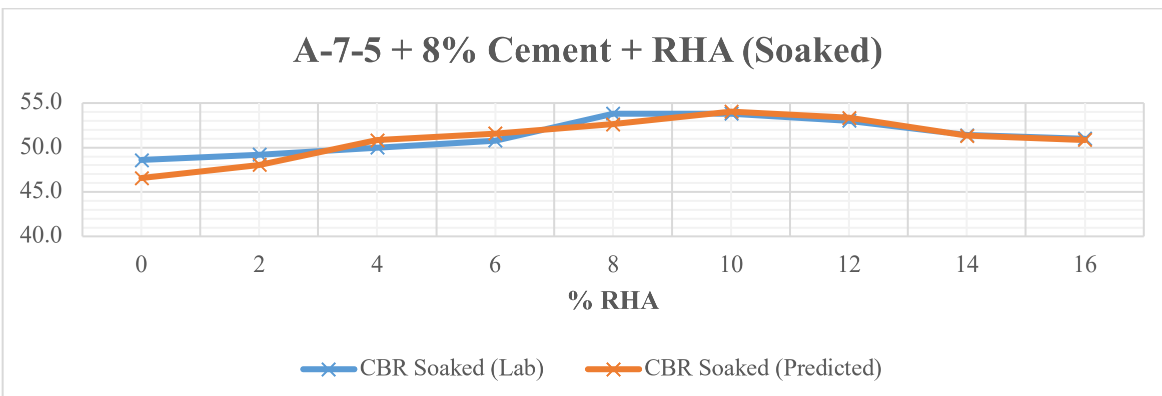

Figure 12. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 8% cement

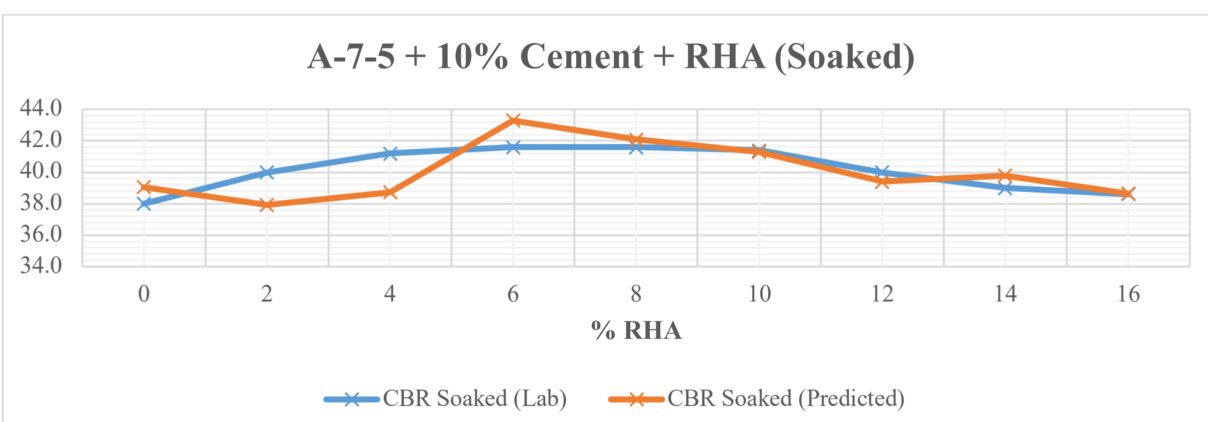

Figure 13. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 10% cement

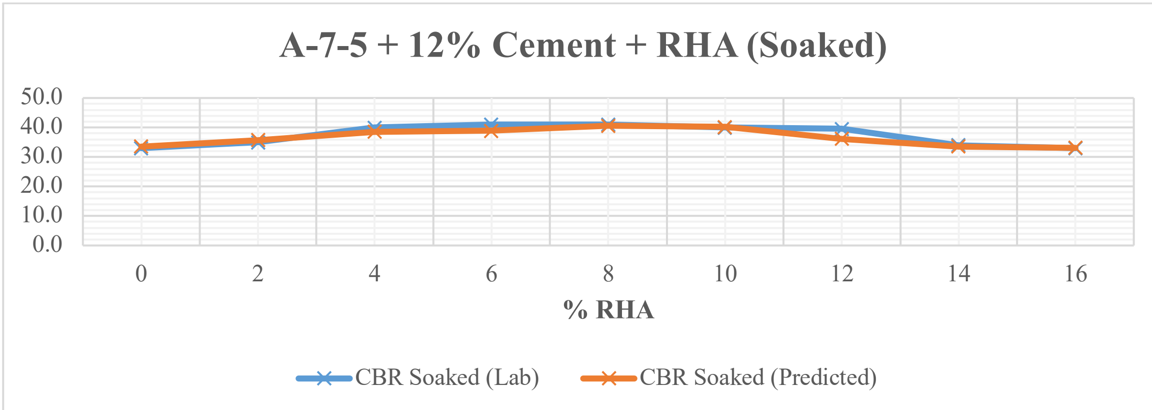

Figure 14. Comparison between observed (lab) and predicted soaked CBR values of A-7-5 + RHA + 12% cement

Regression plots for ANN Modelling results for Rice Husk Ash and A-7-5 soil

Figures 15 to 17 show regression plots between observed and predicted California bearing ratio (CBR) values of the A-7-5 soil stabilized with RHA and cement. Figure 15 shows the predicted (output) and measured (observed) values for training dataset during training stage of ANN model. Figure 16 shows the predicted and target values for testing dataset during testing stage of ANN model. Figure 17 shows the predicted (output) and target (observed) values for validating dataset during validating stage of ANN model. Performance of the neural network as indicated by coefficient of correlation (R^2) at training, testing and validation stages were; 0.99948, 0.9878 and 0.99608 respectively. According to Smith [29], if $R \geq 0.8$, strong correlation exists between two sets of variables. As R-value is 0.99, hence, the model is efficient model for prediction of CBR values.

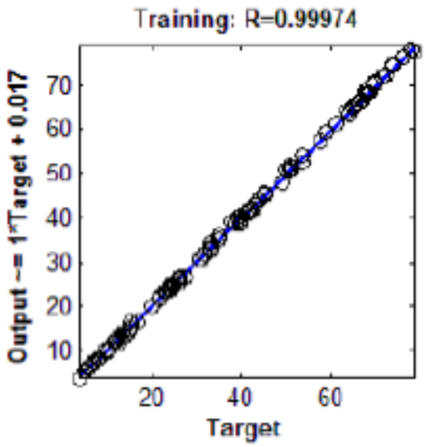

Figure 15. The regression plot showing the predicted (output) and target (observed) values for training dataset during training stage of ANN model (RHA and A-7-5 and cement).

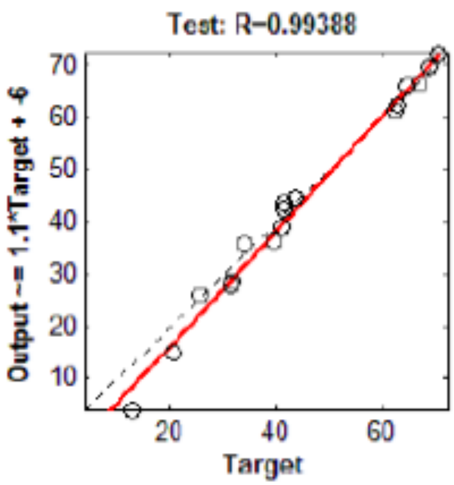

Figure 16. The regression plot showing the predicted (output) and target (observed) values for testing dataset during testing stage of ANN model (RHA and A-7-5 and cement).

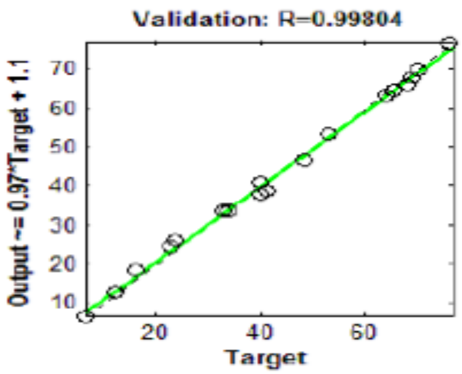

Figure 17. The regression plot showing the predicted (output) and target (observed) values for validation dataset during validation stage of ANN model (RHA and A-7-5 and cement).

Figure 18 shows the training performance. Generally, the error reduces after more epochs of training, but might start to increase on the validation data set as the network starts overfitting the training data in the default setup, the training stops after six consecutive increases in validation error and the best performance is taken from the epoch with the lowest validation error [30].

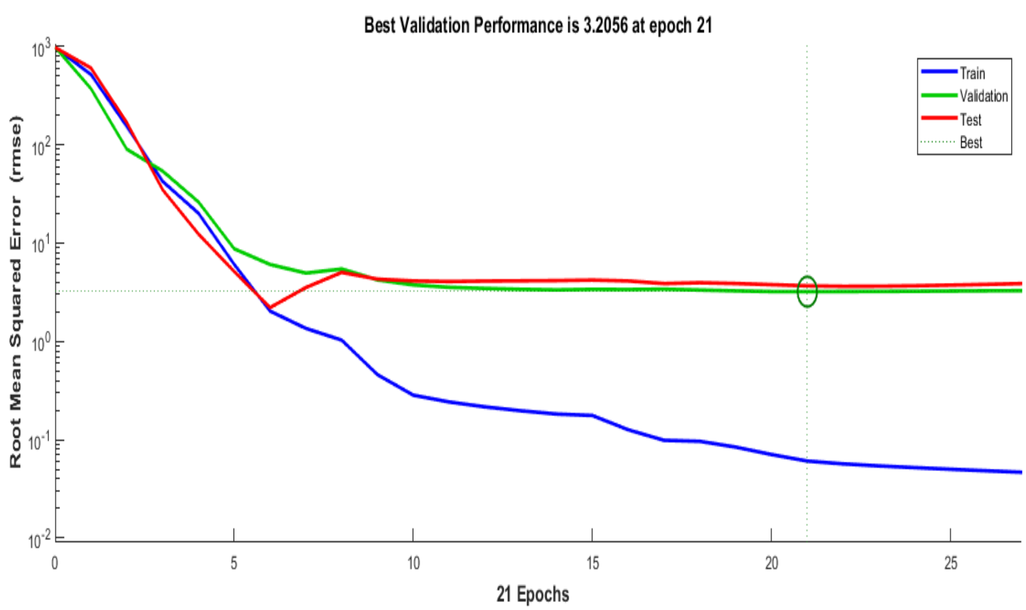

Figure 18. Training performance of the ANN training

Summary of Root Mean Square Error (RMSE) and Coefficient of Correlation (R) results of the ANN modelling.

Table 4 shows the summary of Root Mean Error (RMSE) and Coefficient of Correlation results of the ANN modelling, results on the basis of its closeness to one (1) clearly demonstrated the high precision of the model [29].

Table 4: Summary of Root Mean Square Error (RMSE) and Coefficient of Correlation (R) results of the ANN modelling

A75 +RHA			
	Training	**Validation**	**Testing**
RMSE	0.9949	0.9990	0.9969
R	0.9997	0.9980	0.9939

Conclusion

(i) Based on the index properties, the soil sample was classified to be A-7-5 in the AASHTO rating and in the Unified Soil Classification System, the soil sample was CH respectively, also, on the basis of the chemical composition of the soil, the soil samples was classified as laterite. Chemical composition of RHA showed that it was pozollan;

(ii) The addition of the RHA improved soil sample's properties, the addition of cement further improved the properties of the soil;

(iii) There are optimum amounts (RHA and Cement) of additives for effectively stabilizing the soil sample;

(iv) The ANN models developed can adequately predict the CBR values of cement-treated A-7-5 soil stabilized with Rice husk ash (RHA).

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